Loan Loss Provisions, Non-Performing Loans and Cost Efficiency: Evidence from Greece

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Abstract

This Thesis is a both timely and warranted examination of 'risk management behaviour' in Greek banking inter-linking cost efficiencies with loan loss provisioning practices during 2005 to 2012. Firstly, utilising Stochastic Frontier Analysis, we construct numerous cost efficiency frontiers and examine the evolution of cost efficiency in the banking system. Secondly, we investigate the risk management behaviour and the dominant loan loss provisioning practises in the domestic banking sector. These include capital management, efficiency hypotheses and the cyclicality of loan loss provisioning. Finally, we investigate the evolution of non-performing loans and if they are Granger caused by bad management or cost skimping within our construct of risk management behaviour.

During 2005 to 2012 the 'four core' banks record strong performances and operate at higher levels of cost efficiency than their domestic competitors. This gap was reduced after the 2008 and 2010 financial crises, thus indicating an adverse impact due to the Private Sector Involvement. Overall, despite the so called bond haircut, the Greek banking system still recorded a strong performance where many banks operated close to the optimal efficiency levels, despite the ongoing deepening economic recession.

In addition risk bank management behaviour presents loan loss provisioning practices that are counter cyclical to the Greek business cycle. These results suggest that banks have engaged in capital adjustment via their loan loss provisioning resources. In addition, we present evidence to support that low cost efficient banks reported higher levels of loan loss provisioning indicating difficulties in raising additional external capital. Finally, with respect to the development of non-performing loans we present evidence of cost skimping and little support concerning moral hazard in Greek bank risk management behaviour.

This work is dedicated to my father, George.

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Chapter 1

Introduction

The Greek banking system evolved in parallel with the Greek state. The oldest and largest commercial bank, National Bank of Greece, was established in 1841 and in 1928, the Bank of Greece (BoG) was established as the country's central bank. During the 1920's and the economic boom, several new commercial institutions were established. However, only a small number of banks were able to survive the 1930's crisis. Later on and during the post-war period, Greek banks were assigned the role of financing the development and industrialization of the country. Under the umbrella of Bretton Woods, a system of quantitative and qualitative credit controls was established and the Greek banking system became pivotal in assisting capital accumulation and investment, having overall a positive role in the development of Greece in the post-war era.

This financial interventionism continued after the collapse of Bretton Woods and it transformed into high inflation and large government deficits during the 1980's and 1990's. That is, banks kept failed industries alive and channelled negative real interest-rate credit to various favoured socioeconomic groups. As with other European countries, a liberization and deregulation period begun, allowing Greek banks to raise interest rates to market levels, paving the way for macroeconomic stabilization. The deregulation process of the financial system implied the end of subsidized credit, which had led to inefficient capital allocation and high inflation. Furthermore, the structural modernization that was advocated by the European Union, offered the necessary momentum to Greek banks to become able to withstand international competition. The Economic Monetary Union convergence programme in the 1990's provided the needed framework of discipline that allowed conditions of monetary stability to be restored, for the first time since 1973.

The financial liberalization strengthened the portfolio of Greek banks and together with the boom of the Greek capital market between 1997-1999, accelerated the development of the financial system in the country. Indeed, Greek banks expanded their financial services and activities such as asset management, insurance, mortgage lending and consumer credit became integral parts of their operations. Furthermore, in the early 2000's Greek banks invested in organizational and technological modernization, expanding their distribution networks to include alternative channels, such as the internet and mobile telephony.

The withdrawal of the Greek government from the banking sector was a major development that led to restructuring process mainly due to privatizations of small and middle-sized state banks that were sold to private investors. In addition, after the first restructuring wave of privatizations, second wave of Mergers and Acquisitions (M&A) followed; increasing the degree of market concentration in the Greek banking sector.

The Greek banking sector therefore, has had an intrinsic effect on the development and stability of the Greek economy. The financial intermediation performed by banks, which involves the keeping of savings and development of business and financial resource allocation renders them critically important. Indeed, the performance of banks has been in an issue of major interest for regulators and various stakeholders. Considering the important role the Greek banking sector has played, this Thesis is motivated by recent developments and concerns prompted by the outbreak of the financial crisis. That is, two main reasons lie behind the current research. First, over the past 20 years the landscape of the Greek banking sector has witnessed fundamental changes. For example, the sector has experienced significant technological improvements, such as M&As, deregulations, entry into the Eurozone, internationalization, and considerable growth. In addition, Greek banks have recently been at the centre of an unprecedented crisis. These important developments merit a comprehensive discussion with respect to the recent developments and a challenging future faced by the Greek banking sector.

Following a period of high profitability and growth, Greek banks suffered from a series of hits, the first being adverse economic conditions and increased Non-Performing

Loans (NPL)[1]. Secondly, the sound fundamentals of Greek banks where significantly affected by the restructuring of the Greek sovereign debt through the "haircut" in the Greek bonds. In addition, the financial sector in Greece faced a series of liquidity problems as the banks were cut-off from inter-bank markets and subsequently, the downgrading of government and bank bonds which were used as collateral in acquiring liquidity led to major account losses, impairing banks' equity and total assets. Finally, during the summer of 2015 and after a prolonged period of negotiations between the Greek government and its official lenders, the banking system experienced a significant degree of deposit outflows. The combination of the unsuccessful negotiations, together with the capital outflows, eventually led to capital controls and a bank holiday in all credit institutions operating in Greece (28 June 2015). Thereby, leading to numerous restrictions which were imposed during that period · many of which remain still in place.

It is therefore evident that recent developments during the global financial crisis and the subsequent effect this has had on Greek banks, constitutes a timely, valid, warranted and overall necessary analysis of Greek banking and adds to the literature substantially. That is, the business environment to which Greek banks operate has been subject to major changes due to external factors and a deterioration of asset quality. It is therefore informative to investigate the performance of Greek banks under the impact of the recent developments and to further understand management practices dominating the industry with respect to risk management exposures. Indeed, if we assume that a more efficient banking system is beneficial for economic development, then there is a public benefit in the banking sector becoming more efficient and evaluating its performance (becomes an important factor for stakeholders).

[1] Recent data from The Banker database indicate that six of the top ten banks when it comes to non-performing loans as a percentage of their overall gross loan portfolio are based in Greece or Cyprus.1 These are the Bank of Cyprus (63%); Hellenic Bank (56.6%); Universal Savings Bank (44.5%); Piraeus Bank Group (38.8%); Eurobank Ergasias (33.4%); and Attica Bank (27.9%). (Cited in Bholat et al., 2016).

Motivated by the above discussion, the research objectives of this Thesis are as follows:

- Evaluate the performance of Greek banks by means of operation research methods and provide recent cost efficiency estimates of the Greek banking system.
- Utilizing a carefully constructed dataset as to avoid the "artificial" inflow of resources due to the recapitalization of Greek banks, provide a detailed analysis of the performance of the Greek Banking System and examine how cost efficiency has changed over this period.
- Following Berger et al., (2004) and Goddard et al., (2014), construct an index of relative performance and identify the position of the four core banking institutions with respect to their non-core counterparts.
- Quantify the impact of the 2008, 2009 crises on the performance of banks operating in Greece.
- Examine the evolution of Loan Loss Provisions and identify whether their discretionary component is used for management objectives. More specifically, we build an econometric specification that incorporates in a one-step estimation the cyclical behaviour of general LLP, tests for the evidence of capital management adjustments, and links bank management quality and loan provisioning levels.
- Finally, we investigate the determinants of non-performing loans in Greece. To that end, we extend previous research in the context of Greek banking and use estimated cost efficiencies to examine the presence of bad management, cost skimping and moral hazard hypotheses.

1.1 Achieving the Research Objectives

To address these objectives, the Thesis features five Chapters, each of which represents an integral part towards the successful completion of the aforementioned research objectives concerning Greek banking and bank risk management procedures.

The aim of Chapter 2 is to set the contextual background with respect to the Greek banking sector and discuss bank management decisions and their impact on efficiency and performance. In the process, we examine areas such as the theory and practise of

bank management and look at LLP manipulation and NPLs. We begin our review of the Greek banking system starting from the deregulation period of the 1980's. This Chapter presents a discussion on the historical framework of the Greek banking sector covering the main developments before the introduction of the country into the Economic Monetary Union (EMU) in 2000 and the adoption of the common currency in 2001. Furthermore, we outline significant developments of in Greek banking covering and discuss issues related to the main structural features of the financial services industry. In addition we extend our analysis outside the empirical models' examined period to discuss recent developments including the Private Sector Involvement (PSI) and the substantial recapitalization and restructuring process that was undertaken.

Chapter 3 presents a discussion of efficiency and reviews relevant approaches on modelling technologies concerning financial institutions. The aim of this Chapter is to examine performance indicators utilised within the banking literature and to present theoretical foundations in frontier estimation methodologies. We introduce the concepts utilised in banking studies and discuss the relevant empirical literature for measuring bank performance. We begin by presenting inherent problems present in financial ratios and relevant limitations when these indices are used to gauge bank performance. Next, we present parametric frontier models that have been estimated in the literature, which are based on the seminal work of Farrell (1957), and describe techniques for estimating efficiencies, pre/post-estimation tests, distributional assumptions, and functional forms. Finally, having identified preferred econometric specifications through use of various stability tests, we present a discussion on inputs/outputs utilised in bank models under the assumption of a multi-product cost function; which we believe captures the risk management characteristics of Greek banking.

In Chapter 4 , contrary to the majority of recent efficiency studies focusing on Greek banks that utilise the Data Envelopment Analysis (DEA), we estimate Stochastic Frontier Analysis (SFA) models and provide a comprehensive analysis Indeed, it is important to the note that our theory of including cost efficiency estimates in LLP modelling has been accepted in the literature by my publication using Vietnamese data.

(see Bryce C., **Dadoukis A**., Hall M., Nguyen L., and Simper R., (2015).

Therefore, the Thesis advances the theory of cost efficiency in its inclusion concerning Loan Loss Provisions (LLP) modelling theory and is considered an advancement concerning cost efficiency and LLP estimation. However, unlike the aforementioned publication. Bryce et al., (2015), my Thesis utilises an in-depth analysis of the estimated cost efficiencies extending the Bauer et al., (1998) consistency conditions.

That is, in line with Leamer (1994) and Bauer et al., (1998), who emphasise the significance of assessing the stability and fragility of econometric results, we estimate 15 different SFA frontiers and incorporate in all specifications the adverse macroeconomic environment. Next, the estimated scores are filtered under the consistency conditions proposed by Bauer et al., (1998) and identify preferred SFA results that are subsequently utilised in an LLP panel data model. Finally, we present in-depth discussions with respect to the evolution of the cost efficiency scores of Greek banks and examine differences in the performance between systemically important banks and the smaller asset sized institutions operating in the domestic market.

Chapter 5 advances an under-researched area concerning modelling LLP risk management behaviour of the Greek banks. That is, we estimate a combined econometric model, jointly incorporating business cycle effects and capital management hypothesis following prior research (see, for example, Anandarajan et al., 2007; Ghosh, 2007 and Skala, 2015). Furthermore, and following Bryce et al., (2015), we extend the traditional econometric specifications of Berger and DeYoung (1997) by including cost efficiency scores. The main objective of this Chapter 5, is to provide a comprehensive analysis of the risk management behaviour of Greek banks and to determine whether the banking system contributed towards amplifying the business cycle effects within Greece. Finally, to the best of our knowledge, we also explore for the first time the determinants of ex-post credit risk with respect to cost efficiency. That is, we specifically focus on testing for the presence of bad management, cost skimping and moral hazard hypothesis.

Chapter 6 concludes the Thesis and discusses potential limitations of the current research, presents policy recommendations and offers further research directions.

1.2 Policy Recommendations

The results presented first and foremost suggest that there is fragility in suggested regulatory conclusions across different methodological approaches. That is, comparisons between non-frontier performance indicators (i.e., financial accounting ratios) and cost efficiency estimates lead to negative correlations between the two. The implication is that capturing the economic optimization of banks is subject to methodological choices, hence reinforcing the argument that regulatory authorities should take into account more than one estimation technique as public policy conclusions will differ and depend on the approach utilised. Furthermore, even within a specific methodological choice, suggested policy recommendations could potential be subject to the underlying assumptions followed in each variation.

Our findings stress the importance of controlling for econometric stability over time, as policy recommendations with a long-term implementation period greater than 3 years may not hit the intended banks. Subject to the economic conditions in Greece, policies with an implementation period of 3 years could potentially prove to be more accurate as suggested by the inter-temporal stability of the efficiency estimates. In addition, we find that, on average, the systemically important banks significantly outperform the non-core institutions – despite the initial hit that they suffered in their balance sheets by the 2009 crisis. Given the highly concentrated nature of the Greek banking sector and that the core-banks only marginally passed the recent EBA stress tests, any further regulation could prove to have long lasting effects and impede the recovery of Greek banks – therefore we suggest cautious policy implementation practices. More specifically and with respect to Basel III policies, we find counter-cyclical provisioning practices, indicating towards a gradual and conservative implementation of the counter-cyclical buffer – even during periods of economic expansion. We do not advocate ignoring potential reforms in the provision system, however, at this stage reforms that change the current status, combined with new capital measures could prove to be too demanding for a banking system that is still under recovery.

Furthermore, implementing policies that promote cost efficiency improvements in the Greek banking system may help mitigate issues of capital management. However, it is important that these efficiency improvements are combined with rigorous control over the existing and future loan allocation – as suggested by the presence of the cost

skimping hypothesis. We thus advocate towards maintaining and re-enforcing the close collaboration between credit bureaus and public registers and the swift completion of the legal framework regarding distressed loans in order to unlock loanable funds to the real economy, bolstering investment and employment.

Chapter 2

Financial Intermediation and the Greek Banking System

2.1 Chapter Summary

The aim of this Chapter is to set the contextual background that serves as a basis for the empirical applications with respect to efficiency estimation and loan loss provisioning practices in Greek banks. We begin this section with a discussion concerning the microeconomic theory which examines the role of financial intermediators, the raison d'être and how regulation and accounting regimes could affect management decisions. In the subsequent sections, we provide an overview of the Greek banking sector after the introduction of Greece into the Economic Monetary Union (EMU) in 2000 and the adoption of the common currency in 2001. We discuss issues concerning the main developments in Greek banking for the last 15 years and thereafter changes within the financial services industry - focusing on the period analysed in the Thesis (that is 2005-2012). Finally, we conclude with a discussion on recent developments, thereby covering our analysis after the sampled years. That is, we provide an account of the various developments during 2012–2015, including the Private Sector Involvement (PSI) and the substantial recapitalization and restructuring process of Greek banks due to the Global Financial Crisis and the decline in domestic economic growth and increase in nonperforming loans.

The remaining of the Chapter is structured as following. Section 2.42 serves as the introduction of the Chapter setting the background for the discussion. Section 2.3 examines areas such as the theory and practice of bank management and links with LLP manipulation. Section 2.4 provides an overview of the Greek banking system, where we present a brief historical overview of the main developments with respect to the Greek financial system and we proceed and discuss the key structural features of the Greek banking sector. Section 2.6, extends our discussion beyond the sampled period

and provides a detailed account of the latest developments with respect to Greek banks. That is, we further cover the turbulent 2012-2015 period (where the PSI took place) leading to the consecutive recapitalizations of Greek banks in order to meet appropriate regulatory standards and maintain financial stability in Greece. Finally, Section 2.7 concludes.

2.2 Introduction

With respect to the economic analysis of banking, Freixas and Rochet (2008) argue that the role of banks cannot be explained under the complete market assumption of the Arrow and Debreu (1954) general equilibrium model of resource allocation. That is deviations from the Arrow - Debreu model create a role for financial intermediaries such as banking institutions, whereby banks interact and facilitate the flow of financial resources in the economy. More specifically, they perform the task of bridging two groups: deficit-spending units whose expenditures for investment and consumption exceed their receipts, and; surplus-spending units, whose current income exceeds their expenditures and therefore are in a position to save and/or invest excess funds. Hence, financial intermediaries perform the task of offering services to surplus spending units, attracting funds in the process – funds that are then allocated to deficit-spending units. In the process, economic growth is accelerated via the expansion of available savings in the economy, risk is lowered via diversification and, the social value of capital increases by enabling it to be put to more efficient use.

An on-going debate within the banking literature concerns the question as to why financial intermediaries exist when deviating from the Arrow – Debreu framework. For example, Allen and Santomero (1998) note that in the aforementioned framework there is no need for financial intermediation as firms and households interact directly through the markets and institutions that perform the role of channelling financial resources between the two parties become redundant as the allocation of resources is efficient. However, such views do not hold in reality as proven by the observed practice – where historically banks and insurance companies hold a central role in circular flow of funds within an economy. Indeed, the need for financial intermediaries arises because of imperfections in the financial system and frictions such as information and transaction

costs that arise from information asymmetry between borrowers and lenders. Hence, financial intermediaries thereby assist the efficient functioning of markets and any factors that affect the amount of credit channelled through financial intermediaries can have significant macroeconomic effects.

The following section aims to summarise the key theories surrounding financial intermediaries focusing on the theory and practise of bank management, primarily through the prism of loan loss provisioning (LLP) and nonperforming loan (NPL) practices within the context of Greek banking. That is, we begin our discussion by analysing financial intermediation and their key functions performed specifically by banks:

- Transaction costs
- Information asymmetry
- Liquidity provision
- Asset transformation
- Delegated monitoring

2.3 Financial Intermediation

2.3.1 Transaction costs

In their seminal work, Gurley and Shaw (1960), stress the role of transaction costs as the primary function of financial intermediaries and the fact that they can exploit economies of scale in lending and borrowing to reduce such costs. For example, the fixed costs associated with respect to loan evaluations implies that intermediaries have a cost advantage over individuals because they can allow these costs to be shared. At the same time, trading costs imply that intermediaries can diversify easier than individuals. In subsequent work, Benston and Smith (1976) put the concept of transaction costs in the foreground, stating that "The *raison d'être* for this industry [financial intermediation] is the existence of transactions costs (page 215)".

Furthermore, when attempting to find suitable sources of loanable funds, borrowers incur a set of search costs – costs that in the presence of a financial intermediary can be

avoided altogether. Indeed, Freixas and Rochet (2008) note that financial intermediaries have access to technology that permits them to overcome these transaction costs. For example, information costs are often relatively large for the production of financial commodities (i.e., loans) – which require specialised expertise. As Benston and Smith (1976) note, "financial intermediaries create financial commodities which require the performance of these tasks because they have a comparative advantage in processing documents, in acquiring information about borrowers' ability to repay debts, and in monitoring instruments that can be easily converted into generalized purchasing power (page 222)". That is, intermediaries can reduce these said costs due to economies of scale and standardised processes.

Contrary to the above, Allen and Santomero (1998) suggest that the emphasis on the role of intermediaries in reducing the frictions of transaction costs is too strong – arguing that recent advances in technology and information communication imply that intermediaries should be threatened. Of course, their existence suggests the presence of additional and more fundamental costs, such as participation costs. They further argue that the view that financial intermediaries are facilitators of risk transfer and deal with an increasingly complex maze of financial instruments and markets. More specifically, that risk management has become a key area of financial intermediation, noting that "by dealing in financial assets, intermediaries are by definition in the financial risk business. By virtue of the fact that they originate, trade, or service financial assets, intermediaries are managing and trading risk (page 1478)". Indeed, with respect to the facilitation of participation in the financial markets, the aforementioned service is concerned with the reduction of participation costs; such as the costs of learning and effectively using the financial markets, as well as participating in them on a daily basis. However, Scholtens and van Wensveen (2000) question the validity of the Allen and Santomero (1998) proposition, by questioning the latter's suggestion that the emphasis on the role of intermediaries is to reduce the frictions of transaction costs and asymmetric information, as being is too strong. In contrast, they propose a framework where risk and risk management becomes the main item in the agenda, bringing once again into the foreground one of the key function of banks - the process of risk management and transfer. That is, taking deposits from savers and extending credit to borrowers.

2.3.2 Information Asymmetry

Even though the presence of transaction costs helps us to interpret the existence of financial intermediaries, Leland and Pyle (1977) note that by themselves, such costs do not justify the process of intermediation. Contrary to the view of transactional costs, they suggest that informational asymmetries are particularly pronounced in financial markets, where borrowers typically posess inside information about their projects for which they seek finance. According to Akerlof (1970), the issue of information asymmetry arises when borrowers generally know more about their investment projects than lenders do, thus generating market imperfections.

Leland and Pyle (1977) suggest that financial intermediaries address issues of asymmetric information. For example, for specific classes of assets related to individuals, pertinent and not publicly available information can be collected, which can prove to be beneficial to lenders. Typically, financial intermediaries can obtain information at a lower cost than individual lenders as they avoid duplication of the production of information and take advantage of increasing returns to scale to financial intermediation. Financial intermediaries develop special skills in evaluating prospective borrowers and investment projects, while exploiting cross-sectional (across customers) information and re-use information over time In the presence of economies of scale, coalitions of borrowers collecting such information may be formed – collecting documentation relevant to specific asset classes. However, two reasons may impede the use of such information; appropriability of returns by the firm (aappropriability is the capacity of the firm to retain the added value it creates for its own benefit.); and credibility of information.

With respect to the former, given the public nature of information, agents purchasing information could resell or share their information with other market participants, without diminishing its usefulness to themselves. The implication of the public nature of information is that the original information producer may only appropriate a fraction of what buyers would be willing to pay[2]. With respect to the latter problem, credibility of information, it may be difficult or impossible for the potential users to distinguish

[2] Hirshleifer and Riley (1979) note that, if costly privately-produced information can subsequently be used at less cost by other agents, there will be inadequate motivation to invest in the publicly optimal quantity of information.

good from bad quality information – so the price of information will reflect its average quality. Therefore, if there are low barriers to entry, firms offering poor quality information may enter and firms which expend significant resources to collect good quality information will lose money as they will receive a value reflecting the low average quality.

The aforementioned problems can be overcome if the firm collecting information becomes an intermediary, hence buying assets on the basis of its information – resolving issues of appropriability and credibility. The former is addressed as the public nature of information is embodied in a private good, the invested assets and their returns. With respect to the latter, the financial intermediary is resolving issues of credibility by signalling and by investing its wealth in assets about which it has specialised knowledge and the assets selected based on that information (i.e., loans) – reflecting therefore good quality information. Furthermore, additional signalling effects concerning the quality of bank assets which reflect the value of collected information, may take place via accounting practices and for example adjustments in the provisions for loan losses. Indeed, Beaver et al., (1989) suggest that an increase in LLP indicates the managements' perception of strong earning power in that it can withstand a hit to earnings in the form of additional provisions. That is, an increase in LLPs conveys a good news signal about the strength of a bank's future earnings and asset quality. However, even though Leventis et al., (2012) note that increases in LLPs convey a signal of prudent management and are viewed positively by investors, the dichotomized nature of LLPs (discretionary and non-discretionary) suggests that several motives apart from signalling may be hidden in LLP adjustments – such as capital management, earnings management and management compensation (see, for example, Wahlen, 1994; Collins et al., 1995; Kanagaretnam et al., 2004; and Cheng et al., 2011)[3]. For example, Beatty and Liao (2014) note the importance of LLP as a prominent item in the income statement and observe that "loan loss provisions are accruals of fundamental importance to bank performance, and because they are estimates of loan losses, they also reflect information asymmetry, which is the heart of the banking literature" (page 352). That is, of particular importance in the context of

[3] An in-depth discussion of the relevant empirical literature and the reasons concerning the motives of LLP adjustments is further presented in Chapter 5.

information asymmetry is agency theory as a potential motive for income smoothing behaviour (reducing the variation in the income stream via accounting decisions and adjustments in the discretionary component of LLP levels)[4]. Under certain assumptions, Lambert (1984) shows that ",… the optimal compensation scheme offered by the principal causes the manager to smooth the firm's income" (page 604). In addition, Greenawalt and Sinkey (1988) note that Lambert's (1984) framework can also extend to "artificial" smoothing (which involves accounting decisions).

Furthermore, in an attempt to mitigate information asymmetries, bank managers may have incentives to use accounting practices such as LLP adjustments to convey private information. For example, Nichols et al., (2009) note that public banks provide timelier loan loss provisions to mitigate information asymmetry (the implicit assumption is that public banks face higher information asymmetry than private institutions). An alternative explanation is that managers may exploit their information advantage and engage in earnings, capital or tax management that is either opportunistic or aligned with shareholders' interests (Beatty and Liao, 2014). Indeed, financial reporting discretion as a tool to circumvent minimum capital adequacy requirements (i.e., capital management) has been acknowledged in previous empirical literature (see, for example, Ahmed et al., 1999; Bikker and Metzemakers, 2005; Anandarajan et al., 2007 and Curcio and Hasan, 2015). The capital management literature focuses primarily on agency problems which arise from information asymmetries between banks and regulators, and the relevant implications for financial reporting discretion. Beatty and Liao (2014) note that "specifically, the introduction of explicit numerical capital requirements creates incentives for banks to use financial reporting discretion to circumvent the minimum capital requirement to avoid the need to raise costly outside equity or to reduce lending" (page 348).

2.3.3 Liquidity provision

Another strand of literature – a key study by Diamond and Dybvig (1983) - emphasises the role of financial intermediation as providers of liquidity in which a central role of a

[4] Greenawalt and Sinkey (1988) note that "such behaviour might be exhibited by charging additional amounts to loan-loss expense in years of peak earnings while decreasing the loan-loss provision or delaying recognition of write-offs when earnings are down, page 305".

financial intermediator is to create and enhance liquidity by financing relatively illiquid assets with more liquid liabilities. More specifically, the provision of liquidity by banks assigning to them the explicit economic role of transforming illiquid assets by offering liabilities with a different, smoother pattern of returns over time than the illiquid assets they offer. The optimal contract is a demand deposit with an undesirable equilibrium – the state of a bank run. In this state, all depositors panic and withdraw their deposits immediately, including investors who would prefer to leave their funds in the bank if they were not concerned about the bank failing. That is, identical investors (depositors) are risk averse and uncertain about the timing of their future consumption needs. In the absence of an intermediary party, all investors are locked into illiquid long-term investments that yield high payoffs only to those who consume late. Early consumption implies low payoffs to investors, as it requires premature liquidation of long-term investments. Firstly, banks are in a position to perform this transformation role by pooling loanable funds (deposits) from a number of investors, which maintain the right to withdraw those deposits on demand. Secondly, banks know the normal volumes of withdrawals and provide a relative degree of insurance as they rely on the fact that few depositors would need to do so simultaneously. Therefore, banks improve a competitive market by providing better risk sharing among investors that need to consume at different times. A system where an intermediary exists and investors receive higher (lower) payoffs for early (late) consumption relative to the non-intermediated case, enhances risk sharing and welfare.

2.3.4 Asset Transformation

Financial intermediaries like commercial banks and savings banks perform various kinds of intermediation functions in the capital market. One of the most prominent ones is asset transformation. That is the transformation of market rate sensitive, short-term liabilities (deposits) into fixed—rate, long term assets (loans). The aforementioned process refers to a type of transformation whereby banks use deposits and generate revenues by pooling deposits to make loans. As such, banks undertake asset transformation by borrowing short and lending long. The former compose the liabilities of the intermediator whereas the latter the assets. This asset transformation changes the characteristics of the liabilities and is conducted by four main functions, maturity, liquidity, risk and size transformation.

Commercial banks, investment banks and many shadow banking entities have as their core function maturity transformation, which allows the financing of long-term assets while accommodating investors' preferences for shorter investment horizons (Segura and Suarez 2016). The second core function concerns liquidity transformation. As Bhattacharya and Thakor (1993) note, financial intermediaries will finance illiquid asset with the use of liquid liabilities. One example defining the above relationship is a bank deposit. The holder of the deposit has a liquid claim on the bank – that is the full face value of the deposit which can be drawn at any point in time for any purpose. From the asset side of the financial statement, deposits are primarily invested in assets such as bank loans. These financial assets typically have long maturities and are not liquid. In turn, loans may potentially fund the creation of real assets in the economy, which themselves may be illiquid. Thirdly, risk transformation involves minimising the risk of the funds deposited and lent. Financial intermediaries hold assets with higher risk of default than their liabilities – shifting risk away from the depositors to themselves. These risks can be reduced via diversification of investment funds, pooling risks, screening and monitoring of borrowers and holding capital and formation of reserves in order to cover expected and unexpected losses. With respect to the latter (formation of reserves) even though such provisions are one of the main expenses for banks and they play a critical role as they are set aside to cover the future deterioration of the credit portfolio, they may also be subject to opportunistic behaviour by managers (for a detail discussion covering the underlying reasons for potential manipulation of impaired loan provisions, see section 2.3.2 and Chapter 5). Finally, size transformation refers to the accumulation of a large number of loanable funds by different surplus spending units and the subsequent transformation into loans of large amount directed towards deficit spending units.

2.3.5 Delegated Monitoring

Following from the concept of information asymmetry, another important role performed by banks in reducing information asymmetry between depositors and borrowers, is their superior ability of monitoring of borrowers. Therefore, financial intermediaries act as agents, or groups of agents, who have been delegated with the

authority to invest in financial assets, serving as an agent on behalf of its depositors. Banks possess the financial technology that gives them the ability to serve as the middleman in resource allocation. This process includes screening projects, preventing opportunistic behaviour and verifying that borrowers meet contractual obligations – ensuring that way that depositors will recover their funds. Diamond (1984) presents a model of delegated monitoring theory, whereby banks' scale economies help avoid duplication of investor's monitoring costs. These scale economies give banks a comparative advantage relative to other monitors such as rating agencies for example. A side effect of the delegated monitoring process of intermediaries is that it gives rise to information asymmetry between depositors and bank managers about the bank's monitoring quality and performance (Beatty and Liao, 2014). Banks' financial reports capture different aspects of how banks monitor quality and performance (for example investors' perception of LLPs as a signal of prudential management practices, see discussion in section 2.3.2).

Undeniably, financial intermediaries play an important role in credit markets. They reduce the cost of channelling funds between relatively uninformed depositors to users that are information-intensive and difficult to evaluate. In the process, the economy moves towards a position of more efficient allocation of resources. Some of the key functions of financial intermediaries include, collection of information, liquidity provision, evaluation of projects, monitoring borrowers' performance and risk sharing. Because of the existence of economies of scale, banks and other intermediaries are in a position to provide credit to borrowers on terms which those borrowers would not otherwise be able to obtain – promoting a more efficiency allocation of financial resources. Furthermore, financial intermediaries are active counterparts that offer the specific product of risk coverage. As such, they hold a critical function in the modern economy – even more so in the case of the stagnating Greek economy.

2.4 The Greek Banking System

The World Bank (2016) ranks Greece as the 45th largest economy in the world with $195,212 million nominal Gross Domestic Product (DGP). Greece is a developed country with an economy mainly revolving around services sectors and industry. In

June 19 2000, the country was accepted into the Economic and Monetary Union (EMU) of the European Union (EU) by the European Council (EC), based on a number of criteria using 1999 as the reference year (i.e., inflation rate, budget deficit, public debt, long-term interest rates, and exchange rates). Furthermore, in January 2001 Greece adopted the Euro as its currency, replacing the Greek drachma at an exchange rate of 340.75 drachma to the Euro. This adoption of the common currency was a turning point for Greek banks which begun an expansion into new markets, mainly the Balkans, Turkey and Eastern European countries. This penetration into new markets was mainly supported via access to substantially cheaper funds in the European interbank market, thus reducing the cost of borrowing and boosting the credit expansion in Greece.

Indeed, the decade starting in 2000 saw a continuation of the upward trend and the credit expansion continued following Greece's accession to the euro area in 2001 and the momentum for growth provided by the Olympic Games in 2004 (Petrakis 2012). In addition, further improvements, such as the setting up of a national credit bureau in the form of an interbank company and the new bankruptcy law enacted in 2007 improved the sector's institutional settings (Louzis et al., 2012). The outbreak of the global financial crisis in 2008 and the rapid public finance deterioration of Greece became evident in 2009 and put the banking sector in a stressed situation. After a macroeconomic expansion period, the 2008 crisis hit an already weak Greek economy that had largely exhausted the traditional means of facing a classic recession; these means included an expansionary fiscal policy; as the fiscal deficit had achieved very high levels in the preceding years (Petrakis, 2012). The situation caused a decrease in domestic demand, threatening the banking sector and further aggravating public finances. The 2008 financial developments and subsequent collapse of the inter-bank market, led Greece's banks to use Greek government bonds to improve their liquidity position. However, the Greek economy and consequently Greek banks suffered from the most severe financial and sovereign debt crisis in the country's recent history. The consecutive deficit revisions, the continuous downgrading of bonds and the subsequent PSI programme, directly affected the liquidity of the Greek banking system; leading to economic suffocation in the market.

Until the 1980's, the Greek banking sector was subject to restrictions, administrative regulations and extensive government interventions which influenced, including

pricing, the volume and the allocation of financial resources (Bank of Greece, 1998). Interestingly, Hondroyiannis et al., (1999) note that the degree of government interventionism as "in the past, a major structural feature of the Greek banking system was its institutional specialisation required by law rather than dictated by market forces. The regulation and control of the banking system was carried out through a complex system of credit rules in an environment of administrative fixed interest rates. Credit and interest rate policy aimed at influencing the asset structure of the credit system in a way conductive to the government's economic policy priorities, such as export expansion, promotion of small- and medium-sized enterprises, financing of state-owned firms, etc. (page 378)".

These distortions in the financial system impeded the role of the central bank in its pursuit of an effective monetary policy. The prospects of participating in the Single European Market and in an attempt to keep up with developments and the need for a modern, market oriented more flexible financial system, gave way to the deregulation of the banking sector (beginning in the early 1980's). Indeed, the first stage came in 1982 with (Law 1266/1982) enhancing the role of the central bank in conducting monetary policy, however, a complicated system of direct controls remained in place until the late 1980's (see, for example, Hondroyiannis et al.,1999). After the late 1980's, the deregulation process was carried out in an accelerating pace. More specifically deposit and lending rates were freely determined by markets and banking institutions were permitted to extend credit on their own terms – leading to the adoption of new financial products and services. In addition, commercial credit institutions became free from investment requirements imposed for the financing of small/medium-sized businesses and government enterprises.

The beginning of the next decade saw a series of structural changes taking place. For example, in 1992, the framework defining the operation of banking institutions in the single European financial market was established – providing equal competitive conditions for all European banks operating in Greece. Furthermore, specialized credit institutions were allowed to expand their business in sectors that were until recently

only accessible to commercial banks and vice versa[5]. In addition, financial products such as leasing, factoring and venture capital became available to credit institutions. Finally, banks were permitted to use financial derivatives (such options and swaps) in order to hedge against the increased risks from non-domestic wholesale markets borrowing. Hence, after 1992, the main changes in the Greek banking system included the following important changes: (i) the liberalization of interest rate determination, (ii) the abolition of various credit rules, (iii) the free movement of capital and the increased competition from banks of the European Union and (v) the de-specialization of credit institutions (see, for example, Halkos and Salamouris, 2004 and Pasiouras, 2012). The rapidly changing economic environment in which Greek banks operated, also changed their mode of operation. That is, in order to achieve satisfactory profitability and survive increased competition, Greek banks had to improve their response to the challenges of regulatory liberalization. This came in the form of increased off-balance sheet operations; expansion and modernization of their distribution networks; investments in communication and, technology and upgraded management and risk measurements systems. In addition, the sector underwent a wave of mergers and acquisitions that allowed banks to strengthen their domestic market position and provided the required asset size capability that would allow them to face increased EU market competition from non domestic financial institutions. Indeed, in order to cut operating costs through both scale and scope economies, many large credit institutions merged with their subsidiaries whereas others forged strategic alliances with major European institutions. This brought benefits from improved know-how, large branch networks and presence in international financial centres.

In this new environment, a number of new banks were established (either domestic institutions or branches of foreign banks). For example, from the late 1980s to the late 1990s, ten commercial banks were incorporated in Greece. Furthermore, in 1993, the Bank of Greece set up the framework for the operation of cooperative banks, which allowed the establishment of 15 banks during the next decade (although their market share remained very low with less than 1% of total assets of the banking system). The financial deregulation that took place, together with the enactment of new legislation

[5] For example Agricultural Bank was a founded as non-profit organization which had as its main directive to provide credit to the agricultural sector and enhance rural development. In the 1990, the institution expanded its activities in the non-agricultural sector as well.

that implemented EU directives, led banks operating in Greece to adjust to new conditions of intensified competition, both in the domestic and cross-border markets. The development of new information technology which led to the globalization of the financial markets also increased the systemic pressures experienced by Greek banks. Another key development was the privatisation of state controlled banks in the second half of the 1990s. Between 1995 and 2000, the share of state controlled banks was reduced from 72.3% (in 1995) to 52.9% (in 2000) (Kamberoglou et al., 2004). Finally, in order to further reduce operating costs, banks focused on the branch network and building alternative distribution channels. At the same time, Greek banks benefitted from new technological advances, which allowed them to develop remote banking channels, such as ATMs, telephone/online banking services. For example, in 1990 only 1,529 branches were operating in Greece, whereas the number increased dramatically to 3,004 branches in 2000. In the same period, the number of ATMs increase from 326 in 1990 to 3,472 in 2000 (Kamberoglou et al., 2004).

Turning into the penetration of foreign banks in Greece, the growth of foreign instituitions was driven by the political changes in the intsituitional relationship of Greece with the EU. Traditionally, foreign banks in Greece operated under three forms: representative offices, subsidiaries and branches. The establishment of representative offices started in the early 1970's and increased in the 1990's. This growth may be attributed in the economic development that took place in Eastern Europe countries. The establishment of the subsidiaries was allowed only after the mid 1980s (in 1986) – the only notable exceptions being the Arab Hellenic Bank (est 1978) and the Bank Franco-Hellenic (est 1981).

In Greece, foreign banks conducted business primarily via branches, and in 1981, with the Treaty of Accession of Greece to the EU, foreign credit institutions were allowed to establish branches without any legal discriminations compared to domestic institutions. In addition, the Treaty enacted a common lagal framework that provided equal competitive condition for all institutions. As a result of the aforementioned regulatory changes, the number of foreign banks increased. More specifically, in 1981, 19 foreign banks with 45 branches were operating in the country, whereas in 1985, 19 foreign credit institutions had established 49 branches and by 1992, 72 branches (19

foreign banks) were present in the banking sector (data collected from Hondroyiannis & Papapetrou 1996).

More recently and since the 2000s, the Greek banking system could be characterized as a relatively mature financial sector, where market forces govern its functioning. Furthermore, the decade after the adoption of the common currency, saw a continuation of the upward economic trend and credit expansion. Indeed, Louzis et al., (2012) attribute the high rates of credit growth to the shifts both in the demand and the supply curve, noting that "on the supply side, the liberalization of the financial system, which took place in the 1990s and the ensuing competition between banks for market share, fuelled credit growth. On the demand side, the increase in debt ceilings, brought about by bank competition, induced households to attempt to smooth their consumption through borrowing (page 1013)". That is, the liberalization of the financial system and the subsequent competition between Greek banks fuelled credit growth, whereas the increase in debt ceilings induced higher levels of borrowing for Greek households. Furthermore, since Greece joined the Eurozone the four largest banks; namely Alpha Bank AE, Eurobank Ergasias SA, National Bank of Greece SA and Piraeus Bank SA, managed to develop rapidly through penetration in the South Eastern Europe's countries. This was a strategy that was followed until the 2008 crisis and in a different direction than the one followed by financial institutions, such as the US and UK that invested in ''toxic'' products (Tsolas and Charles, 2015).

Since the beginning of the financial crisis in 2008, the euro area banking sector has been going through a rationalisation process which has resulted in a reduction of the overall number of credit institutions. The Greek banking sector was not able to remain unaffected by economic developments and was severely hit by the combined effects of:

- The cut-off from international markets and deposit outflows.
- The adverse economic conditions, which resulted in deteriorating asset quality.
- The restructuring of the Greek sovereign debt through the PSI (Bank of Greece, 2012).

At the beginning of the crisis, not only the Greek banking system was stable since commercial banks had satisfactory capital adequacy and were not significantly exposed to the toxic bonds but was also able to help temporarily improve the financial stability by purchasing public debt. Indeed, Provopoulos (2014) states that prior to the outbreak of the sovereign crisis, the Greek banking sector had sound fundamentals with high capital-adequacy ratios, low loan-to-deposit ratios and essentially no toxic assets of the kind that set-off the 2007 global financial crisis (see Table 2.1 for more details). However, due to the severity of the Greek sovereign debt crisis, banks eventually faced a series of significant liquidity problems. Furthermore, Georgantopoulos and Tsamis (2013) report that the downgrading of government and bank bonds which were used as collateral in acquiring liquidity posed the first major problem, lead to major account losses impairing banks' equity and total assets. The increase in the cost of borrowing of Greek banks due to increased bond spreads, together with capital migration, amplified the liquidity problem. Finally, the overall adverse economic climate, the increase in non-performing loans and the reduction in new lending resulted in a significant reduction in bank net interest profits. That is, the biggest problem that the Greek Banking System faced was the excessive exposure to Greek bonds. Indeed, the shareholders of major banks suffered significant losses, initially due to bonds price deductions (2010-2011). This process reached its peak in early 2012 as Greek banks took a huge hit on their bond portfolios through voluntary restructuring of Greek sovereign debt that took place in March 2012 and finally through the obligatory buy of new Greek bonds at a lower price (we further discuss the PSI in subsequent sections).

As a result, these factors put great strain on Greek banks and affected their liquidity thus threatening the stability of the banking sector and the long-term sustainability of the industry. Recognising the importance of the banking system in an attempt to restructure and steer the future of the Greek economy, the Bank of Greece (BoG) together with the EC, the European Central Bank (ECB) and the IMF proceeded into a major restructuring charge of the banking industry thus creating a viable and well capitalised banking sector. More specifically, and in light of the adverse economic conditions, the BoG and the Greek government implemented a series of measures to safeguard the financial stability and protect depositors' interests. Such actions comprised inter alia:

- Meeting banks' short-term liquidity needs by allowing access of eligible banks to Emergency Liquidity Assistance (ELA).
- Securing sufficient public resources (Financial Envelope) to cover the recapitalisation needs and restructuring costs of the Greek banking sector for the period 2012-2014, which were estimated at €50 billion.
- Resolving distressed banks, within an enhanced legal framework.
- Requesting all banks to increase their capital to a conservative level (Bank of Greece, 2012)[6].

The main restructuring undertaken during 2012 and 2013, where within the enhanced legal framework overall twelve distressed banks, including two major state-controlled banks (Agricaltural Bank of Greece and Hellenic Postbank), were resolved. In addition, problems of contagion from the Cypriot crisis in March 2013 were averted through the acquisition of Cypriot banks' by Piraeus Bank SA. Furthermore, in the second quarter of 2013, the four systemic banks (Alpha Bank AE, Eurobank Ergasias SA, National Bank of Greece SA and Piraeus Bank SA) completed their recapitalisation on the basis of the 2012 capital needs assessment and along the recapitalisation framework (Law 2010 and Cabinet Act 38/2012)[7]. Through the contribution of €3.1 billion towards the recapitalisation of systemic banks, the presence of private management was secured in three of the four systemic banks. These three core banks concluded that the processes needed to increase their capital by the amounts required – a private-sector threshold of at least 10% for private sector participation set by the BoG. The National Bank of Greece, Alpha Bank AE and Piraeus Bank SA raised the minimum 10% of their capital needs through the market and remained under private control. The remainder of these banks' capital is fully subscribed by the Hellenic Financial Stability Fund (HFSF)[8]. The fourth core bank – Eurobank – had to be fully recapitalised by the HFSF.

[6] The overall needs of the banking system were determined as the sum of: (1) the amounts needed for the recapitalization of core-banks (€28 billion); (2) the amounts needed for the resolution of non-core banks (€17 billion); and (3) a buffer of €5 billion to cover any unexpected adverse developments (Provopoulos, 2014).

[7] The main legislative function in Greece is assigned to the Parliament which is bound to exercise its powers within the limits of the Constitution. The Parliament votes for a Bill to become a Law in three voting sessions: firstly in principle, then per article and then as a whole. Once the bill is passed, it is sent to the President of the Democracy to promulgate and publish it in the National Gazette.

[8] The HFSF is a special purpose vehicle established in July 2010 to provide capital support to Greek credit institutions.

Throughout the restructuring process, the systemic banking institutions facilitated the resolutions of banks through the acquisition of the good parts and the subsidiaries of foreign institutions that withdrew from the Greek market (a more detailed discussion on the restructuring of the Greek banking system follows in Section 2.6). This resulted in a highly concentrated market, where the four systemic institutions currently (as of March 2014) account more than 90% of domestic banking sector assets (Bank of Greece, 2014a).

2.5 Structural Features of the Greek Banking Sector

With respect to the number of financial institutions operating in Greece, according to data from the BoG, as of December 2012, 52 credit institutions were operating in the country[9].

- 29 credit institutions (16 commercial and 13 co-operative banks) regulated under the "single licence" regime (single EU "passport") of Law 3601/2007, (Directive 2006/48)
- 18 branches of banks incorporated in other European Union countries also regulated under the "single licence" regime (single EU "passport") of Law 3601/2007.
- 4 branches of banks incorporated in third countries (non-European Union countries) regulated by the BoG since they do not fall under the "single license" regime.
- 1 credit institution exempted from the provisions of Law 3601/2007, namely the Consignment and Loans Fund

The above institutions have been integral in the evolution of the Greek economy. Indeed, the financial depth of banking intermediation has developed considerably

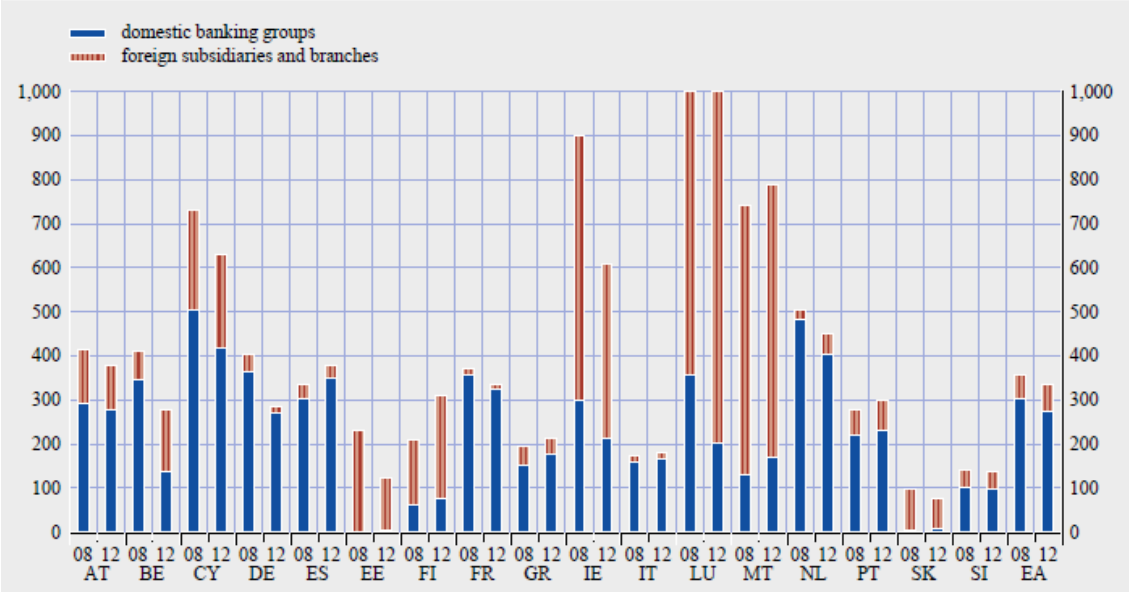
[9]As of July 2016, the respective number are as follows: 17 credit institutions (5 commercial and 9 co-operative banks) regulated under the "single licence" regime (single EU "passport") of Law 4261/2014, (Directive 2013/36/EU); 16 branches of banks incorporated in other European Union countries also regulated under the "single licence" regime (single EU "passport") of Law 4261/2014; 4 branches of banks incorporated in third countries (non-European Union countries) regulated by the BoG since they do not fall under the "single license" regime; and 1 credit institution exempted from the provisions of Law 4261/2014,, namely the Consignment and Loans Fund.

during the past decade. This fact is reflected by the increase in the ratio of total assets of the credit institutions to the GDP, ranging from 107.03% in 1997 to approximately 180% in 2012 (the same figure rises to more than 230% when including foreign controlled subsidiaries) (Figure 2.1; Pasiouras, 2012; ECB, 2013). It is evident that this number differs considerably if we take into account Luxembourg's' banking sector, representing 1666% of the country's GDP, followed by Malta, Cyprus and Ireland, with banking assets representing 789%, 630% and 609% of GDP respectively. Over the recent years, 2009-2012, the size of domestic banking assets, as opposed to banking assets under foreign control, increased in Greece (under EU-IMF financial assistance programmes). Focusing in 2008, it is interesting to highlight that at the outset of the global financial crisis, the size of the Greek banking sector was smaller, relative to the other European countries that were also affected by the crisis. In 2008 the Assets to GDP ratio amounted to 193% of the GDP, whereas in Ireland it was equal to 777%, in Italy 232%, 280% for Portugal, 311% for Spain and 685% for Cyprus (Table 2.1). As reported in Table 2.1, prior to the crisis, the Greek banking sector had sound fundamental indicators; high capital adequacy ratios; low loan-to-deposit ratios and essentially no exposure to toxic assets that set off the 2007 crisis. Therefore, the small banking size together with the sound financial indicators, combined support the idea that in Greece it was the sovereign crisis that led to a banking crisis – in contrast to some other EU countries.

In Table 2.2 we present information about the capital to total assets ratio in the EU-15 member states for the entire period 2005-2012. Due to data unavailability there are some missing values for the years 2011 and 2012 for Greece and other countries. Clearly, the capital to total assets ratio for the Greek banks has been relatively stable throughout the sample period (5.9% in 2005 and 5.8% in 2011). The capital adequacy of the credit institutions improves for the first part of the period (2005-2007) and records a decrease (from 6.8% in 2007 to 4.9% in 2008) in the year of the outbreak of the financial crisis, following the EU-15 average trend which also declines from 5.62% is 2007 to 4.95% in 2008. The commercial banking sector in Greece shows sound capital adequacy performance, remaining above the EU average throughout the sample period. For brevity, only the capital to total assets ratio is presented here since it

includes the core capital component (Tier 1) in its calculation[10]. Even though the sample banks comply with the Basel II capital requirements of a minimum 4% and 8% respectively, some credit institutions record negative values (i.e. National Bank of Greece SA and Piraeus Bank SA both have negative core and Tier 1 capital values for 2011 and 2012). The financial positions of these institutions were strained due to their acquisition activity of distressed banks as part of the on-going consolidation process of the banking system.

Figure 2.1. Total assets of domestic banking groups and foreign-controlled subsidiaries and branches in relation to GDP in euro area countries in 2008 and 2012



Source: ECB (2013).

[10] Bank capital to assets is the ratio of bank capital and reserves to total assets. Capital and reserves include funds contributed by owners, retained earnings, general and special reserves, provisions, and valuation adjustments. Capital includes Tier 1 capital (paid-up shares and common stock), and total regulatory capital, which includes several specified types of subordinated debt instruments that need not be repaid if the funds are required to maintain minimum capital levels (these comprise tier 2 and tier 3 capital). Total assets include all nonfinancial and financial assets.

Table 2.1. EU Banking Sector Stability

	Loan to Deposit Ratio		*Capital Adequacy Ratio*		*Assets to GDP Ratio*	
	2008	2009	2008	2009	2008	2009
Ireland	1.57	1.52	10.80	10.90	7.77	8.09
Greece	0.78	0.77	9.90	11.90	1.93	2.06
Spain	1.14	1.10	11.30	12.20	3.11	3.27
Italy	1.52	1.46	10.40	11.80	2.32	2.43
Cyprus	0.97	1.00	11.00	12.10	6.85	8.22
Portugal	1.33	1.30	9.10	10.30	2.80	3.10

Source: Provopoulos (2014)

Table 2.2. EU-15 Bank capital to Total Assets ratio (%) - EU 15 Countries

Country Name	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Austria	4.8	5.2	6.5	6.3	7	7.5	7.2	7.4
Belgium	2.7	3.3	4.1	3.3	4.5	5	4.7	
Germany	4.1	4.3	4.3	4.5	4.8	4.3	4.4	4.4
Denmark	5.7	5.7	6.2	4.2	4.5	5.4	5.1	5.6
Spain	6.8	6.4	6.7	5.9	6.4	6.2	6.1	
Finland	9.2	9.4	8	6.2	6.4	5.5	4.4	4.4
France	4.4	4.5	4.1	3.7	4.1	4.9	4.8	
United Kingdom	6.1	6.1	5.5	4.4	5.4	5.4	5.1	
Greece	5.9	7	6.8	4.9	6.7	6.5	5.8	
Ireland	4.7	4.5	4.6	4.7	5.4	5.5	6.4	7.1
Italy	7.6	7	7.9	7.6	8	9.3	9.4	
Luxembourg	4.1	5	5	4.8	5.5	5.2	5.7	6.5
Netherlands	3.1	3	3.3	3.2	4.3	4.4	4.3	8.9
Portugal	5.8	6.6	6.5	5.8	6.5	6.7	5.3	6
Sweden	4.8	4.9	4.8	4.7	5			
Average EU-15	*5.32*	*5.53*	*5.62*	*4.95*	*5.63*	*5.84*	*5.62*	*6.29*

Source: World Bank

We now turn to what is the biggest change and constitutes the greatest challenge for Greek banks – that is Non-Performing Loans (NPL). Focusing on the period just before the outbreak of the economic crisis, Greece recorded the second highest percentage of NPL to Gross Loans ratio amongst the EU-15 member countries (4.3%), well above the EU average of 2.44% (Table 2.3). In the following years it is evident that the banking industry suffered from a sharp increase in the NPL, thus worsening the financial positions of credit institutions and compromising the stability of the banking system. In 2012, the ratio reached a record high of 23.3%, which brings Greece in the second worse position within the Eurozone, behind Ireland with 24.6% and significantly higher

than the EU average of 7.41%. The increase of the NPL ratio could be be attributed to the continuous economic contraction, the high unemployment rate; reaching post World War II figures of 24.2% in 2012, or to bank level information such as management qualities (Monokroussos et al., 2016). It is important to note that exploring the determinants of NPLs is an issue of great importance for macroeconomic and financial stability. A significant body of literature examined the determinants of credit risk, especially after the outbreak of the global financial crisis (see, for example, Berger and De Young, 1997; Williams, 2004; Podpiera and Weill, 2008; and Louzis et al., 2012). Prior literature has looked for drivers of NPLs on both systematic factors, such as macroeconomic conditions and bank specific determinants, such as management quality. More specifically, the relationship between NPLs and bank specific factors, first popularised by Berger and DeYoung (1997) links the development of ex-post risk (proxied by NPLs), bank capital, and management efficiency (proxied by either profit or cost efficiency estimates). The theories are based upon the intertemporal relationship between NPLs and the different bank specific factors associated with the evolution of impaired loans – linking that way bank managerial behaviour and quality with loan portfolio management practices[11].

The bad management hypothesis proxies managerial performance and quality by considering efficiency levels. More specifically, the premise of the hypothesised link is that low efficiency is a signal for poor managerial performance which effects loan granting behaviour and future levels of NPLs. Low bank cost efficiency levels can been seen as signalling poor managerial quality that affects the day-to-day operations of the bank and the management of the loan portfolio. The bad management theory provides a link between managers with poor skills in credit control, loan monitoring, risk appraisal and monitoring borrowers to deteriorations in the quality of the banks' assets. That is, inefficient managers will not cope successfully with the process of granting and monitoring loans – which eventually leads to lower bank credit quality and increases in impaired loans. So called "poor managers" do not monitor the loan portfolio adequately due to poor skills or insufficient resource allocation.

[11] Even though the authors do not use the term "behaviour" it is worth noting that the authors associate low efficiency with "bad managers" – a characterization that entails a behavioural element in our view. Indeed, this association is present in Williams (2004).

Because bank management fails to control operating expenses, increasing costs translate to immediate reduction in cost efficiency and increases in NPLs due to poor managerial practises will be realised after a lag. In addition, substandard managers may be prone to: selecting relatively high proportions of investments with a low or negative net present values; improper valuation of pledged collaterals; and inadequate customer monitoring in order to ensure contractual compliance with the loan agreement. The relationship between management characteristics and the evolution of NPLs is further analysed in Chapter 5 – where an in-depth discussion if presented.

Further examination of the data reveals that the deepening of the crisis and the continuous structural adjustments that took place in the country, leading to an overall decrease in the disposable income and the standard of living in Greece, affected the Greek banking sector during the later years, namely 2010, 2011 and 2012 (9.1%, 14.4% and 23.3% respectively), feeding into the liquidity problem already faced by the banking system. In addition, and further reflecting the deepening of the economic recession in Greece, we note an increase in post-2012 NPL levels. That is, Greece holds the highest NPL to Gross Loans in Europe, equal to 32%, 34% and 35% for 2013, 2014 and 2015 respectively. The deepening of the crisis becomes even more apparent when comparing the respective ratios of the other 'under-performers' of Europe, Italy and Ireland. Both countries report similar high ratios, however, they also show low increases and in some cases the upward trend is reversed That is, Ireland, after an increase in 2012-2013 (25% to 26%) managed to reduce the ratio to 15% for 2015. Finally, Italy also shows relative stability over the last two years (Table 2.3). Furthermore, with respect to the asset quality of Greek banks, Table 2.4 presents additional key indicators, reflecting the deterioration of the loan portfolio of Greek banks. That is, we present data on Loan Loss Reserves (LLP) to NPL and NPL to Equity ratios. It is evident that the quality of assets has deteriorated significantly after the sovereign debt crisis in 2010. For example, the LLR/NPL ratio, an index relating loan loss reserves to NPL, exhibits a declining pattern, starting from a maximum of 66.7% in 2005, leading to a minimum of 38.1% for 2011. This finding strongly indicates that Greek banks are not protected against risk exposures and again reflects deteriorated asset quality. Finally, even though the NPL to Equity ratio does not show a continuous pattern, the data suggest that Greek banks, in the last 8 years have lost their ability to cover their risk exposure through their capital positions. Indeed, Greek

banks have reported a minimum of 69.1% in 2007, whereas the respective maximum is equal to 437.4% for 2012. This sharp increase indicates the strong weakness of the loan portfolio relative to the industry capital.

Table 2.3. NPL to Total Gross Loans (%) – EU 15 Countries

Country Name	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*
Austria	2.6	2.739	2.242	1.903	2.250	2.830	2.706	2.813	2.866	3.473	3.460
Belgium	2	1.28	1.163	1.665	3.114	2.798	3.302	3.738	4.244	4.175	3.737
Germany	4.05	3.41	2.65	2.85	3.31	3.2	3.03	2.86	2.7	2.34	
Denmark	0.2	0.3	0.6	1.2	3.3	4.068	3.660	5.950	4.618	4.400	3.553
Spain	0.794	0.701	0.897	2.807	4.121	4.668	6.007	7.483	9.380	8.452	6.258
Finland	0.3	0.2	0.3	0.4	0.6	0.6	0.5	0.5			
France	3.5	3	2.7	2.819	4.021	3.758	4.291	4.294	4.495	4.162	3.982
United Kingdom	1	0.9	0.9	1.556	3.508	3.954	3.961	3.586	3.111	1.757	1.441
Greece	6.3	5.4	4.6	4.672	6.953	9.117	14.42	23.270	31.898	33.775	34.671
Ireland	0.48	0.535	0.629	1.922	9.796	13.04	16.127	24.987	25.708	20.648	14.934
Italy	6.996	6.568	5.778	6.282	9.446	10.027	11.742	13.746	16.542	18.033	17.967
Luxembourg	0.2	0.1	0.4	0.6	0.670	0.247	0.379	0.145	0.213		
Netherlands	1.2	0.8		1.681	3.201	2.832	2.710	3.097	3.227	2.982	2.711
Portugal	1.5	1.3	2.827	3.608	4.824	5.194	7.508	9.800	10.645	11.894	12.808
Sweden	0.8	0.105	0.082	0.462	0.834	0.783	0.654	0.700	0.6143	1.238	1.165
Average	*2.128*	*1.822*	*1.840*	*2.295*	*3.996*	*4.472*	*5.400*	*7.131*	*8.590*	*9.025*	*8.891*

Source: World Bank
Bank nonperforming loans to total gross loans (%)

Table 2.4. Greek Banking Sector - Asset Quality

	LLR/NPL (%)	*NPL/EQ (%)*
2005	66.712	90.489
2006	54.804	107.094
2007	53.490	69.1570
2008	63.774	120.351
2009	41.856	109.430
2010	41.598	226.226
2011	38.191	413.405
2012	45.170	437.45

Where, LLR/NPL (%): Loan Loss Reserves to Non-Performing Loans and NPL/EQ (%): Non-Performing Loans to Equity.
Source: Bankscope and author's own calculations.

Market Concentration

The relationship between market structure and the performance of firms in any industry is a complex one, and there has been considerable debate over the direction of causality. The banking literature focuses on four theories that disentangle the aforementioned relationship.

- The Structure-Conduct-Performance (SCP) hypothesis: The traditional SCP hypothesis asserts that the degree of market concentration affects the level of competition, and thus influences the conduct of firms (banks) within the industry. In other words, market structure influences banks' competitive behaviour and their performance. The costs associated with collusion between leading banks are low when market concentration is high, thus leading to increased levels of market power and higher prices and increased profits. In such an environment, the dominant agents do not have much incentive to improve their efficiency levels.
- The Relative Market Power (RMP) hypothesis: Shepherd (1982) proposed a related theory under which, only firms that possess a large market share and a well-differentiated portfolio of products are in a position to exercise market power when pricing these products. The implicit assumption of the RMP hypothesis is that large banks normally produce better quality products and that customers are more inclined to pay higher prices to obtain better services. For example, Berger (1995) argues that better banking services may entail the better location of bank branches, improved service quality and increased number of financial products.
- The Efficient Structure (ES) hypothesis: In contrast to the aforementioned hypotheses, ES hypothesis argues that efficient firms outperform their competitors and gain higher market share – resulting in higher concentration of the market structure. The implication is that higher levels of profit are derived from improved efficiency levels and lower costs – while treating higher concentration levels as is a result of higher firm-specific efficiencies. Under the X-efficiency version of the ES hypothesis, banks with superior management or production technologies can maximise profits by reducing prices. These firms are able to gain large market shares that may result in high levels of concentration. The positive relationship between profit and market structure is

an indirect one and it is driven by improvements in bank-specific efficient levels. Under the second version, scale-efficiency, bank have the same quality of managements and technology and the differentiating factor becomes the unit cost of production. That is, some firms produce at more efficient scales than others and therefore have lower unit costs and higher unit profits. As before, these firms are assumed to have increased market shares which lead to high concentration levels. As with the X-efficiency version of ES, the positive profit-structure relationship is a spurious outcome, driven by improvements in bank-specific scale (Berger, 1995)

- The Quiet Life (QL) hypothesis: Hicks (1935), suggested the "quiet life" hypothesis. Under this premise, if high levels of market concentration allow firms to charge prices in excess of competitive levels, then managers may benefit on in terms of increases in profit, but rather in the form a "quiet life" – implying that the do not have to work hard to maintain costs under control. The difference between the actual price and the competitive price provides a safety net and managers may allow unit costs to increase and consume part of that extra monetary cushion, while still experiencing economic rents, without the explicitly minimising costs.

From the above discussion, it is evident that the policy implications differ substantially and are based on the prevalence of either the market-power hypotheses (SCP and RMP) or the two efficient-structure hypotheses. For example, in the case where market-power hypotheses are confirmed, bank merger could be motivated by incentives to set prices in levels that are unfavourable to consumers. On the other hand, under the efficient-structure hypotheses, mergers are driven by efficiency considerations that eventually will increase the total surplus.

Finally, given the aforementioned theoretical link between performance and market structure, incorporating this dynamic relationship into the estimation of efficiency becomes an important consideration as for example, efficiency may allow firms to survive competition and grow, but the resulting market concentration may lead to deteriorations in firm efficiency. It is therefore important to examine the business environment in which Greek banks operate. That is, we turn our attention to two market concentration indicators; the k-bank concentration ratio (CRk) and the Herfindahl-

Hirschman Index (HHI). Even though, theoretically it is not clear whether a CRk concentration ratio or the HHI is the most appropriate measure for market concentration (Sander and Kleimeier, 2004), the importance of these two indices arises from their ability to capture structural features of a market (see for example Staikouras and Koutsomanoli-Fillipaki, 2006).

With respect to the degree of market concentrations in Greece, the ratio of the five largest credit institutions indicates that the degree of concentration for the period 2005-2012 recorded an increase of approximately 21.19%, from 65.6% in 2005 to 79.5% in 2012 (Table 2.5). Even though this increase is in line with the trend in Europe, the change in the Greek banking sector is significantly higher (EU countries, overall, exhibited an average increase equal to 8.45%). This phenomenon can be attributed to M&A, especially during recent years and hence the restructuring of the industry. Throughout the whole period, the Netherlands (84.71%), Finland (81.94%), Belgium (77.88%), Greece (70.5%) and Portugal (69.43%) are the five most concentrated banking systems in the European Union for the years 2005-2012[12].

The advantage of the CONC5 ratio is that it provides a measure of market concentration in a computationally easy way. However, one of its drawbacks is that it does not consider the size distribution of the remaining credit institutions in the market. Therefore, the HHI is calculated as the sum of squares of all the credit institutions' market shares in terms of total assets and offers better analytical intuition as it includes all firms in the industry and the weights of firms according to market share. Whereas the HHI presents values between zero; indicating a large number of credit institutions with very low market share, and 10,000 and indication of a monopolistic banking sector. As a general rule, a HHI below 1,000 signals low concentration, while a HHI above 1,800 signals high concentration. Values between 1,000 and 1,800 indicate a moderately concentrated industry. Consistent with the CONC5 ratio, the banking system in Greece experienced an increase in the HHI index of 35.68%, with an average

[12] The ECB notes that "taking a cross-country view, concentration indices reflect a number of structural factors. Banking systems in larger countries, such as France, Germany and Italy, are more fragmented and include strong savings and cooperative banking sectors, particularly in the latter two. Consequently, concentration levels tend to be lower in these countries. By contrast, banking systems in smaller countries tend to be less fragmented and more concentrated, such as in Cyprus, Estonia, Finland, Greece and Lithuania (page 26)" (ECB, 2015).

of 1,203 (1,096 in 2005 compared to 1,487 in 2012) (Table 2.5). The corresponding figures for the EU-15 countries are 15.70% and 981.34. Looking at the averages of the HHI for the whole sample period, Finland (2,974) and the Netherlands (1,985) fall in the high concentration zone, whereas Belgium (1,690) Greece (1,203), Denmark and Portugal (1,156) belong to the moderate concentration zone. The remaining countries, with an average below 1,000 are characterized by a low degree of market concentration. More analytical results on the individual countries and years are presented in Table 2-6 and Table 2.7.

Table 2.5. Concentration of five largest banks and Herfindahl-Hirschman Index

	CONC5		*HHI*	
	Average 2005-2012	*% change 2005-2012*	*Average 2005-2012*	*% change 2005-2012*
Austria	39.83	-18.89	461.25	-29.46
Belgium	77.88	-22.27	1,690.63	-49.76
Germany	26.55	52.78	231.75	76.44
Denmark	65.19	-1.06	1,122.00	1.35
Spain	44.11	22.38	521.25	34.29
Finland	81.94	-4.70	2,974.29	10.26
France	49.34	-14.07	646.63	-25.03
United Kingdom	38.50	11.85	424.63	-15.01
Greece	70.05	21.19	1,203.50	35.68
Ireland	52.25	24.51	775.00	66.67
Italy	33.64	48.13	330.88	78.26
Luxembourg	29.96	7.82	313.00	-7.51
Netherlands	84.71	-2.84	1,985.63	12.81
Portugal	69.43	1.74	1,156.75	3.21
Sweden	58.96	0.17	882.88	0.95
Average EU-15	*54.82*	*8.45*	*981.34*	*15.70*

Source: Based on various ECB and EU reports on banking structure.

Table 2.6. EU-15 CONC5: Share of Total Assets of five largest institutions (%)

Country	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Austria	45	43.8	42.8	39	37.2	35.9	38.4	36.5
Belgium	85.3	84.4	83.4	80.8	77.1	74.9	70.8	66.3
Germany	21.6	22	22	22.7	25	32.6	33.5	33
Denmark	66.3	64.7	64.2	66	64	64.4	66.3	65.6
Spain	42	40.4	41	42.4	43.3	44.3	48.1	51.4
Finland	82.9	82.3	81.2	82.8	82.6	83.8	80.9	79
France	51.9	52.3	51.8	51.2	47.2	47.4	48.3	44.6
United Kingdom	36.3	35.9	40.7	36.5	34.1	39.8	44.1	40.6
Greece	65.6	66.3	67.7	69.5	69.2	70.6	72	79.5
Ireland	45.7	44.8	46.1	55.7	58.8	56.8	53.2	56.9
Italy	26.8	26.2	33.1	33	31	39.8	39.5	39.7
Luxembourg	30.7	29.1	27.9	27.3	29.3	31.1	31.2	33.1
Netherlands	84.5	85.1	86.3	86.8	85.1	84.2	83.6	82.1
Portugal	68.8	67.9	67.8	69.1	70.1	70.9	70.8	70
Sweden	57.3	57.8	61	61.9	60.7	57.8	57.8	57.4
Average EU-15	*54.05*	*53.53*	*54.47*	*54.98*	*54.31*	*55.62*	*55.90*	*55.71*

Source: Based on various ECB and EU reports on banking structure.

Table 2.7. EU-15 Herfindahl Index (Total Assets)

Country	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Austria	560	534	527	454	414	383	423	395
Belgium	2,112	2,041	2,079	1,877	1,622	1,439	1,294	1,061
Germany	174	178	183	191	206	298	317	307
Denmark	1,115	1,071	1,120	1,229	1,042	1,077	1,192	1,130
Spain	487	442	459	497	507	528	596	654
Finland	2,730	2,560	2,540	3,160	3,120	3,550	3,700	3,010
France	727	726	679	681	605	610	600	545
United Kingdom	399	394	449	412	360	424	523	436
Greece	1,096	1,101	1,096	1,172	1,184	1,214	1,278	1,487
Ireland	600	600	600	800	900	900	800	1,000
Italy	230	220	328	344	298	410	407	410
Luxembourg	312	294	276	278	310	343	346	345
Netherlands	1,796	1,822	1,928	2,168	2,032	2,052	2,061	2,026
Portugal	1,154	1,134	1,098	1,114	1,150	1,207	1,206	1,191
Sweden	845	856	934	953	899	860	863	853
Average EU-15	*955.8*	*931.53*	*953.07*	*1022*	*976.6*	*838.93*	*1040.4*	*990*

Source: Based on various ECB and EU reports on banking structure.

Regarding the profitability of Greek banks, indicated by Return on Average Assets (ROAA) and Net Interest Margin (NIM), we can determine that banks were more able to generate profits from their assets before the 2008 crisis, even though both ROAA and NIM show a downward pattern (Table 2.8 and Figure 2.2). Indeed, ROAA turns negative in 2008 (-0.137), reaching a maximum value of -8.160 in 2011. With respect to the NIM ratio, it is evident that prior to the financial crisis in 2008, Greek banks were in a position where they could obtain cheaper funding. However, the dire state of the banking sector is clearly indicated by the reduced NIM values reported after the 2010 Greek debt crisis, with a minimum value equal to 1.950 for 2012. This low NIM value is unsurprisingly observed in a period of financial distress for Greek banks (accompanied with sharp increases in NPL (23.27% for 2012, Table 2.3)). Finally, with respect to customer loans and deposits, it is interesting to note that most of the credit expansion in Greece took place after the accession in the EMU, when Greek banks increased their interbank borrowing activity in order to satisfy the high demand for loans.

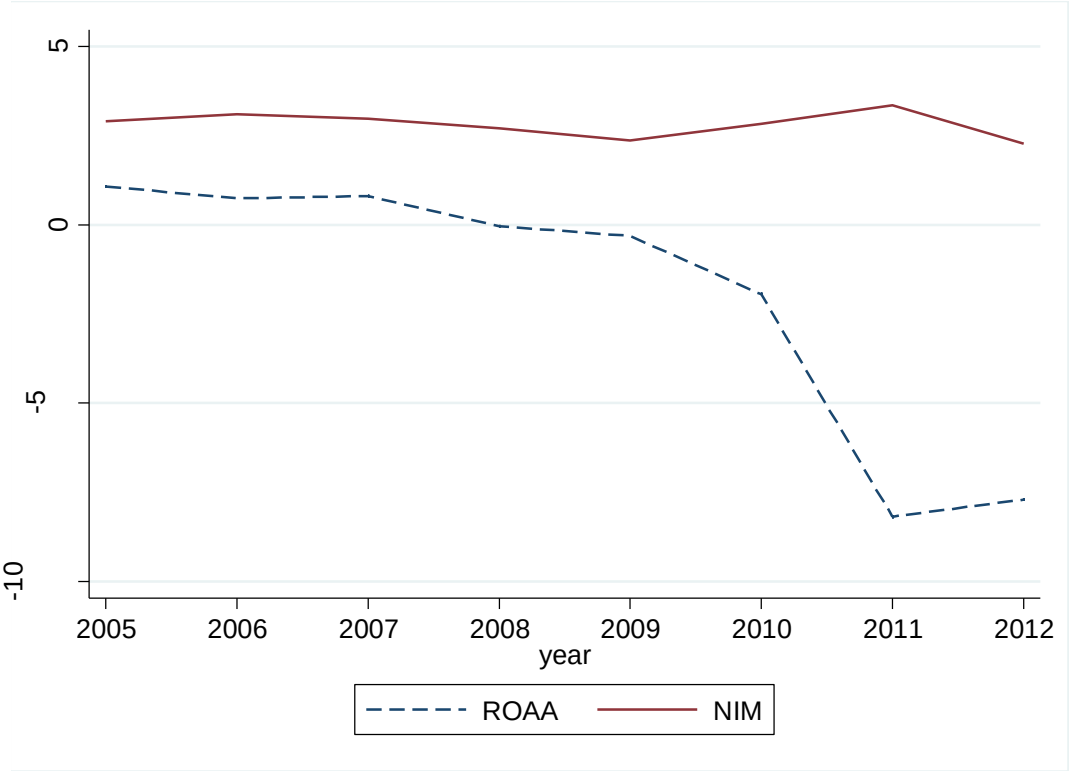
However, as discussed above due to the recent 2010 crisis, a considerable amount of loans has been characterised as bad debt. Similarly, deposits experienced a sharp decline as depositors became nervous about the safety of their deposits. We can identify two distinct patterns in the data. That is, 2010 and 2014, whereby total customer deposits report sharp decreases and thus reflecting an overall economic uncertainty prevalent in the country (Figure 2.4).

Table 2.8. Greek Banking Sector Profitability Fundaments and Macroeconomic Indicators

	ROAA (%)	*NIM (%)*	*GDP (%)*	*Inflation (%)*	*Unemployment (%)*
2005	1.211	3.109	2.280	3.545	10
2006	0.766	3.134	5.507	3.195	9
2007	0.804	2.953	3.536	2.895	8.4
2008	-0.137	2.650	-.215	4.152	7.8
2009	-0.414	2.343	-3.136	1.21	9.6
2010	-1.292	2.455	-4.943	4.712	12.7
2011	-8.160	2.671	-7.105	3.329	17.9
2012	-3.300	1.950	-6.972	1.501	24.5

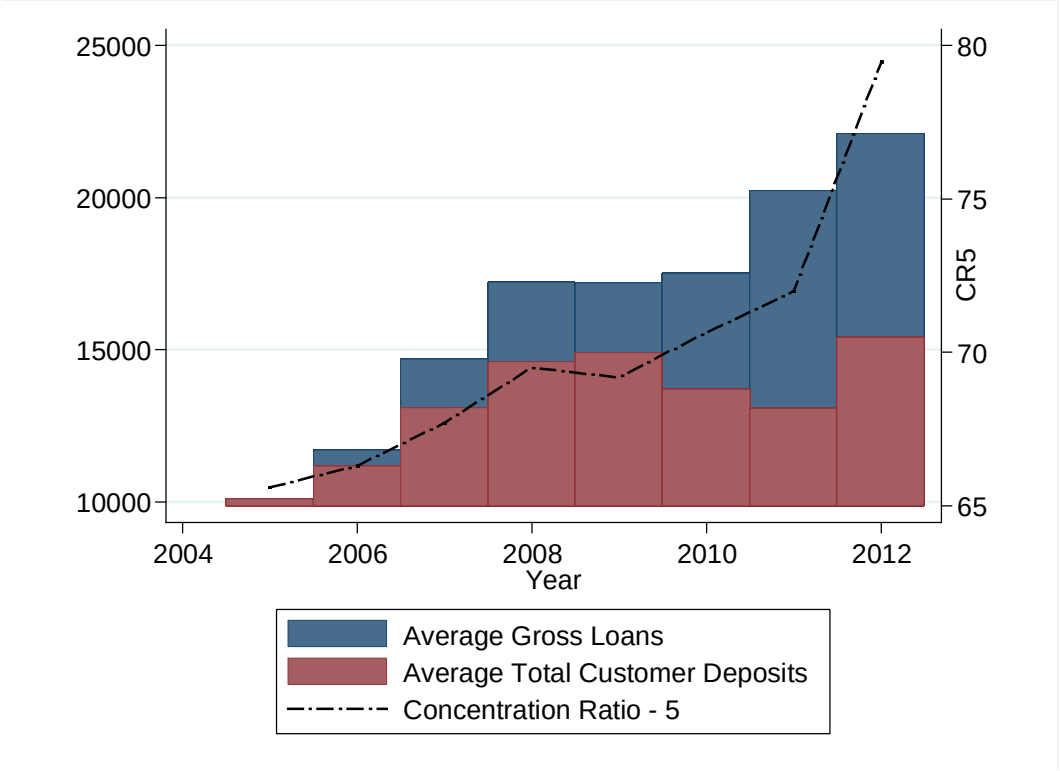
ROAA (%): return on Average Assets ,estimated as Net Income divided by Average Total Assets; NIM (%): Net Interest Margin, estimated as Net Interest Income divided by Total Earning Assets; GDP: Annual change of Gross Domestic Product (%),Inflation: Annual inflation rate (%), Unemployment: Unemployment rate.
Sources: World Bank, the European Central Bank, Eurostat database, Bankscope and author's own calculations.

Figure 2.2. Greek Banking Sector Profitability Fundaments



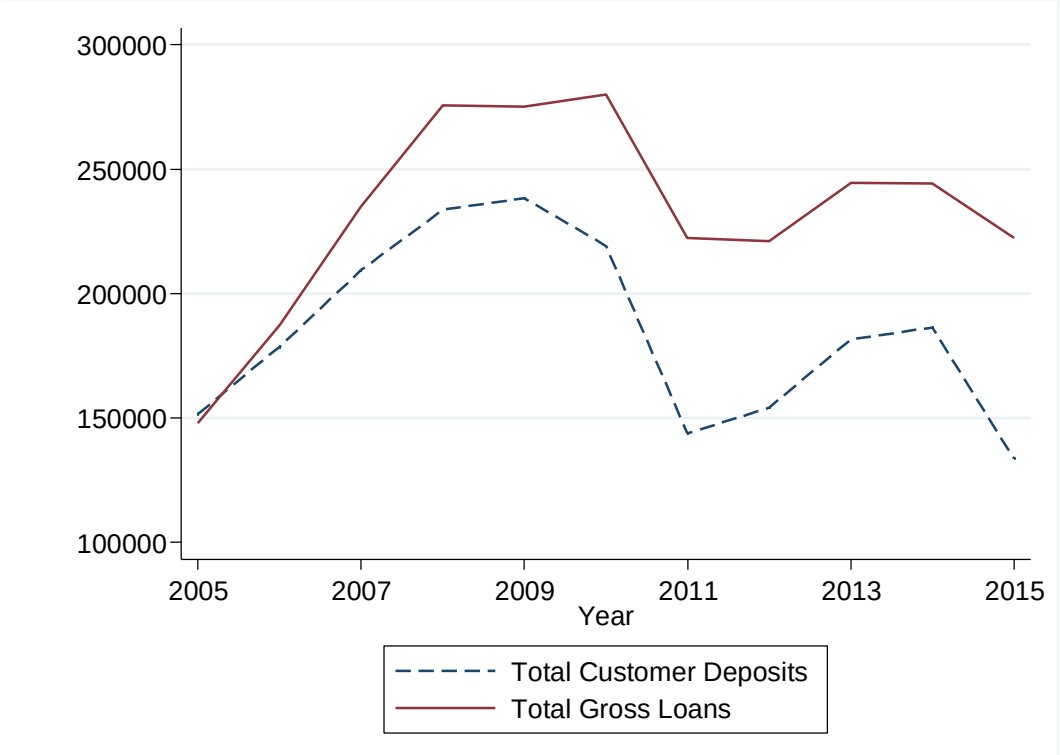
ROAA (%): return on Average Assets, estimated as Net Income divided by Average Total Assets; NIM (%): Net Interest Margin, estimated as Net Interest Income divided by Total Earning Assets. Source: Bankscope and author's own calculations.

Figure 2.3. Greek Banking Sector Fundamentals



Author's own calculations.

Figure 2.4. Evolution of Customer Deposits and Gross Loans



Source: Bankscope and author's own calculations

2.6 The PSI and Post-2012 developments

The majority of Greek banks became insolvent in 2012 and many of the financial institutions had to rely on the ELA mechanism for funds. In June 2011 Barclays Capital circulated a report that estimated the exposure to Greek debt (bonds, bills and loans). The report indicates that public institutions held more that 50% of Greece's debt at that time. According to estimates, Greek banks were also heavily exposed to Greek debt, with approximately €51.1 billion – an amount reflecting 14.2% of the total Greek debt. In December, the International Monetary Fund (2011) confirmed the above numbers and reported that the banks owned Greek government bonds with a nominal value of approximately €45 billion with an aggregate core capital of Greek banks amounting to €22 billion. This extensive exposure indicates that the Greek banking sector depends heavily on the agreed terms for the PSI. Finally, the IMF (2011) report summarizes the following key points:

- The six largest banks hold approximately 97% of the Greek Government bonds, raising their capital needs to €17 billions in the case of a 50% cut.
- The capital base could be wiped out for some banks while some other would end up being undercapitalized.

However, core institutions, based on wider information such as risk management, business model and plans, could be deemed viable after PSI and; the IMF stresses that importance for private ownership of the Greek banks after the public recapitalization, as the government has shown poor record of managing state-owned banks.

Under the initial design of the restructuring process, private sector holders of Greek government bonds were invited to voluntarily exchange their holdings for new bonds with longer maturities and lower coupons. This transaction would reduce their Net Present Value (NPV) by approximately 21%. Greek banks recorded the related provisions in their June 2011 statements. However, the Euro summit of October 2011 decided that a deeper PSI programme would further enhance the likelihood for a sustainable Greek debt – hence adopting a modified PSI. The aim of reducing debt to GDP to 120% by 2020 would be accomplished with a reduction in face value in terms of Greek sovereign debt and the implementation of a programme of fiscal and structural reforms. More specifically, the PSI involvement was completed on 25 April 2012 with

a participation rate of 96.6% of the total outstanding amount of eligible bonds, with a discount of 53.5% (Bank of Greece, 2012)[13].

In the context of the PSI, Greek banks exchanged Greek Governments bonds and state-related loans of a total face amount of €48.6 billion, for New Bonds issued by the Hellenic Republic and PSI Payment Notes issued by the European Financial Stability Facility (EFSF) (Bank of Greece, 2012). According to the Report on the Recapitalisation and Restructuring of the Greek Banking Sector issued by the Bank of Greece in 2012, the NPV loss from the debt exceeded 78% of the face value of the old bonds and these losses translate to €37.7 billion – of which €5.8 billion had already been recorded on June 2011 financial statements. According to the above stated report, the four systemically important institutions registered Total Gross PSI loss/Total Assets of 11.0%, 7.5%, 8.1% and 12% for National Bank of Greece SA, Eurobank Ergasias SA, Alpha Bank AE and Piraeus Bank SA respectively. TT Hellenic Postbank reported the largest losses with 24.8% (for details see Table 2.9).

[13] For a more detailed analysis on the exposure of Greek banks to the PSI and the subsequent consequences, see Pasiouras (2012).

Table 2.9. Impairment losses of Greek government bonds and state-related loans under the PSI

Banks	*Face Amount of GGBs (1)*	*Face amount of state-related loans (2)*	*Total Face amount (3)=(1)+(2)*	*PSI loss of GGBs (4)*	*PSI loss of state-related loans (5)*	*Total gross PSI loss (6)=(4)+(5)*	*Total PSI loss/Core Tier 1 (Dec 2011) (7)*	*Total gross PSI loss/Total Assets (Dec 2011) (8)*
NBG	13,748	1,001	14,749	10,985	751	11736	161	11
Eurobank	7001	335	7,336	5517	264	5781	164.5	7.5
Alpha	3898	2145	6,043	3087	1699	4786	105.7	8.1
Piraeus	7063	280	7,343	5686	225	5911	226	12
Emporiki	351	415	766	270	320	590	40.3	2.7
AteBank	5164	608	5,772	3873	456	4329	1,144.20	17.1
Postbank	4197	175	4,372	3306	138	3444	618.3	24.8
Millenium	185	0	185	137	0	137	29	2.2
Geniki	384	7	391	287	5	292	78.1	8.9
Attica	199	0	199	142	0	142	38.8	3.4
Probank	415	0	415	295	0	295	105.1	8.7
New Proton[1]	934	0	934	216	0	216	378.8	12.6
FBB	70	0	70	49	0	49	33.8	3.1
Panellinia	34	0	34	26	0	26	31.7	3.5
Total	*43,643*	*4,966*	*48,609*	*33,876*	*3,858*	*37,734*	*3,155*	*126*

GGB represents Greek government bonds, PSI represents the Private Sector Involvement
Source: Bank of Greece.
[1] *For New Proton Bank, part of the impact has been funded through the resolution of Proton Bank.*

After the restructuring of the Greek debt in 2012 and the subsequent 53.5% reduction in the Greek debt, the balance sheets of domestic financial institutions suffered a significant hit. That is, combined with a gradual increase in NPLs, the sector's equity levels suffered significantly and Greek banks had to undergo a substantial recapitalization process to meet the requirements of the supervisory framework. The creation of the European Support Mechanism (ESM) was proposed, establishing a credit line for Greek banks. In light of the deepening of the Greek sovereign crisis, in January 2012, the BoG conducted an assessment of the capital needs of the banking sector. This exercise included the activities of Greek commercial banks on a consolidated basis and the assessment was carried out under a Baseline and an Adverse Scenario, for the period 2012-2014. The main objective was to estimate the capital need of all Greek commercial banks and to ensure minimum Core Tier 1 capital levels for the aforementioned period. The assessment concluded that for the period 2012-2014, the Greek banking sector would require €40.5 billion to be adequately capitalised, out of which an injection of €27.5 billion from the four largest domestic institutions (National Bank of Greece SA, Eurobank Ergasias SA and Piraeus Bank SA). In late May 2012, the HFSF, in cooperation with the Troika sign pre-subscription agreements with the four largest banks on the upcoming capital increases and injected €18 billion in the form of EFSF notes (Bank of Greece, 2014d). The BoG, estimated that under reasonable levels of economic uncertainty, the amount of €50 billion was enough to cover the recapitalisation and restructuring costs of the Greek banking system, allowing at the same time to include a capital buffer for addressing any unexpected capital increases. Furthermore, the BoG conducted a viability assessment in order to assess which banks were good candidates for recapitalisation via the HFSF. As a result, the four core banks were recapitalised with public-sector funds as they were assessed as the most likely to repay such funds within a reasonable timeframe. One non-core bank was also to be recapitalized through private capital. When the process started, 17 banks were operating in Greece; four core banks and 13 non-core banks (in addition, 16 cooperative banks also operated with a combined market share of 1% of the banking system).

In parallel to the above developments, the Greek banking system underwent a significant restructuring process whereby Alpha Bank acquired Emporiki Bank (a large subsidiary of Credit Agricole) and integrated the deposits of Dodecanese, Evia and

Western Macedonia cooperative banks. In addition, Eurobank acquired New Proton Bank and New Hellenic Postbank. Next, National Bank Greece integrated the good part of First Business Bank and Probank as well as the deposits of Achaia, Lamia and Lesvos-Lemnos cooperative banks. Then, Piraeus Bank integrated the good part of ATE bank, the branches of Cypriot banks operating in Greece, Bank of Cyprus, Laiki Bank and Hellenic Bank. Those purchases helped limit any contagion stemming from the Cypriot banking system to the Greek financial system. Finally the BoG revoked the license of TBank mid-December 2011 due to its inability to restore its capital adequacy and subsequently TT Hellenic Postbank acquired the full amounts of all their deposits, employment contracts and assets.

In the context of the on-going restructuring of the Greek banking sector, a health check was run by the BoG to see whether the allocated resources where sufficient to secure financial viability of Greek banks. On the basis of the above discussion, the BoG estimated the target amount of Core Tier 1 capital for each bank at the end of each calendar year until 2016 based on the target Core Tier 1 ratio set for each scenario and the respective adjusted Risk Weighted Assets (RWAs). Under the binding Baseline Scenario, the BoG concluded that the Greek banking sector would require approximately €6.4 billion enabling for further strengthening of its capital base. In line with the above, in May 2014 a second round of recapitalisations were conducted in which the banks were financed by private investors. In July 2015 and after a 5 month period, the government agreed to a third bailout programme funded with €86 billion, out of which €25 billion were set aside to address potential recapitalization needs of viable banks and resolution costs of non-viable institutions (€5.4 billion of the first €10 billion sub-tranche was released to Greece in December 2015)

More recently and due to political uncertainty, deposit holders withdrew significant funds from Greek banks in 2015 (see Figure 2.4 for the evolution of deposits in Greek for 2005-2015). That led to Greek banks facing an increase in payment delays as borrowers waited to see whether the government would introduce debt relief measures. The ECB conducted an evaluation of the capital needs of the four significant Greek banks ECB's Single Supervisory Mechanism (SSM), in line with the decision by the Euro Summit on 12 July 2015 and the Memorandum of Understanding between the European Commission acting on behalf of the European Stability Mechanism (ESM).

The result, the Hellenic Republic and BoG signed on 19 August 2015 and undertook a comprehensive assessment of Greek banks.

The aforementioned assessment included an asset quality review and a stress test, including a baseline scenario and an adverse scenario. These stress tests uncovered significant adjustments, as it identified systemic banks which needed €14.4 billion of additional capital (out of which €4.4 billion under the Baseline Scenario plus €10 billion under the Adverse Scenario). During the recapitalisation period, Alpha Bank AE and Eurobank Ergasias SA, raised enough capital to also meet the adverse scenario and as a result did not require further funds. However, Piraeus Bank SA and National Bank of Greece SA received additional financial support through the HFSF (the first disbursement of €2.72 billion on 1 December 2015 covered their capital needs and a second disbursement of €2.71 billion on 8 December 2015 was used to recapitalise National Bank of Greece. Finally, it is worth noting that in June 2015 the Greek government introduced capital controls, when the bailout extension programme came to an end without reaching an agreement on a further extension with its creditors. This development led the ECB to decide not to further increase the level of its ELA for Greek banks. As an immediate reaction and in order to avoid a bank run, the Greek government closed Greek banks for approximately 20 days and implemented capital controls on transfers to foreign banks (thus imposing a limit on cash withdrawals). The capital controls remain enforced until present.

Evidently, banks have been in the forefront of recent economic and financial developments in Greece but a lack of political stability has harmed investor confidence and increased uncertainty. In this adverse environment, banks are facing increasing levels of NPL, in turn impeding the flow of capital towards viable ventures that would help revive the Greek economy. The reported losses on NPL could erode capital once again, thus leading to a fourth round of recapitalisation. The main challenge for the banks that survived this turbulent period is to restructure their loan portfolio. However, as Yannis Stournaras, the head of the central bank, astutely observed at the 83th Annual Meeting of Shareholders (2016), "bold and innovative initiatives" to clean up bad loans will be required and "this cannot be ensured by the current 'business as usual' approach". Therefore, this Thesis provides a timely and warranted analysis through presenting empirical evidence examining the risk management of Greek banks. Our

discussion and results give a background to the above financial recapitalisation process and we believe offer interesting insights into provisioning behaviours.

2.7 Conclusion

In recent years, the Greek banking system experienced significant changes as a result of deregulation, the establishment of the common EU market and the introduction of the Euro. In response to the above developments, Greek banks responded with a series of mergers and acquisitions, modernization of their technology and risk management measures and expansion of their activities abroad. The years after the introduction of the Euro in Greece was followed by a period of economic stability for the country - a factor that contributed significantly and helped Greek banks achieve higher levels of profitability. This upward trend was sustained for the Greek banks as their business model was not dependent on toxic assets and the relatively closed Greek economy was able to weather-the-storm. However, weakening Greek economic conditions and later the sovereign debt crisis in 2010 delivered a significant hit to the Greek banking system. Initially, Greek banks played an important part in stabilising the economy. But their involvement came with a cost, that is, the PSI process significantly hit their financial positions and inevitably led to the first recapitalization in 2012. The deepening of the crisis and structural problems in the economy led Greece into a 7 year recession, whereby Greek banks were the centre of the economic developments as they no longer served their primary purpose (intermediating funds across the Greek economy). On the contrary, they were severely affected by the recession and the political instability in the country to the point that two additional rounds of recapitalization were required for the banking system to maintain its capital base and stability.

In this Chapter we presented the main events that shaped the Greek banking sector in the last 15 years. We briefly discussed the deregulation period in the Greek banking system and the first years after the introduction of the Euro in Greece. We further focused on the main structural features of the sector including an analysis of the number and types of banks, concentration, loan-to-deposits ratio, asset quality ratios and capital levels. Finally, we present the current state of the Greek banking system, extending our discussion after the sampled period (2005-2012) and covering the PSI and post-2012 years (the end of the Thesis sample period). Our aim is to present a contextual background of the Greek banking sector, which serves as a basis in an empirical estimation of cost efficiency and LLP modelling.

Chapter 3

Methodological Framework

3.1 Chapter Summary

This Chapter examines two performance indicators commonly used within the banking literature and presents the theoretical foundations of the prevalent frontier estimation methodologies. We begin with a discussion on the use of financial ratios and how ratios, originally based on the DuPont method, are widely used by academics and practitioners. Our analysis in this Thesis presents the inherent problems in the use of financial ratios to gauge bank performance and thus leads us to Section 3.4. In the latter section, econometric programmes that have been used in the literature, based in the seminal work of Farrell (1957), are presented. In terms of our analysis, this Thesis is a parametric approach and hence will only outline the most commonly employed parametric frontier models. This approach gives us a coherent grounding to enable us to specify a functional form relevant to Greek banking that can be estimated to obtain efficiency scores. The functional forms/production methodologies discussed allow, unlike financial ratios (as presented in Section 3.3), a multi-product cost function. A comprehensive and coherent strategy is then presented to allow pre/post estimation tests. Hence, having specified our preferred specification, modelling strategy and stability tests, we present a discussion on the inputs/outputs utilised in our bank models under the assumption of a multi-product cost function. Furthermore, we discuss, given the data constraints and the nature of the Greek banking market, our preferred input/output model which we believe fully captures the business management characteristics of Greek banks. Section 3.4 describes the techniques for estimating efficiency which are common in the banking literature; the available pre/post estimation test; the distributional assumptions related; and the relevant functional forms. Section 3.5 discusses the choice of the input/output mix when investigating bank efficiency. Finally Section 3.6 concludes.

3.2 Introduction

Banking systems are fundamental to the financial development of an economy. Their role makes monitoring performance a key factor that will enable regulators to ensure stability and promote further financial and economic advancements. Crucial issues arise from both the micro and the macro perspective. Stability and increased performance in the financial system is of key interest for the regulatory authorities given issues relating to competition and improvements in the regulatory and supervisory framework. Operating at optimal levels of cost is also important since deviations from that level increases the cost of financial intermediation for banks, thus influencing overall market, and potentially leading to spill-over effects in economic development. For example, Delis et al., (2009) observe that "an improvement in bank performance indicates a better allocation of financial resources, and therefore an increase in investment that favours growth (p. 191)". The Greek banking system is an interesting field of research as it has undergone significant changes in the last twenty years. More importantly, the Greek banking sector has been subject to significant structural reforms during the recent Greek debt crisis. Indeed, the highly volatile business environment in which Greek banks operate renders an analysis of the performance of institutions operating in the market as both timely and warranted given the problems experienced during and after the global financial crisis (see Chapter 2).

3.3 Financial Ratios and Frontier Estimation

The use of ratios by both academics and practitioners is well embedded in applied economics, organisation studies and financial theory. However, despite their popularity and regardless of their use, ratios are not without limitations and have numerous shortcomings discussed in the literature. The following discussion attempts to bring to the fore the debate surrounding the use of ratios from two different strands of the literature. Firstly, we focus on the comparison between traditional performance indicators and more advanced frontier estimates. Secondly, we revisit evidence concerning the problems related to estimation and inference that could arise when ratios are used in statistical estimation; a strategy which is popular in empirical banking studies (for example, Anandarajan et al., 2003; Fonseca and González 2008 and Leventis et al., 2012).

That is, before an analysis of Greek banks can be presented, it is necessary to build a foundation in which we can analyse the differences between key financial performance indicators and frontier techniques. In relation to the former, frontier techniques are based on a production technology which allows for the transformation of inputs into outputs; irrespective of the nature of the method followed[14]. The main goal is to estimate the maximum level of output given the level of inputs, or a minimum input level for given output levels. This type of operating efficiency effectively determines whether a firm is cost minimising (consuming less inputs for the same level of outputs) or profit maximising (producing more outputs for the same amount of inputs) (Beccalli et al., 2006).

This concept of efficiency, proxies by cost efficiency and estimated via cost frontier construction, can be considered as a managerial best practice indicator (it is commonly estimated as a tool for measuring bank performance (see Berger and Humphrey, 1997). Furthermore, these operating efficiency measures are believed to be better indicators of bank performance compared to traditional accounting ratios (Berger and Humphrey, 1992). That is, limitations of traditional performance ratios are well documented within the efficiency literature. More specifically, accounting ratios do not take into account

[14] Two main methodologies are prominent within the efficiency literature, parametric and non-parametric. This thesis is using one of the most popular parametric methods which will be further analysed in the following sections.

information regarding the composition of the output produced and input prices (Berger and Humphrey, 1992 and Berger et al., 2009). In addition, they cannot accommodate a multiple output mix and input prices (Berger and Humphrey, 1997a). Finally, ratios do not incorporate in a direct manner the impact of exogenous factors on the production/cost function and are more relevant in a single output single input context as ratios are offer insights on factor-specific performance (see for example, Thanassoulis et al., 1996).

These differences between the two techniques are present in the construction of an efficiency frontier. For example, a cost function allows the efficiency indicators to incorporate both the vector of production and input prices in the final efficiencies produced. It considers simultaneously all aspects of the performance of the firm identifying a firm as a good performer even when its performance in individual financial performance indicators does not signal efficiency. For example, as DeYoung (1997b) observes, "myopic analysis of expenditures can be misleading—reduced spending on labour, materials, or physical plant is no guarantee that a bank is being run efficiently, and high levels of spending on these items does not necessarily signal inefficiency (p 21)". With respect to financial ratios an example of such a misspecification is the cost to income ratio that may increase due to three reasons. Firstly, increased competition could lead to an increase in the cost to income ratio through a reduction in the interest margins. Secondly, the cost to income ratio could also increase because a cost efficient bank is producing a high-cost output vector, for example more loans and less liquid assets. Thirdly, an increase may occur because a bank is facing higher input prices (i.e., labour costs). Therefore, examination of the cost to income ratio alone might produce misleading information about how well a bank converts its inputs to outputs, thus incorrectly identifying a bank as a poor performer. That is, exogenous factors outside of management behaviour may explain these discrepancies over and above the implementations of a poor business model. This is most relevant in terms of Greek banks where the economic environment decreased GDP growth and led to a dramatic increase in the unemployment rate and subsequently NPL, as discussed in Chapter 2.

In addition, inferring relative performance between banks may lead to ill-defined conclusions and can only be appropriate under restrictive conditions. Indeed, DeYoung

(1997) observe that "[….] comparing the cost ratios of two different banks is inappropriate unless both banks are nearly identical in terms of product mix, bank size, market conditions, and other characteristics that can affect the banks' expenses (page 30)". An alternative recommendation could be the comparison of the average of the cost ratio across the relevant peer group. Such peer group limitations are addressed by the estimation of frontier cost measurements given adequate data.

A second strand of criticism against the use of financial ratios draws heavily from areas outside the banking literature and is concerned with measuring correlations. Historically, controversies regarding the use of ratios link back to Pearson's (1987) examination of correlation analysis. In relation to this strand, Cohen et al., (2003) offer a summary of the major challenges when using ratios by building on the original work of Pearson and arguing that ratios confound result interpretations and may contribute to spurious findings. Interestingly, they observe that "when a ratio score is correlated with another variable or with another ratio score, the resulting correlation depends as much on the denominator of the score as it does on the numerator. Because it is usually the investigator's intent to "take the denominator into account" it may not be immediately obvious that the correlations obtained between ratio scores may be spurious—that is, may be a consequence of mathematical necessities that have no valid interpretive use (p 60)". Hence, there is a need to carefully consider the use of ratios in any financial analysis setting.

However, within the empirical literature financial ratios are still employed; as conceptual ratios capturing multi-dimensional constructs such as the CR (industry consolidation), to deflate data or scale in order to control for the size effect and finally control for a heteroskedastic error term in regressions (Bollen and Ward 1979 cited in Wiseman, (2009)). For example, the first use addresses issues regarding ratios when they hold a theoretical meaning apart from that expressed by their components. The purpose is to capture the theoretical concepts that are not able to be captured by a single component alone. Indeed, Wiseman (2009) suggests that such relationships when included either as a dependant variable or explanatory covariates, are likely to generate biased results and/or lead to inaccurate interpretations of the associations involving ratio variables. Indeed, Wiseman (2009) proposes a solution to overcome these problems. That is, an alternative model specification which includes the ratio's

components in a model, and then adds the ratio itself in a hierarchical manner to determine if the ratio contributes to an explanatory power above that of the ratio's components. This provides a test for the theoretical meaning reflected in the ratio measure, whilst at the same time controlling for potential problems related to the use of ratios.

Finally, inferences drawn from ratio analyses and comparisons could be biased when the purpose is to track the evolution of the ratio of interest across time and proceed with intertemporal comparisons. This is a common characteristic found in efficiency studies where the examination of bank performance across the sampled years offers interesting insights. As stated, one of the main reasons for the use of ratios, instead of the actual accounting data is the ability to control for size. However, in order to successfully control for the aforementioned effect, two restrictive conditions must be met:

- Strict proportionality between the two components of the ratio, y and x (Lev and Sunder,1979 and Whittington 1980), and
- The scale invariance condition must be satisfied (McLeay and Trigueiros 2002).

That is, the former can expressed as follows, equation (3.1),

$$y = \alpha + \beta x + \mu. \tag{3.1}$$

With respect to the former, strict proportionality requires that when the power of x equals to 1 the intercept term α equals to zero, implies linearity and a zero intercept. With respect to the latter, McLeay and Trigueiros (2002) argue that the above proportionality condition is insufficient to make ratio transformations valid and adequate. They note that the above relationship (equation (3.1)) emphasizes the relationship between two ratio components; however, it does not take into account in how changes in the numerator should relate to changes in the denominator. That is, when y is proportional to x, then the rate of change of y with respect to x must remain constant and similar to the ratio itself, thus the following relationship must hold, equation (3.2),

$$\frac{y}{x} = \frac{dy}{dx}. \tag{3.2}$$

And thus, by definition, scale invariance must also by true, equation (3.3),

$$\frac{dy}{y} = \frac{dx}{x}. \tag{3.3}$$

Potential sources of deviation from strict proportionality in equation (3.1) could be attributed to two key factors: (i) the presence of an intercept and (ii) the presence of an error term in equation (3.1) (Lev and Sunder (1979). In both cases, such deviations exist and size control is not achieved. In the case where size control is incorrectly achieved, misleading inferences may be obtained – an important limitation exacerbated when the aim is to map the performance of banks, across time, utilising financial ratio based indicators. In relation to valid inter temporal comparisons of ratios, the underlying proportionality relationship between the ratio components should remain stable over the examined period. Theoretical misspecifications could be present when the relationship changes from strict proportionality to a log linear form (McLeay and Trigueiros (2002) note that because of the double book-keeping system, accounting figures are multiplicative, therefore, the linearity and proportionality is unlikely to fit the reality and instead, log linear relationship should be the predominant relationship). That is, for a lognormally distributed variable, the geometric mean is the median and this value becomes the appropriate central tendency for ratios of the lognormal form (Sudarsanam and Taffler 1995). Therefore, in the presence of a shift from a strictly proportional relationship to a lognormal one, intertemporal comparisons may be compromised. Indeed, empirical evidence of shortcomings of profitability ratios come from areas outside banking, as De Andrés et al., (2009) and Hopwood and McKeown (2003), confirm the presence of residual effects with respect to size on ROA[15]. The latter authors argue that the relationship between numerator and denominator in profitability ratios is indeed affected by firm size. Further, they find that inter-temporal relationships of ratio components is more stable for large firms than small firms, thus raising concerns when comparing across time and across asset sizes within one industry.

[15] Even though both studies do not focus on banking institutions, the intuition behind the potential ratio complications remain unaltered.

Considering that the relationship between ratio components reflects external economic conditions (in an indirect manner), this relationship is subject to external shocks in the economy. The discussion in Chapter 2 notes the severity of the impact of the debt crisis in Greek banks, and potentially the relationship between various components of accounting data. That is, an empirical testing of the relationship between ratio components is feasible via a Box-Cox transformation model (see Sudarsanam and Taffler 1995 for details in the estimation process). However, the aforementioned empirical testing of the relatioship betwenn the ratio components is not applicable in our current study as it requires the Box-Cox regerssion to be estimated on annual data estimating a Box-Cox transformation on both dependent and independent variables (that is, the numerator and denomitor of the examined ratio). However, this testing could potentially lead to biased results given the limited number of banks per year in our sample (16 banks). Indeed, Spitzer (1978) stresses the limitations of this type of analysis and examines the limited sample properties of the estimator, noting that "the small-sample properties of models which transform both the dependent and independent variables using the same Box-Cox transformation are investigated in sampling experiments. Bias does not appear to be a serious problem; however, the sign and size of the transformation parameter, which changes the coefficient of variation of the dependent variable, seriously affects the variances of the estimators (page 488)".

The previous discussion is aimed at highlighting the potential shortcomings of using financial ratios and scaled variables, irrespective of the research discipline. That is, researchers from areas outside banking have provided evidence of the potentially problematic model specifications. Even so, similarities exist between these models, for example, profitability models share the same logic of scaling variables in order to address size effects. It is therefore likely that each application will have its own special characteristics and careful consideration must be presumed to a wide range of alternatives if appropriate estimates are to be obtained.

Given the underlying differences between traditional performance indicators utilised in the banking literature and frontier estimates, the latter is deemed as a more appropriate measure when modelling banks (see for example, Beccalli et al., 2006). Indeed, Thanassoulis et al., (1996) also contrast frontier estimates (DEA) and ratio analysis as alternative methods for assessing the performance of organisational units such as bank

branches. Thanassoulis et al., (1996) note that performance indicators (i.e., financial ratios) can lack operational meaning (contrary to frontier measures where the measure of overall efficiency does have a meaning in terms of input-output levels). Furthermore, frontier estimates have an advantage in that they can take into account, simultaneously, input and all output levels of a unit; an appealing feature with respect to the multi input/output characteristics of banks. Thus, estimating an index of operational efficiency will allow comparisons of managerial performance amongst Greek banks. To that end, the next section discusses the various approaches used to model frontiers and estimate efficiency indicators within the banking literature.

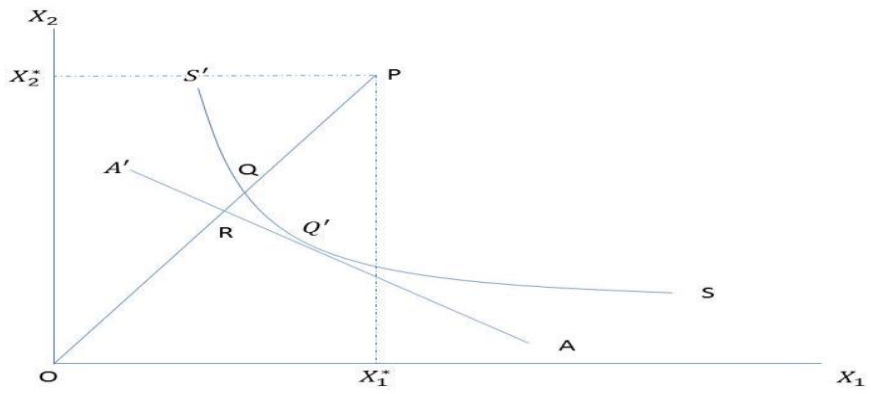
3.4 Different Approaches to Modelling Efficiency

A fundamental decision in measuring financial institutions' efficiency concerns which concept to use in a coherent modelling strategy. Overall, bank inefficiency can be measured in terms of a deviation from a best practice frontier that represents the industry's underlying production technology (Goddard et al., 2014). The three main concepts of efficiency focus on cost, standard profit, and an alternative profit efficiency specification. As Berger and Mester (1997) note: "these concepts have the best economic foundation for analysing the efficiency of financial institutions because they are based on economic optimization in reaction to market prices and competition, rather than being based solely on the use of technology, (page 3)". They further define cost efficiency as "a measure of how close a bank's cost is to what a best practice bank's cost would be for producing the same output bundle under the same conditions. It is derived from a cost function in which variable costs depend on the prices of variable inputs, the quantities of variable outputs and any fixed inputs or outputs, environmental factors, random error, and efficiency (p 898)". This was expressed more technically by Kumbhakar and Lovell (2003) who provide a formal definition of cost efficiency as the ratio of minimum cost to observed cost. The analysis can be easily presented in Figure 3.1 which shows a graphical representation of the concept of cost efficiency in a two input two price case.

In terms of analysis and elucidation, a firm uses two inputs X_1 and X_2, with respective prices p_1 and p_2 while producing output Y. The unit isoquant of the fully efficient firm

is represented by $S'S$ and line $A'A$ is the isocost line. Cost minimization behaviour implies a shift in the isocost as low as possible to point Q', where $A'A$ is tangent to $S'S$. If we let w represent a vector of input prices and X represent the observed input quantity vector associated with point P, then X^* represents the cost-minimizing input vector associated with point Q'. In this case, the cost efficiency of the firm will be represented by the input costs associated to input vector X^* and X, which is associated with points P and Q'.

Figure 3.1. Cost Efficiency for Two inputs, One output case



Therefore, the standard definition of firm specific Cost Efficiency (CE) can be formally expressed as equation (3.4), (see Kumbhakar and Lovell 2003),

$$CE = \frac{w'X^*}{w'X} = OR/OP, \quad 0 < CE \leq 1. \tag{3.4}$$

Where CE takes a value of one in the case of a fully efficiency firm. More specifically, to financial firms, cost efficiency offers a measure of how close a bank's cost is to what is deemed as the best practice bank cost suggest to be for production of the equivalent outputs under the same conditions. It is derived from a cost function in which variable costs depend on the prices of variable inputs, the quantities of variable outputs, any fixed inputs or outputs, environmental factors, random error, and efficiency (Berger and Mester, 1997). This technique therefore offers an analysis of efficiency without

the problems outlined in Section 3.3 above. That is, cost frontier analysis provides an alternative to accounting-based efficiency ratios. Indeed, DeYoung (1997b) observes that frontier analysis attempts to estimate the maximum amount that a bank could reduce its costs while still producing the same output and combination (scope economies) of financial services. The banking efficiency literature refers to these potential cost savings simply as cost inefficiencies, or sometimes as X-inefficiencies. Whereas, cost efficiency suggests cost minimizing behaviour from producer and implies that the bank chooses inputs in such a manner that it minimizes its production costs, holding its outputs fixed. Under this assumption, cost is defined as the cost of the input vector calculated at exogenously determined prices.

It is interesting to note that the price exogeneity argument is considered to be reasonable when a bank acquires its inputs from a competitive market (Färe and Primont, 1995) and/or when examining heavily regulated firms/industries, such as in the context of the banking sector (Kumbhakar, 2011). As Färe and Primont (1995) argue, regulated firms face exogenous output prices and are required to satisfy all market demands at given prices, which in turn suggests that their output vector is determined exogenously. In this context a cost frontier can be estimated and systematic deviations from the optimal cost minimizing behaviour can be attributed to inefficiency.

Cost efficiency, can be further expressed as the product of technical efficiency and allocative efficiency - where the latter refers to the ability of a financial firm to utilise an optimal input mix, given their prices [16]. Consequently, cost efficiency shows an ability to provide services without wasting resources as a result of technical or allocative inefficiency (Fethi and Pasiouras, 2010). That is, even though profit efficiency is naturally a firms' ultimate goal, cost efficiency is an important means of reaching long-run profit efficiency (Delis et al., 2009). Such behaviour is observed in Greek banks since the emergence of the national debt crisis and their main focus towards cost reduction and optimization of branch network coverage through selective

[16] Even though analysing technical efficiency is a discussion that extends beyond the scope of this project - a production unit is technically efficient if an increase in any output requires a reduction in at least one other output or an increase in at least one input, and if a reduction in any input requires an increase in at least one other input or a reduction in at least one output (Koopmans, 1951).

branch closure[17]. In addition, Kumbhakar and Lovell (2003) observe that cost minimization is an appropriate objective, particularly in competitive environments, where input prices are exogenous and output is demand driven.

Hence, given cost minimization behaviour of Greek banks and following prior research, cost efficiency measures are considered as an appropriate performance indicator taking into account macroeconomic conditions in Greece[18,19]. The next Section discusses methodologies of estimating efficiency and the different assumptions involved.

3.4.1 Modelling Efficiency

Within the efficiency literature two main methodologies for estimating efficiency are prominent. Frontier efficiency is generally estimated by employing either parametric or non-parametric techniques and both utilised as a tool for measuring bank performance (see for example, Berger and Humphrey, 1997). The main non-parametric methods employed are the DEA and the Free Disposable Hull (FDH). As noted before, this study only considers parametric approaches in the stochastic frontier estimation stage of cost efficiencies. A rationale for our analysis is that a two-stage regression – our main advancement in LLP literature – would constitute an over complication beyond the scope of the subject of the study. That is, it is commonly known that any two-stage regression should be undertaken using the Simar and Wilson (2007) econometric procedure (examples include Hadad et al., 2011 and Hadad et al., 2012). Our model specification as shown in Chapter 5 is dynamic and as far as we are aware no econometric studies have been published a 2-stage parametric strategy. It should be noted that Simar and Wilson (2007) originally test is a single period test (and as far as we are aware has not been updated to a dynamic panel data specifications).

[17] Table 8.1 in Appendix A provides an overall summary of the branch network for the sample period and banks under examination.

[18] In an extensive survey of the bank efficiency literature with operational research and artificial intelligence techniques, Fethi and Pasiouras (2010) observe that by far, studies in banking obtain efficiency estimates under the input-oriented approach. This is most likely due to the assumption that bank managers have higher control over inputs (e.g. personnel, expenses) rather than outputs (e.g. loans, income, etc.)

[19] Even though a discussion on duality theory is beyond the scope of this project, Shephard in (1953), (1970) and (1974) developed established a relationship between the Input Distance Function and the Cost Function - both implying a cost and/or input minimizing behavior. For more details see Färe and Primont (1995).

When a parametric functional form is assumed, there are various techniques utilised in estimating the frontier function *f(x)*. The technique depends on the distributional assumptions concerning the error component. One approach is not to make any distributional assumptions and this approach is known as the *distribution free approach*. Another is to impose specific distributional assumptions on the error components and apply Maximum Likelihood and has ben coined as the *parametric approach*. In the former approach techniques such as the Corrected Ordinary Least Squares (COLS), Modified Ordinary Least Squares (MOLS) the Thick Frontier Analysis (TFA) and the Distribution Free Approach (DFA) can be found.

There are three main differences that distinguish between the two methodologies and concern the assumptions which follow regarding the data:

- The parametric approach is a stochastic technique and is able to distinguish between the error term and the inefficiency while the linear programming approach is deterministic and assumes that all deviation from the frontier is attributed to inefficiency.
- The parametric approach assumes a restrictive, pre-specified functional form, which might lead to an inaccurate efficiency estimates which could be linked to functional misspecification; in contrast to the less restrictive non-parametric techniques, which do not specify a functional form.
- There are differences in the assumptions regarding the distribution of the efficiency term (the parametric approach assumes either a half normal or a truncated distribution whereas, the non-parametric programmes makes no such assumptions).

Both methodologies are popular and are applied in analysing efficiency levels of banking institutions (see Berger and Mester (1997) and Fethi and Pasiouras (2010) for an overview in the literature). The main problem with the application of SFA is in disentangling the inefficiency term from the random error. According to Berger et al., (1993), this fact creates a major econometric problem in that distinguishing Cost Efficiency (CE) differences from the random error that temporarily give certain banks relatively high or low cost. The next sections are devoted to the analysis of the main parametric techniques.

3.4.2 Deterministic and distribution free Approaches

First we will examine the deterministic approaches. One appealing characteristic of these techniques is that the estimation is not computationally intense and coefficient parameters can always be obtained. In the next sections the COLS, MOLS, TFA and DFA techniques are discussed.

3.4.2a Corrected Ordinary Least Squares

An early approach to estimate a production (cost) frontier is the COLS estimator first proposed by Winsten (1957). This model specification follows a deterministic approach and effectively assumes that all deviations from the frontier are due to inefficiency effects. As Giraleas et al., (2012) observe, COLS is a deterministic, parametric approach and one of the numerous ways that have been suggested to 'correct' the inconsistency of the OLS-derived constant term of the regression when cost inefficiency is present in the production process.

Following equation (3.4), the definition of CE can be re-written as equation (3.5) in terms of Total Costs (TC) which is deemed to be associated with an output vector y_i with input prices w_i,

$$TC_i = \frac{f(y_i, w_i)}{CE_i}. \tag{3.5}$$

To enable estimation via OLS, equation (3.5) can be expressed in the form of a deterministic cost function, as in equation (3.6), in which we assume linearity by taking the natural log (ln),

$$lnTC_i = lnTC_i^* + u_i, \qquad lnCE_i \geq 0, \tag{3.6}$$

where

$$lnTC_i^* = f(y_i, w_i), \tag{3.7}$$

and

$$u_i = -lnCE_i. \tag{3.8}$$

Where u_i represents cost inefficiency and the remaining parameters of equation (3.7) are defined as before (see equation (3.4)). Cost inefficiency can be seen as the

percentage by which observed costs need to be reduced in order for the firm to become fully cost efficient (that is, produce the observed output at the minimum cost).

Separating out the intercept for equation (3.7) and expanding terms, a simple representation of a cost function can be given by equation (3.9),

$$lnTC_i = \beta_0 + f(y_i, w_i)\beta + + u_i. \quad (3.9)$$

Where; w_i is a vector of input prices and other environmental variables (the variables can be in logs and the vector in may follow one of the suggested functional form specifications); and y_i represents the bank specific output vector[20]. In the estimation of a cost function, it is required that the estimated frontier bounds all observations from below. The first step is to obtain consistent estimates of the slope coefficients and then shift the estimated cost function downward to the extent that it envelopes all observations.

$$lnTC_i = \beta_0 + f(y_i, w_i)\beta + e_i. \quad (3.10)$$

It is important to note that the OLS parameters are consistent but have a biased intercept. Cost functions as in equation (3.10), when estimated by OLS gives e_i residuals, which as Lovell et al., (1994) note, in logarithmic terms, each modified residual provides an indication of how far from the frontier an individual's bundle of resources is from an estimated hypothesized frontier. By adjusting the OLS intercept downward by the minimum residual $\min\{e_i\}$ (representing the lower cost observation), the adjusted function bounds all observations from below. Therefore, cost inefficiency can be expressed as $u_i = e_i - \min\{e_i\}$. Following equation (3.8) cost efficiency can be estimated as,

$$CE = \exp(-\hat{u}_i). \quad (3.11)$$

The above estimate gives us therefore an estimate of the distance of the estimated residual from the minimum residual.

[20] The various functional forms are discussed in more detail in Section 3.4.7.

3.4.2b Modified Ordinary Least Squares (MOLS)

Modified OLS is an alternative to the COLS estimation. The difference between the two estimation processes is that under the MOLS framework the regression line is shifted based on the Residual Sum of Squares (RSS). By construction the mean of the stochastic error is 0, but the variance of e_i is a consistent estimator of the variance of u_i since we assume that the shift from average cost to the frontier is a constant. The variance of e_i is given by the RSS. By using this information and by assuming that the u_i term follows a one-parameter distribution[21] we derive estimates of cost inefficiency. The two common distributions available in the literature are the exponential and the half-normal. The regression line is thus shifted based on equation (3.12),

$$\hat{\sigma}_u = \sqrt{RSS/n - (K+1)}. \tag{3.12}$$

Where $\hat{\sigma}_u$ is the root mean squared error, *n* is the number of observations and *K* the number of estimated coefficients. Hence, in the case of the exponential distribution, equation (3.13),

$$\hat{E}(u) = \hat{\sigma}_u. \tag{3.13}$$

And in the case of the half-normal distribution, equation (3.14),

$$\hat{E}(u) = \left(\sqrt{2}/\sqrt{\pi}\right)\hat{\sigma}_u. \tag{3.14}$$

Similar to the COLS framework, cost inefficiency is estimated using equation (3.15),

$$u_i = \hat{E}(u) + \varepsilon_j \tag{3.15}$$

[21] By one-parameter distribution it is meant the expected value (mean) of the distribution depends only on the variance of the distribution

Thus, cost efficiency can be estimated in a similar manner to the COLS framework following equation (3.11).

Both COLS and MOLS follow a deterministic approach assuming that all deviations from the frontier are due to inefficiency in the production process (that is, they do not allow for a stochastic element in the specification). In the COLS framework this characteristic implies that the data are error-free and that the econometric model is perfectly specified. However, one of the consequences of COLS is that the technique is highly sensitive to outliers. For example, if one DMU has experienced an unduly large value in one of its output observations, then COLS would overestimate the efficiency frontier – this is common during banking mergers and acquisitions. However, the MOLS is less severe, in that based on the RSS, which is a measure of good fit, it accounts for model imperfections in the specification in an indirect way.

Therefore, both approaches are not ideal as they ignore the stochastic error and explicitly assume that the model is near-perfect. However, they are easy to estimate with solid theoretical foundations and a main advantage is that they can be easily estimated using small datasets (this can be a real advantage since OLS is a robust estimator)

The empirical modelling strategy undertaken in this Thesis utilises these models as a first stage analysis and takes advantage of the aforementioned theoretical properties and lack of computational intensity of COLS and MOLS. That is, we estimate cost efficiencies based on both approaches. The derived scores are then used as an exploratory tool of the Greek bank efficiency frontiers and serve as a benchmark for the efficiency scores estimated using the more advanced econometric models discussed in Section 3.4.4. Interestingly, to the best of our knowledge, the use of the deterministic approaches previously discussed is limited to areas outside of banking. That is, the aforementioned methods have been extensively used in the evaluation of industries such as railways, airlines and for the assessment of the performance of public services. For example, (presenting historical reviews), Cornwell et al (1990) examine the efficiency of the US airlines industry for the years 1970-1981 using three different estimators; Generalized Least Squares, the within estimator; and the efficient instrumental variables estimates. Comparisons across the three techniques were yielded different

results between the GLS efficiency levels and those produced via the within and efficient instrumental variables. In all cases though, the results suggest considerable change in efficiency over time. Lovell et al., (1994) use MOLS and estimate input/output oriented distance functions to measure degrees of inequality in the levels of "well-being" in Australia using a sample of 1069 individuals for 1987. The main purpose of their study is to construct indices that rank people on their material well-being in terms of the extent to which they are experiencing a satisfactory life. That is, to develop an index of relative proficiency with which individuals convert their commodities and capabilities into functioning's. Finally, Evans et al., 2000 and Tandon et al., (2002) employed a variety of fixed effects production models in a cross-country wide study of health system performance using data for 191 countries in total. The authors evaluate the performance of the selected countries in terms of population health maximisation in the first instance and expanding their framework by including a broader set of health system outcomes, stressing the importance of health of routinely measuring the inputs/outputs of individual country health systems, especially when new health reforms are introduced.

3.4.2c Thick Frontier Approach

Berger and Humphrey (1991) proposed the Thick Frontier Approach (TFA), which first proceeds into dividing the sample into classes by size and within these size classes group the observations into quartiles according to an observed efficiency estimator; in the case of a cost frontier model this estimator is the average cost. A cost function for the lowest average cost quartile is then estimated. This lowest cost quartile is termed as the "thick frontier" and it is hypothesized that the firms present have a higher than average efficiency. Respectively, a cost frontier is also estimated for firms belonging in the highest average cost quartile; these firms are assumed to exhibit a lower than average efficiency score.

TFA requires two assumptions for the construction of the frontiers. The within-quartiles error terms only reflect random error and luck, whereas variations between the two cost frontiers for each quartile (evaluated at their respective mean) are attributed to either market factors or inefficiency. In other words, the differences between the predicted costs are separated into exogenous bank market factors and the inefficiency

residual. This approach is therefore not aimed towards econometric rigor but at drawing quick inference on cost inefficiency that does not rely on a particular econometric distributional assumption (Kumbhakar et al., 2015). As the authors observe, the main purpose of the TFA is to provide the basic idea of the magnitude of cost inefficiencies in banking and to identify their sources by decomposing them into several categories (Berger and Humphrey 1991). More specifically, the inefficiency residual can be separated into three distinct parts:

- The part owed to operating costs.
- The part owed to produce deposit interest costs.
- And finally, the part owed to purchased funds interest costs.

Overall, Berger and Humphrey (1991) yield inefficiency estimates of 25% or more of average costs. When the inefficiency residual was further decomposed into technical operating inefficiencies (proportionate overuse of all physical resources) these dominated on average the financial inefficiencies, for both branch banking and unit banking states. More specifically, inefficiencies owed to operating costs amounted to 53.88% (73.57%) for the branch banking states (unit banking states).

Given its design, the TFA approach is not appropriate for estimating firm specific efficiency, as it focuses on differences in efficiency between the constructed groups. Another potential problem may be the presence of a functional relationship between average costs used in the pre-sorting process and the dependent variable, leading to biased slope coefficients. An additional question has also been raised by DeYoung (1998), who raises concerns about the validity of the standard thick cost frontier approaches fundamental feature – the use of raw unit costs to generate the cost quartiles separating cost-efficient from cost-inefficient firms. That is, instead of using *a priori* cost information in order to classify upper and lower samples, DeYoung (1998) instead utilises management quality information[22]. Using US banking data for the period 1991-1992 DeYoung (1998) finds that well managed banks incurred higher raw unit costs than banks classified as poorly managed. Even though the results support the belief that well managed banks exhibit higher cost efficiency scores, banks with higher

[22] For classification purposes, DeYoung (1998) is using an adjusted measure of management quality – cleansed of the influence of financial performance - based on the management/administration (M) dimension of the CAMEL rating system.

management quality also incurred higher accounting based unit costs than their counter parts included in the high cost part of the sample. As the DeYoung (1998) notes, "this implies that cost-efficiency bank management requires expenditures generally not made at poorly managed banks. Another implication of the findings is that they suggest that blind pursuit of accounting-based cost benchmarks actually might reduce a bank's cost efficiency by cutting back on expenditures essential to a well-run bank. Finally, this result raises questions about the validity of the standard thick cost frontier approach, which uses raw unit costs to separate cost- efficient from cost-inefficient firms (page 5)". Indeed, an additional drawback is that TFA requires a large data set, otherwise the sample grouping process could lead to small sub-samples that may prove to offer little or no information.

Despite the drawbacks previously analysed, the lack of strict specificity in the statistical assumptions makes TFA less likely to be violated by the data. That is, there is no assumption of orthogonality of the inefficiencies with respect to outputs and regressors in the cost function. In addition, it allows for any number of exogenous variables to be added in the cost function without changing the number of comparison firms or necessarily creating a downward bias in inefficiency estimates (Berger and Humphrey, 1991). Thereby, remaining a valid comparison tool of average inefficiency among low and high cost banks.

TFA has been used a frontier estimation technique using banking data in prior research. For example Bauer et al.,(1993) in a comparative study use both the TFA and the Stochastic Frontier Analysis (SFA) to estimate cost efficiencies for a panel data set of 683 U.S. banks with over $100 million in assets. Their findings indicate that the two methods yield different results in identifying best and the worst performers despite the fact that both methods find roughly similar levels of inefficiencies (X-inefficiencies averaged around 21% over an 11-year period beginning in 1977). In a similar vein, Bauer et al., (1998) apply a variety of techniques (one of which is the TFA) on a data set of 683 US banks over the period 1977-1988[23]. The authors suggest six consistency criteria in an attempt to produce a standardized framework of evaluating the robustness

[23] The study is using the all the popular frontier estimation techniques; Stochastic Frontier Analysis, Thick Frontier Approach, Data Envelopment Analysis and Distribution Free Analysis.

of frontier efficiency measures. That is, compare the efficiency distributions, the rank order correlation of the efficiency distributions and the correspondence of best-practice and worst-practice. The aim is to stress the importance of reporting methodological cross-checks in an attempt to ensure that policy makers are aware of the different information contained in efficiency measures derived with alternative methods. This methodological estimation procedure advocated in Bauer et al., (1998) is thereby used as a foundation in the research results presented in this Thesis.

In addition, Lang and Welzel (1998) used a sample of 1490 banks for the year 1992 and covering 40% of German banking system, specify a multi-product translog cost function. The authors followed the TFA approach to control for cost inefficiencies and identified external factors as the main driver behind the deviation of costs between the most efficient and least efficiency banks in their sample. The use of time series data in the study is one potential limitation as panel data offers more wealth of information. Finally, Gropper et al., (1999) propose the use of a finite mixtures of probability distributions to estimate cost functions on a large panel data set for the years 1987-1989 (3,339 observation in total) of US savings and loan associations. In order to evaluate the behaviour of the proposed methodology the conventional TFA techniques was also used on the same data. Their results indicate that the proposed methodology of a mixed cost function, generated estimates that uniformly lie between the other estimated cost curves.

3.4.2d Distribution Free Approach

Berger (1993) proposed the Distribution Free Approach (DFA) as an alternative to the strong distributional assumptions that other parametric techniques were suggesting. The approach assumes a composed error term including both the stochastic random error component and an inefficiency element. In the context of a panel data set, Berger assumes that the random error component of the composed error term is by definition random and it will average out to a zero value over time and that efficiency is persistent. The DFA involves the estimation of a separate cost function for each year of the panel with an associated composed error term. When the error term is averaged over each year for each individual firm, given that the random component expectation is zero, it will produce a measure of average cost efficiency across the sample.

That is, consider a cost function expressed in logarithmic terms, equation (3.16) with a composed error term shown in equation (3.17),

$$lnC_{it} = lnf(Y_{it}, w_{it}) + ln\varepsilon_{it}. \tag{3.16}$$

$$ln\varepsilon_{it} = lnv_{it} + lnu_{t}. \tag{3.17}$$

Where C is a measure of total costs, $f(\cdot)$ is the cost function, Y represents a vector of bank specific output quantities, w represents a vector of bank specific input prices and ε_{it} is the bank specific composed error term. In the composed error term, v_{it} and u_i represent the noise and bank specific efficiencies respectively. All the terms in equations (3.16) and (3.17) are allowed to vary over time, with the exception of the efficiency term which by assumption remains constant. The estimated residuals are then averaged across T years for each bank in the sample. The random error component lnv_{it} tends to cancel each other out and the averaged residual is an estimate of lnu_t.

The DFA estimator for bank *i* for T years can be expressed as given in equation (3.18),

$$dfe_i(T) = \frac{1}{T}\sum_{t=1}^{T} ln\varepsilon_{it} = ln\hat{x}_i. \tag{3.18}$$

This estimator is the rescaled and expressed as a percentage of the cost efficiency of the most efficient bank, see equation (3.19),

$$CE_i(T) = \exp[dfe_{min}(T) - dfe_i(T)]. \tag{3.19}$$

Where $dfe_{min}(T)$ is the minimum value of $dfe_i(T)$ over all banks. The estimates of efficiency are non-negative, they increase with cost efficiency and are bounded by unity. Because the averaging process is imperfect and in order to control for outliers in $CE_i(T)$, prior to rescaling, the $dfe_i(T)$ are truncated typically at the 5th and 95th percentiles of the cross sectional distribution of $dfe(T)$.

One advantage of DFA over other techniques is that it uses multiple years of data for each bank. This allows for the inclusion of additional information than when using data for only one year, ensuring that in the case of an extraordinary event in a single year, this event does not get overemphasized, leading to inflated (deflated) efficiency values. However, an important consideration of the DFA is related to the sample size employed. In the case of a small time period, the noise component of the composed error term might not average to zero; in this case the stochastic component will be present in the estimated efficiency. If on the other hand the time period increases substantially, the assumption of persistent inefficiency is compromised. For example, this assumption may be violated as time passes and banks experience either organizational change (for example, changes in top management positions M&A) and/or regulatory interventions, thus affecting in turn the efficiency levels of banks.

In order to address this potential shortcoming and address the issue of including too few or too many observations in the DFA estimation, DeYoung (1997) posited a diagnostic test. Interestingly it is a test for choosing an appropriate time dimension value such that will allow capturing the bulk of the averaging out effect without compromising the validity of the persistent inefficiency assumption. By substituting equation (3.17) into (3.18) and expanding we obtain equation (3.20),

$$dfe_i(T) = \frac{1}{T}\left[\left(lnu_{i,t} + lnu_{i,t+1} + . + lnu_{i,T}\right) + \left(lnv_{i,t} + . + lnv_{i,T}\right)\right]. \tag{3.20}$$

Where $lnu_{i,t}$ is allowed to be time varying and follows the time path:

$$lnu_{i,t}\begin{cases} lnu_{i,1} & for\ t \le J \\ lnu_{i,t-1} + a_i lnu_{i,1} & for\ t > J \end{cases}. \tag{3.21}$$

Then substituting equation (3.21) into equation (3.20) and simplifying, we obtain (3.22),

$$dfe_i(T) = lnu_{i,1} + \frac{\max\{0 \mid T - J \mid \times (T - J + 1)\}}{2T} \times \lambda_i + \frac{1}{t}\sum_{t=1}^{T} lnv_{i,t}. \tag{3.22}$$

Where the first term represents the initial level of cost inefficiency for the ith Decision Making Unit (DMU), the second is the average annual accumulated drift in cost inefficiency from $t = 1$to $t = T$ and the third term is the mean of the noise component. The main idea of the DeYoung diagnostic test it to select a time dimension T that will be long enough to minimize the mean of the random error component and short enough to limit any distortions caused by the temporal drift in $lnu_{i,t}$. For a given value of T, the cross sectional sample mean and variance is given by equations (3.23) and (3.24) respectively:

$$\mu(T) = \frac{1}{N}\sum_{i=1}^{N} dfe_i(T). \tag{3.23}$$

$$\sigma^2(T) = \frac{1}{N-1}\sum_{i=1}^{N}[dfe_i(T) - \mu(T)]. \tag{3.24}$$

Substituting equations (3.22) and (3.23) into (3.24) we obtain equation (3.25),

$$\sigma^2(T) = \frac{1}{N-1}\sum_{\iota=1}^{N}\Big[(lnu_{i1} - \frac{1}{N}\sum_{\iota=1}^{N} lnu_{i1}) + \frac{\max\{0 \mid T - J \mid \times (T - J + 1)\}}{2T} \times \left(\lambda_i - \frac{1}{N}\sum_{1}^{N}\lambda_i\right) + \frac{1}{T}(\sum_{\iota=1}^{T} lnv_{it} - \frac{1}{N}\sum_{\iota=1}^{T}\sum_{i=1}^{N} lnv_{it})\Big]. \tag{3.25}$$

Hence, the focus is on the changes of the three terms in the square brackets of equation (3.25) as the time dimension T increases. The initial level of cost inefficiency (the first term) is time invariant and hence unaffected by changes in T . The average annual

accumulated drift in cost inefficiency (the second term) is equal to zero from $T = 1$ to $T = J$. For values greater to J ($T > J$) it increases in absolute values as T increases. The absolute value of the noise component (the third term) decreases as T increases. As a result, until $T = J$ the magnitude of the variance $\sigma^2(T)$ decreases as T increases which results in the estimate of cost inefficiency to approach the true values lnu_{i1}. For values $T > J$, $\sigma^2(T)$ will either remain constant, increase or decrease as T increases. This change will depend on whether the marginal reduction in the noise component remains equal, exceeds or falls short of the marginal drift of cost inefficiency. Therefore, the optimal number of years is defined as the first values of *t* for which $\sigma^2(T)$ stops decreasing.

This approach has been used by a number of studies in the banking efficiency literature. For example DeYoung and Nolle (1996) estimate profit efficiency and for a sample of 1,812 annual observations of 62 foreign owned U.S. banks and 240 US owned for the period of 1985-1990. They find that foreign-owned U.S. banks were significantly less profit efficient than U.S.-owned banks. In order to prevent extremely high residuals from defining the efficiency frontier, two ways of truncating the residuals where imposed and both truncation methods produced different magnitudes but consistent results. That is, in both cases larger banks (over $5 billion in assets) reported lower profit inefficiency-to-assets estimates than smaller banks (less than $100 million in assets). The reported values range from 12.06% (7.45%) for small banks to 1.29% (5.02%) for large banks depending on the truncation method followed. Akhavein et al., (1997) evaluate the efficiency and price effects of "megamergers" by using the DFA methodology to estimate both standard and alternative profit functions. Using a panel data set on US mergers for 1981-1989, they find that merged banks experience a statistically significant 16% average increase in profit efficiency rank relative to other large banks. Berger et al., (1997) using a Fourier-flexible cost function and estimated X-efficiencies of 760 (769) US branches using the intermediation approach (production approach) for US commercial banks for the 1989-1991 period. They report inefficiency levels of 20% of operating costs.

An extension of the standard DFA approach can be found in an examination of country specific factors affecting the performance of banks (see, Dietsch and Lozano-Vivas

2000). The authors use a stepwise DFA process in a cross-country comparison of efficiency estimates in order to identify a common banking technology and environmental conditions affecting cost efficiencies in Spain and France for 1988-1992 on commercial and savings banks. In the first step, two cost frontiers are constructed for each country, including the environmental variables as control factors. Once the significant macro specific variables were identified, cross-equation equality restrictions were imposed on the parameters of each country's cost frontier suggesting a common banking technology. Next a common stochastic cost frontier is estimated, holding the significant country-specific environmental factors constant at their respective mean values for each country. Failing to reject the restrictions confirmed the common banking technology assumption and cost efficiencies were then estimated. The results indicate that when excluding the control covariates, Spanish banks generated lower cost efficiency scores compared to French banks. However, when the environmental variables were included in the model specifications, the differences between the two banking industries reduced substantially. They conclude that this indicates that the Spanish sector is prone to suffering from excessive costs mainly due to their particular environmental and regulatory conditions.

This technique of separating out the important environmental effects was not followed by Weill (2004) who estimates national cost frontiers on a sample of five European countries for the years 1992-1998. Using data for 688 commercial, cooperative and savings banks in France, Germany, Italy, Spain and Switzerland he investigates the robustness of cost efficiency results produced via three different frontier methodologies – Stochastic Frontier Approach, DFA and DEA. Using a number of the Bauer et al., (1998) consistency conditions they compare means, correlation coefficients, two public policy issues, and the correlation with standard measures of performance. Overall, lack of consistent results across methods is the predominant finding, even when there are some similarities between parametric approaches. However, some correlation is observed between all frontier approaches and across standard measures of performance (average cost ratio, cost-to-income ratio, return-on-assets, and return-on-equity). Therefore, as Weill (2004) finds, the potential to misinterpret results with DFA is real if the noise cannot be deemed to go to zero. We next present out preferred parametric approach that assumes a stochastic noise component and which is estimated as the preferred methodology in this Thesis.

3.4.3 Parametric Approach

3.4.3a Stochastic Frontier Analysis (SFA)

The literature that influenced the development of SFA was based on productive efficiency and more specifically the works of Debreu (1951), Koopmans (1951) and Shephard (1953). Advancing the works of Debreu and Koopmans , the first to measure the productive efficiency empirically was Farrell (1957). He showed how to define Cost Efficiency (CE) and its respective components, Technical Efficiency (TE) and Allocative Efficiency (AE), via an application to U.S. agriculture data, without the use of econometric techniques. The work of Farrell (1957) influenced a significant body of research that begun the association of technical inefficiency with specific one-sided error distributions. The work of Afriat (1972); Aigner and Chu (1968); Timmer (1971); Seitz (1971) and Richmond (1974) eventually led directly to the development of SFA (Kumbhakar and Lovell, 2003, Chapter 1, offers an in-depth discussion on the developemements in the field of stochastic frontier analysis).

Indeed, SFA was developed independently by Meeusen and van Den Broeck (1977) and Aigner et al., (1977). The approach is based on the notion that the systematic observed deviations from the frontier could be attributed to both inefficiency and random effects, including measurement error. The aim of the SFA technique is to disentangle these random effects whilst decomposing the residual of the parametric formulation of the production process into the symmetric part of the error (the stochastic component) and the skewed part (inefficiency). The original models all share a composed error term and they can be expressed in terms of a production frontier context, equation (3.26),

$$y = f(x;\beta) * \exp[v - u]. \tag{3.26}$$

Where y is scalar output, x is a vector of inputs and β is a vector of technology parameters. The composed error term, $v \sim N(0, \sigma_v^2)$ is capturing the statistical noise and $u \geq 0$ is intended to capture the inefficiency effects. Converting the specification to a stochastic cost frontier model implies a change in the sign of the inefficiency error term, thus giving the following cost form, equation (3.27),

$$E = c(y, w; \beta) * \exp[v + u]. \quad (3.27)$$

Where E represents expenditure, $[c(y, w; \beta) * \exp[v]$ is the stochastic cost frontier and u is the inefficiency effect. It is clear that key to the SFA methodology remains the decomposition of the error term into a component that is normally distributed with mean 0 (noise) and a component with only positive values (inefficiency).

3.4.3b Auxiliary Variables

Prior research has provided evidence that the production process can be influenced by three different aspects; managerial inefficiency; environmental effects impeding production; and statistical noise, such as the luck factor captured by the error term of a regression based approach when measuring producer performance (Fried et al., 2002). The first phenomenon is endogenous, while the second and third are exogenous. Distinguishing among these components is important when assessing the performance of producers on the basis of their inputs and outputs. Efficiency estimation through the means of frontier measures can differentiate the impact of various factors that are outside the control of the producer on firm performance by examining how and to what extent they influence firm efficiency. Deprins and Simar (1989) first posed the question of whether these exogenous factors should be modelled in such a way as to influence the position of the frontier or the ability of management to attain that frontier (cited in Bos et al., 2009). In other words, the impact of exogenous factors may either lead to parallel shifts of the frontier or lead to systematic different deviations from it. Hence, it is necessary to analyse both components in a coherent and consistent modelling strategy.

Thus, the first involves the estimation of the frontier which is used as a performance benchmark. The main task in this stage is to obtain efficiency estimates of producers in employing inputs to produce outputs; subject to the various behavioural and distributional assumptions (i.e., cost minimization). The second component investigates the reason for differences in the efficiency scores across firms. This is achieved via the incorporation of either firm specific characteristics or variables exogenous to the production function. In the context of examining a banking system, such variables typically include a range of macroeconomic (for example, private

consumption expenditure, GDP, unemployment rate, fiscal deficits to GDP), regulatory factors (for example, ownership structure, location characteristics, government regulation) and general country-specific factors (for example, market concentration, presence of foreign banks, and ratio of private investments to GDP). These variables are therefore outside the control of the managers and despite the fact that they are neither an input or an output they affect the production process (prior research employing the same or similar exogenous variables include (Hauner, 2005; Kasman and Yildirim, 2006; Pasiouras et al., 2008; Pasiouras, 2008; Liadaki and Gaganis 2010; Goddard et al., 2014).

The main goal of the second component is to associate variation in producer performance with variation in the exogenous variables characterizing the environment in which production occurs (Kumbhakar and Lovell, 2003). The environmental variables have been taken into account in efficiency analysis in a variety of ways and are assumed to capture features of the environment in which production takes place, and as stated before, they are beyond the control of the managers. In the case were the environmental variables influence production itself, it is appropriate for them to be directly incorporated in the production function. In addition, a second early approach to the incorporation of exogenous influences has sought to associate variation in estimated efficiency with variation in exogenous variables. This approach consists of two stages. In the first stage, efficiency estimates are constructed via the means of a stochastic frontier without the exogenous variables, and in the second stage the estimated efficiencies are regressed against the exogenous variables. Prior research following the two-stage method include, Hasan and Marton (2003), Bonin et al., (2005a, 2005b).

However, the latter two-stage estimation approach has serious econometric problems (Kumbhakar and Lovell, 2003) and is not recommended (Kim and Schmidt, 2008). As discussed in 3.4.4, through the early 1990's model specifications allowing a single-stage estimation in which the explanatory variables are incorporated directly into the inefficiency error component were developed. Employment of such model specifications addresses the Wang and Schmidt's (2002) critique against the two-stage estimation process, which through Monte Carlo simulations investigated both the one and two-stage estimators and provide evidence of a downward bias. In the case of the

two-step estimation method, the first step suffers from the usual omitted variable bias. Since $E(y|\mathrm{x},\mathrm{z})$ (in this case we assume a production function) depends both on the inputs, x, and the z variables, the regression of y on x only will give biased estimates in the case where the inputs and the variables assumed to be outside the managerial control are correlated. This implies a biased estimate of the inefficiency component and in turn leads to a bias in the second step, the regression of $\hat{u}$ on z (the environmental, regulatory, macroeconomic and industry specific variables).

To deal with the bias outlined by Wang and Schmidt (2002) we therby intergrate directly the z's into the specification following Battese and Coelli (1995) and Greene (2005a, 2005b). As a background, the following sections discuss popular panel data model specifications, the relevant distributional implications and pre/post-estimation tests and finally the various functional forms available

3.4.4 Stochastic Frontier Panel Data Models

Early panel data models assumed that inefficiency was time-invariant. This may be a viable assumption in small T data sets, but becomes less tenable in data sets with longer time dimensions. However, the time invariant nature of the inefficiency term has been questioned, especially in the presence of empirical applications based on long panel data sets. Since the early 1990's different model specification were proposed relaxing this assumption (for example Cornwell et al., 1990; Kumbhakar, 1990; Lee and Schmidt, 1993 and Battese and Coelli 1992).

For example, Cornwell et al., (1990) proposed the following stochastic frontier model with individual-specific slope parameters. The authors include in the production function a flexible quadratic function of time (ω_{it}) whose parameterization depends on an individual firm, given by equation (3.28),

$$y_{it} = a + x'_{it} + u_{it} \pm v_{it}\; i = 1, \dots, N \; and \; t = 4, \dots, T. \qquad (3.28)$$

Where the quadratic time trend is given by equation (3.29),

$$u_{it} = \omega_{i1}t + \omega_{i2}t^2. \quad (3.29)$$

Hence, equation (3.29) represents productivity growth, at a rate that varies over firms, and implies that levels of inefficiency for each firm vary over time allowing for heterogeneity both in slopes and intercepts, effectively permitting for a firm specific temporal pattern of inefficiency (Cornwell et al., 1990). However, one limitation of the models is that it requires the estimation of a large number of parameters ($N \times 3$), a point noted by Mahadevan (2004) "the above specification is empirically useful for relatively small time periods, and for large time periods, the estimation has to be done for too many parameters (page 62)". To overcome this potential problem a similar specification introduced by Lee and Schmidt (1993) re-evaluated u_{it} as in equation (3.30),

$$u_{it} = g(t) \times u_i. \quad (3.30)$$

In this case, $g(t)$ represents a set of time dummy variables. This model is suitable for applications in which the number of firms is large and the number of time-series observations per firm is relatively small (Lee and Schmidt, 1993). In a similar manner, Kumbhakar, (1990) first proposed a time-varying SFA model specification, estimated via Maximum Likelihood, where g(t) is specified as follow in equation (3.31),

$$g(t) = [1 + \exp(\gamma t + \delta t^2)]^{-1}. \quad (3.31)$$

This parameterization allows for a nonconstant level of technical inefficiency which follows the same temporal pattern for all firms. That is, when $\gamma = \delta = 0$ the model reverts to a time-invariant model. Finally, the time-decay model was proposed by Battese and Coelli (1992) where:

$$g(t) = \exp[-\eta(t - T_i)]. \quad (3.32)$$

Where, η is a parameter to be estimated. This specification allows inefficiency to increase or decrease exponentially depending on the sign of η.

However, these specifications face criticisms. For example, as Ahn et al., (2000) note, "such models define inefficiency effects as a fixed function of time and thus only provide reasonable approximations for the dynamics of short-run technical inefficiency and are inappropriate for analysing the long-run dynamics of technical inefficiency. The specifications of the inefficiency effects are only arbitrary functional approximations with little theoretical or intuitive justifications (cited in Mahadevan 2004 (page 62))". In addition, Wheat and Smith (2012) examine the sensitivity of the Battese and Coelli (1992) specifications. They find that the $(t - T)$ functional form adopted results in a sharp reduction in efficiency scores in the last year of estimation, when a allowing for firm specific patterns of temporal inefficiency variation (as proposed by Cuesta, 2000). This implication may lead to misguided policy recomedations as firms appear to "falling-off" the frontier when in fact such behaviour is not supported by the data.

In the case where efficiency varies both across time and producer, determinants of efficiency variation need to be found. The next sections discuss two popular panel data model specifications. These models form the basis of our estimation strategy as they allow us to incorporate a one-step estimation process and factors that are exogenous to the managers of Greek banks. The next section discusses the various distributional assumptions surrounding them, the relevant pre/post estimation tests and the different functional forms used in when estimating efficiency within that banking industry context[24].

3.4.4a Time Varying Model - Battese and Coelli (1995)

Among panel data models, the inefficiency specification popularized by Battese and Coelli (1995) (thereafter denoted as TVM – Time Varying Model) is frequently used in empirical studies (Pasiouras et al., 2009; Lozano-Vivas and Pasiouras, 2010; Akinci et al., 2013; Lensink and Meesters, 2014; Akinci et al., 2013). The TVM model specification allows inefficiency to be expressed as an explicit function of a vector of either firm-specific or exogenous variables so that one can investigate how exogenous

[24] As Kumbhakar et al., (2014) note ,although there are many other specifications, empirical researchers mostly seem to use either the Battese and Coelli (1995) or the Greene (2005a, 2005b) models.

factors influence inefficiency. The general model specification can be expressed as in equation (3.33)[25],

$$Y_{it} = x_{it}\beta + (v_{it} - u_{it})\ i = 1,2,\ldots.N, t = 1,2,\ldots.T. \quad (3.33)$$

Where Y_{it} is the production (in logarithmic terms) of the ith bank;
x_{it} is a kx1 vector if input quantities of the ith firm;
β is a vector of unknown parameters and
v_{it} are random variables which are assumed to be i. i. d. $N(0, \sigma_v^2)$ and are independent of the inefficiency term u_{it}. With respect to the inefficiency component, is is a non-negative random variable and is assumed to account for the technical inefficiency in production. Furthermore, we assume u_{it} to be $i.i.d$, truncated at zero $N(m_{it}, \sigma_u^2)$ and follows equation (3.34),

$$m_{it} = Z_{it}\delta. \quad (3.34)$$

Where Z_{it} is a $k \times 1$ vector of variables which may influence the efficiency of a firm. These variables refer to the discussion presented in Section 3.4.3b, and δ is a $k \times 1$ vector of parameters to be estimated.
The method of maximum likelihood is proposed for simultaneous estimation of the parameters of the stochastic frontier and the model for the technical inefficiency effects. Following the parameterisation of Battese and Corra (1977) the likelihood function is expressed in terms of the variance parameters replacing σ_v^2 and σ_u^2 with $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and

$$\gamma = \sigma_u^2/\sigma_v^2 + \sigma_u^2. \quad (3.35)$$

Where σ_u^2 and σ_v^2 represent the inefficiency and random error variances respectively (Battese and Coelli, 1995).

One appealing characteristic of the TVM model is that it adds flexibility to the distributional shape of the firm specific inefficiency term u_{it}. This is achieved since

[25] The notations follow the Battese and Coelli (1995) notations.

each observation has an observation specific mean of the pre-truncated distribution, with mean, m_{it}, determined by the observation specific auxiliary variables, z_{it}, (equation (3.34)). In the literature where the distributional assumptions regarding the one-sided error term is critical and also open to criticism, more flexibility is desirable.

Indeed, the TVM model has been comprehensively utilised as the preferred estimation strategy due to its flexibility in estimation. For example, recent studies include Pasiouras et al., (2009) who examined the impact of regulation and supervision on bank efficiency by constructing a common frontier for 74 countries over a five year period spanning between 2000 - 2004. Using 2,853 observations from 615 commercial banks, they investigate two main conditions; (i) the impact of Basel II, capital adequacy requirements, official supervisory power and market discipline mechanisms and (ii) restrictions on bank activities. They estimate both cost and profit efficiency frontiers, while taking into account country specific characteristics. Unsurprisingly, regulations designed to enhance market discipline and strengthen the role of the supervisory authorities increase both cost and profit efficiency. Furthermore, imposing stricter minimum capital requirements reduces profit estimates which lead to an increase in cost efficiency. Finally, restrictions on bank activities lead to opposing findings – reductions in costs while profit scores improve.

Following this approach, Lozano-Vivas and Pasiouras (2010) investigate the relevance of Off-Balance Sheet (OBS) items and Non-Interest Income (NIN) in the estimation of cost/profit efficiency via SFA. By estimating both a traditional function considering loans and other earning assets as the only outputs and two additional including OBS and NIN respectively, bank efficiency levels are examined and the impact of the non-traditional activities is analysed taking into consideration the various levels of economic development, regulatory conditions and country specific characteristics. Cost efficiency estimates trends remains unaltered (an increasing trend) irrespective of the inclusion the frontier construction of OBS or NIN. The results regarding profit efficiency are mixed. Similarly, as in the findings of Pasiouras et al., (2009), an enhanced supervisory framework leads to increased cost and profit efficiency estimates. However, in contrast to Pasiouras et al., (2009), in the presence of regulations that restrict banking activities, cost efficiencies follow the same increasing behaviour as profit scores.

Finally, in a different, Lensink and Meesters (2014) focus on the examination of the impact of institutions on bank efficiency and technology. Using an aggregate governance indicator set as a proxy for institutional differences, which is assumed to impact banking efficiency in the same way as the more traditional macroeconomic variables (for example, via the inclusion as a covariate in equation (3.34), the authors estimate TVM specifications across a sample of 136 countries). Their findings confirm the importance of well-developed institutions, such as control of corruption, rule of law and political instability index amongst others. Further analysis reveals that institutional reforms improve bank efficiency while the estimated results are robust to adjustments in country specific effect and different risk profiles. As discussed, the recent literature utilising the TVM uses extensive data sets covering a wide sample of banks from different countries over a number of years. As discussed in Chapter 3, a potential problem as sample size increases is the introduction of heterogeneity. To check for stability, one could also estimate the Greene models which advanced the TVM through the inclusion of Fixed and Random Effects.

3.4.4b True Fixed Effects (Greene, 2005a, 2005b)

The common feature the time-varying SF models is that the intercept is the same across productive units, thus generating a mis-specification bias in the presence of time-invariant unobservable factors, unrelated with the production process but affecting the output. As a result, the effect of these factors may be captured by the inefficiency term, producing biased results (Belotti et al., 2012). Greene (2005a, 2005b) propose two model specifications incorporating unobserved heterogeneity, in the context of panel data stochastic analysis. Compared to previous models, this specification allows the disentangling of time-varying inefficiency from unit specific time invariant unobserved heterogeneity.

As Greene notes, unobserved heterogeneity enters the stochastic frontier through the form of either random or fixed effects and confounds cross firm heterogeneity with the inefficiency term, leading to biased results. In order to address this issue, the author extended the traditional fixed effects panel data model into a SFA framework. This

approach is known in the literature as the True Fixed Effects (TFE) model. The general specifications proposed take the following form, equation (3.36),

$$y_{it} = \alpha_i + \beta' x_{it} + v_{it} \pm u_{it}. \quad (3.36)$$

Where y_{it} is the output, profit or cost of the ith firm in period *t*, x_{it} is the vector of inputs or input prices, α_i are firm specific characteristics, v_{it} is the random error and u_{it} indicates the inefficiency term. The sign of the last variable depends on whether a cost (positive sign) or a production and/or profit (negative sign) frontier is estimated. Even though empirical research that involves only a modest number of firms could be produced by simply creating dummy variables (the so called brute force approach), when the number of firms increases, this method becomes impractical. The fixed effects model proposed by Greene (2005) offers the advantage of correlating the effects to the included variables.

Within this specification a number of distributional assumptions for the inefficiency term can be accommodated when using the TFE model; exponential, half-normal and the truncated. In addition to the TVM model specifications, the TFE can also allow for the inefficiency error component to depend on exogenous variables in the same manner as previously explained. However, lack of extensive empirical research using the TFE model implies that this fairly recent development in the SFA framework is not very popular when estimating efficiencies in the banking sector. Indeed, very limited research has utilized the TFE model so far within the context of banking efficiency (Goddard et al., 2014) [26]. Recent examples including application on US banks, Greene (2005a), who uses a random sample of 500 US banks and estimates a stochastic cost frontier with fixed and random effects. Among the key findings are that the treatment

[26] Additional studies examining banking systems using non-standard SFA models that are addressing the cross-firm heterogeneity problem without directly applying the TFE model include: a) Barros and Williams (2013) who estimated the True Random Effects model proposed by Greene (2005a, 2005b) and they show that the obtained mean cost efficiency score is higher than that obtained from standard panel data estimates, b) Bos et al., (2009) report sensitive to heterogeneity ranking for a sample of German banks c) Tecles and Tabak (2010) who use a Bayesian stochastic frontier to estimate cost and profit efficiency for Brazilian banks between 2000 and 2007. Their results indicate that large institutions are more cost and profit efficient. Public banks' cost efficiency levels improve over time but they remain relatively profit inefficient, and d) Sun and Chang (2011) who follow Wang (2002) and use a heteroscedastic SFA model where they permit the determinants of inefficiency to affect the one-sided error term in a non-monotonic manner.

of heterogeneity in the data impact the resulted efficiency estimates, and produce striking differences in results which may be overlooked when we focus on summary descriptive statistics. Finally, both the TFE and the TRE provide comparable results. On a similar note, Greene (2005b) examines several SFA models taking into account firm specific heterogeneity. The findings suggest that model specification impacts on the precision of the estimated efficiency scores. Bikker and Bos (2008) construct cost and profit efficiencies employing 45 countries, 13,000 private and public banks, where TFE profit efficiencies equal approximately 50%. In line with prior research, the average cost efficiency formed is greater than 80%. However, more specifically and by identifying groups (banks in Canada, Denmark, India and Sweden), findings suggest average cost efficiencies of more than 90% and the respective banks operate closer to the efficient frontier. In the second group (Argentina, Belgium, Brazil, France, the United Kingdom and the U.S.), average cost efficiencies estimates are below the 80% benchmark – with a much wider spread in the estimated score. Finally, as expected, the fixed effects capture differences in cost efficiencies across the various countries showing the necessity on deciding whether this approach will offer optimal results on non-fixed or random effects econometric counterparts.

Indeed, more recently Goddard et al., (2014) estimate a standard fixed and random effect cost/profit model accommodating cross-sectional parameter heterogeneity. The data under consideration cover the years between 1985 and 2010 for Argentina, Brazil, Chile and Mexico. Between the years 1985-1993 and 1994-2000 mean cost efficiency deteriorated, with state-owned banks exhibiting the highest drop. Furthermore, the impact of the crisis on bank efficiency was not the same for the countries under examination and finally, Latin American banking systems seem to have recovered from the worst effect of by the sub-prime crisis.

3.4.4c Concluding remarks and the incidental parameters problem

As discussed in Section 3.4.4, early frontier models made some rather rigid assumptions about efficiency behaviour. Cornwell et al., (1990) relax the assumption that technical inefficiency is time invariant by introducing into the production function a flexible function of time with coefficients varying over firms. Therefore, a cross-sectional and temporal variation in the inefficiency levels is permitted. In a similar manner

Kumbhakar's (1990) specifications are flexible enough to accommodate decreasing, increasing or time-invariant inefficiency estimates. The model considers a formulation of technical inefficiency which is flexible enough to handle different types of time behaviour. The deterministic function of time $g(t)$ (equation (3.31)) takes values between zero and one, depending on the values of γ and δ. This functional form could be monotone, decreasing, or increasing. Finally, Battese and Coelli (1992) proposed a stochastic frontier production function model for panel data in which the firm effects are an exponential function of time. The proposed model is constructed in such a way that the non-negative firm effects (estimated inefficiency effects) decrease, increase, or remain constant over time, if the time parameter $\eta > 0$, $\eta < 0$ or $\eta = 0$ respectively. The implicit assumption is that in the case where $\eta > 0$, firms improve over time and hence inefficiency effects are reduced as firms improve their technical efficiency level. However, Battese and Coelli (1992) observe that "the exponential expression in equation (3.32) is a rigid parameterization in that technical efficiency must either increase at a decreasing rate ($\eta > 0$), decrease at an increasing rate ($\eta < 0$), or remain constant ($\eta = 0$)". Finally, as discussed above, one additional criticism of the of the Battese and Coelli (1992) parameterization is with respect to the $(t - T)$ functional form in the case where firm specific patters of temporal inefficiency are adopted (see Wheat and Smith 2012). This functional forms leads to a counter-intuitive "falling-off" from the frontier in the last year of the sample. Therefore, policy decisions are compromised as these "falling-offs" are not supported by the data but are an artefact of the model.

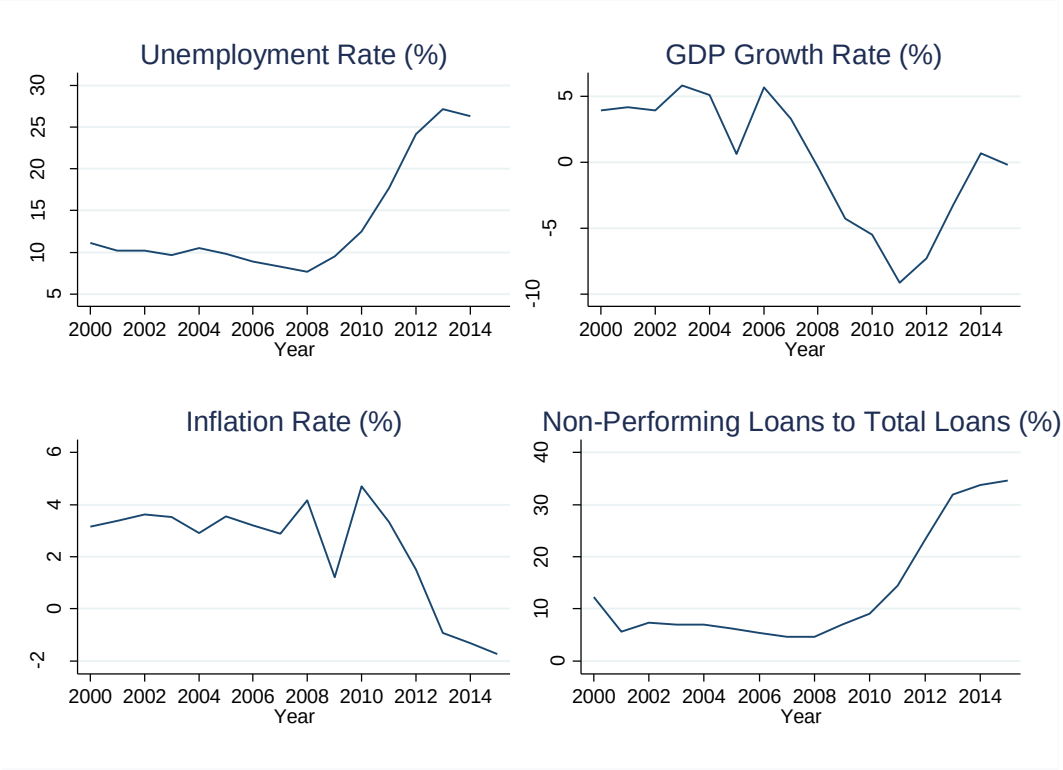
Later developments in the field of stochastic frontier production/cost function analysis were able to formulate econometric models that estimate technical/cost inefficiency effects in terms of appropriate explanatory variables in a one-step estimation. Thus, these specifications offer increased flexibility. Overcoming the problems of the two-step estimation process (Wang and Schmidt, 2002) and the rather unrealistic time-invariant nature of inefficiency, Battese and Coelli (1995) and Greene (2005a, 2005b) built upon existing techniques and propose specifications that permit the simultaneous estimation of the stochastic frontier and the inefficiency component [27]. Subject to the stochastic nature of the inefficiency effect, these models permit the estimation of both

[27] For example, Greene (2005a) observes that this assumption is a questionable one in a long panel.

technical change in the stochastic frontier and time-varying technical inefficiencies. Both model specifications allow the inclusion of auxiliary variables into the estimation via the assumption that the inefficiency effects are a function of explanatory variables that may be represented by variables that are outside of the control of the management. This is an appealing estimation characteristic as it introduces more flexibility into the construction of the production/cost frontier, making this feature particularly relevant in the context of the banking sector; an industry that is particularly distinct as it is subject to rapid change and is affected by macroeconomic conditions.

In terms of our preferred specifications we therefore base our models on TVM and Greene (2005a, 2005b) TFE. The rationale for our choice is due to the changing nature of Greek banking as outlined in Chapter 2 and due to the fact the chosen specifications allow the inclusion of exogenous variables. Indeed, Figure 3.2 shows the development of some of the key macroeconomic indicators and NPL to total gross loans in Greece prior to the introduction of the common currency to 2001. Up to 2005, for the most part all the indicators exhibit a relatively stable trend, indicating the economic stability in the country. However, after 2005, due to the Global Financial Crisis and consequently the Greek debt crisis, a sudden shift is observed. That is, GDP and the inflation rate show a sharp decrease, whereas, the unemployment rate increases dramatically potentially causing a dramatic increase in NPLs. This fact, lead to increasing numbers of commercial and business borrowers becoming unable to repay their debts.

Figure 3.2. Macroeconomic indicators and Non-Performing Loans



Data Source: World Bank and author's own calculations

However, the treatment of NPLs within banking is a complex matter as it is not easy to distinguish whether or not this is exogenous or endogenous to the banking system. Theory proves inconclusive as NPLs could be viewed as endogenous to the extent that management is inefficient; or management made a conscious decision to cut short-run expenses by cutting back on loan origination and monitoring resources; or by following poor business practices that result in loan arrangements with subpar borrowers. On the other hand, a plausible assumption is that despite the risk management procedures set in place by banking institutions, managers could not have foreseen the sudden deterioration in the asset side of their balance sheet. As such, NPLs are exogenous and hence outside the immediate control of management. Therefore, given the economic conditions in Greece and the sample size employed[28], such considerations can only be addressed via the use of the more flexible frontier models proposed in Sections 3.4.4a and 3.4.4b. Both econometric specifications allow the inefficiency effect to move outside the rather rigid framework of allowing the inefficiency component to move

[28] Greene (2005a) questions the validity of time-invariant inefficiency estimates in a sample of US commercial banks spanning over 5 years – a sample smaller than the one employed in the current study.

smoothly through time under the assumption that this move is upward or downward monotonic and the same for every firm. This feature renders both the TVM and TFE models suitable to map the volatile Greek banking sector, thus permitting a more accurate estimation of a cost frontier.

However, we note that Kumbhakar et al., (2014) argues a potential limitation of Greene's maximum likelihood dummy variables estimator in relation to the incidental parameters problem. This arises when the number of parameters to be estimated increases with the number of cross-sections in the data, for example the α_i term in equations (3.36). Therefore, consistency of the estimated parameters is compromised even in the case where the sample size, $N \rightarrow \infty$, because the number of α_i increases with N; thus the usual asymptotic results may not apply (Kumbhakar et al., 2015). In the standard linear panel data literature, in order to deal with this shortcoming the model is transformed and α_i is removed before estimation[29]. Recent developments in the area include Wang and Ho (2010) who developed an alternative model specification to address Greene's (2005a) problem. They propose a fixed-effect panel stochastic frontier model by applying first-difference and/or within transformation methods. Using a similar strategy as Wang and Ho (2010), Chen et al., (2014) also remove the individual effect by using the within transformation and then apply MLE, leading to a model that does not depend on the sample size N, thus eliminating the incidental parameters problem. A key distinction between the Chen et al., (2014) and Wang and Ho (2010) models is that the former allows u_{it} to vary randomly over time, whereas the latter specifications impose a time invariant random portion of the one-sided error term.

In conclusion, Greene (2005a) observes that "the accepted pessimism about the fixed effects estimator may be greatly overstated (page 28)" and Greene (2005b) states that "however, our evidence suggests that the bias in the parameter estimates may be somewhat less severe than other familiar results might lead one to expect. Some bias does appear to remain in the transformation to the inefficiency estimates. This is an

[29] Two methods of transformation are usually applied, conditioning the model on α_i's sufficient statistic to obtain the conditional MLE and either the within-transformation or first-difference transformed models (Kumbhakar et al., 2015). However, Greene (2005b) notes that these methods do not apply in the SFA framework.

outcome that seems to merit further study, as the fixed effects model has other attractive features (page 299)". As discussed in Section 3.4.4b, the TFE model has been applied on banking data despite these potential shortcomings. Indeed, it is important to note that implementation of the TFE model may not be immune to the incidentals parameter problem as Greene's simulations suggest that in short panel this approach may produce inconsistent variance estimates due to the incidental parameters problem (Belotti and Ilardi, 2012). For this purpose and in order to confirm model stability and consistency, a set of criteria proposed by Bauer et al., (1998) is applied in our final efficiency estimates both in the case of the TVM and the TFE specifications. In this manner a "filtration" process is applied and potential limitations are identified before proceeding to the second stage panel data analysis.

3.4.5 Distributions and estimators for the inefficiency term

3.4.5a Distributional Assumptions

The selected distribution must be one-sided (taking only positive values). A common assumption in the SFA context is that higher inefficiency is less likely to be observed. Thus, the chosen distribution must be decreasing at higher values with the literature suggesting the following candidates: half-normal and exponential distributions. Depending on the model specification chosen, other possible candidates are the truncated-normal and the gamma distributions. Based on the distributional assumptions regarding the inefficiency term, the final Technical/Cost Efficiency estimates will differ. It is worth noting that efficiency estimation is also sensitive to the input/output mix employed. Selecting the distributional assumption of the inefficiency term is a key assumption in the context of SFA and does not depend on the model's characteristics. This is a decision that the researcher has to take in the beginning of the analysis and there are no standardized econometric tests to control for the validity of the choice. However, in most empirical applications, the inefficiency estimates from various distributional assumptions are similar overall. In the modelling strategy applied in this Thesis we thereby assume a half-normal approach due to simplicity and convergence issues found[30].

[30] Throughout the time period assigned to the thesis covering 1 year – numerous techniques were deployed but due to the lack of sample data, we could only find practical and believable results from the

3.4.5b Predicting firm level efficiencies

After the model parameters are estimated, observation specific efficiency estimates can be obtained. These estimates can then be used to construct ranks and identify banks deemed to be operating on the efficiency frontier. Such information can be very useful in discussing policy implications and policy design. For example, in regulated sectors such as banking, efficiency rankings may be used in order to evaluate efficiency performance before and after M&As, or in a way such that the regulatory authorities can set tough cost reduction targets in order to ensure that consumers do not pay for inefficiency.

As previously discussed, the error term in the stochastic frontier model is of the form $v \pm u$ (equations (3.26) and (3.27)), where v represents the normal random error term and u is the non-negative error term representing technical inefficiency. For example, consider the following production frontier given by equation (3.37),

$$y_i = g(x_i, \beta) + \varepsilon_i \;\; i = 1 \ldots., N. \tag{3.37}$$

Where y_i represents the observation specific output level, x_i represents the observation specific input vector, β represents a vector of parameters to be estimated and ε_i represents the composed error term $v_i - u_i$. Jondrow et al., (1982) observe that by estimating the residuals $\hat{\varepsilon}_i = y_i - g(x_i, \beta)$, the composed error term can be obtained. The average efficiency scores can also be estimated by calculating the mean of the distribution of u_i. In the case of the half-normal model, the mean efficiency estimate will be equal to $\sigma_u \times \sqrt{2/\pi}$. However, of key interest in SFA is the estimation of the observation specific technical/cost efficiency. This process requires the separation of the composed error term to its respective components, v and u.

As Jondrow et al., (1982) first observe, this should be possible because $\varepsilon_i = v_i - u_i$ can be estimated and it contains information on u_i. The suggested solution to this problem is to consider the expected values of u_i, conditional on the realized values of

using the half-normal specification. Of course, in future research we hope to extend the discussion and incorporate additional distribution specifications in our analysis in order to provide a more comprehensive examination of the Greek financial system.

the composed error term ε_i. However, the Maximum Likelihood Estimator (MLE) does not provide a direct estimate of the inefficiency term since its parameter is unobservable, though it does provide enough information to generate an estimate of the conditional mean of inefficiency $E(u_i \mid \varepsilon_i)$. The authors propose that for the commonly assumed cases of half-normal and exponential distributions, observation specific *technical inefficiency* estimates can be obtained based on either the mode of the distribution $M(u_i \mid \varepsilon_i)$ or the mean $E(u_i \mid \varepsilon_i)$.

One limitation of the original work of Jondrow et al., (1982) is that the specifications are restricted to a cross-sectional model in which the firm inefficiency effects have either a half-normal or an exponential distribution. Battese and Coelli (1988) proposed a generalisation of the results suggested by Jondrow et al., (1982), assuming that panel data are available and that the inefficiency term follows a truncated distribution. Battese and Coelli (1988) obtain the best predictor for the firm-effect random variable and the appropriate *technical efficiency* of an individual firm, given the values of the disturbances in the model. More specifically and in a similar manner as Jondrow et al., (1982), Battese and Coelli (1988) consider the following panel data production function with time-invariant inefficiency, given by equation (3.38),

$$y_{it} = g(x_{it}, \beta) + \ \varepsilon_i \ \ i = 1 \ldots., N, t = 1 \ldots., N. \tag{3.38}$$

Where y_{it}, x_{it}, β and ε_{it} are defined as in equation (3.37), including the time notation t to account for the panel nature of the specification. The random component is assumed to follow a normal distribution $N(0, \sigma_v^2)$ and the non-negative inefficiency part of the error term is truncated at zero $N(\mu, \sigma_u^2)$.

Battese and Coelli (1988) define firm specific technical efficiency as the ratio of its mean production given its realized firm effect to the corresponding optimal mean production (in this case the firm effect is equal to zero). Formally, this relationship is expressed as in equation (3.39),

$$TE_i = \frac{E(Y_{it}^* \mid u_i, x_{it}, t = 1, 2 \ldots)}{E(Y_{it}^* \mid u_i = 0, x_{it}, t = 1, 2 \ldots)}. \tag{3.39}$$

Where Y_{it}^{*} represents the value of production (in original units) for the ith firm in the time period t. That is, when the production function takes the form of equation (3.38) and is defined in the original units of production, technical efficiency can be written as in equation (3.40),

$$TE_i = (\bar{x}\beta_i - u_i) \times (\bar{x}\beta_i)^{-1}. \quad (3.40)$$

Indeed, as Battese and Coelli (1988) suggest that if the frontier production function is defined in logarithmic terms, then the firm specific production in the period t is $\exp(Y_{it})$ and the equivalent measure of technical efficiency for the ith firm is thus given by equation (3.41),

$$TE_i = exp(-u_i). \quad (3.41)$$

This technical efficiency measure expressed in equation (3.41) is equivalent to the ratio of the firm specific production at time t, $\exp(Y_{it}) = \exp(x_{it}\beta + v_{it} - u_i)$, to the corresponding production when the firm inefficiency effect is equal to zero, $\exp(x_{it}\beta + v_{it})$. Given that the conditional distribution of u is known, one can derive moments of any continuous function of $u \mid \varepsilon$ (see for example, Kumbhakar et al., 2015). That is, Battese and Coelli (1988) use the same technique as Jondrow et al., (1982) in order to obtain observation specific *technical efficiency* by using the mean of the distribution of $E[\exp(-u_i) \mid \varepsilon_i]$. The final estimates have a value between 0 and 1, whereby 1 indicates a fully efficient firm.

3.4.6 Pre and Post Estimation Tests of Model Specifications

3.4.6a A skewness test on the OLS residuals

Schmidt and Lin (1984) propose an OLS test on the residuals to check for the validity of the model's stochastic specifications. Since this test is easy to compute, it can serve as a pre-computational test for the model. When estimating a cost function, with a composed error term $v_{it} + u_{it}$, the distribution of the OLS residuals should exhibit positive skewness. Thus, a test of the null hypothesis of no skewness can be constructed

using the OLS residuals. If the estimated skewness has the expected sign, rejection of the null hypothesis provides support for the existence of the one sided error term. Building upon Schmidt and Lin's (1984) original proposition, Coelli (1995) suggests and alternative variant test. That is, under the null of no skewness, the third moment of the OLS residuals is asymptotically distributed as a normal random variable with mean 0 and variance $6m_2^3/N$. The statistic is given by the following, equation (3.42),

$$\mathrm{M3}T = m_3/\sqrt{6m_2^3/N}. \tag{3.42}$$

The main advantage of this alternative test is that the critical values are commonly available. Despite the fact the skewness of the residuals is an important indicator of a correct specification of the stochastic frontier model, it is not free of limitations. Indeed, in the context of a production function (in this case negative skewed residuals are expected), Greene (2008) emphasizes that "this is merely a sample statistic subject to sampling variability and the skewness is only suggestive – m_3 could be positive even if the stochastic frontier model is correct (p 116)"[31,32].

3.4.6b A Likelihood Ratio Test of Inefficiency

Key to the Stochastic Frontier Analysis framework is the absence of the inefficiency term. In the case where the evidence of the presence of the one-sided error term is not found, a simple OLS model would suffice. The null hypothesis of no presence of the one-sided error term can then be easily tested by a generalized Likelihood Ratio (LR) test (constructed based on the log-likelihood values of the OLS (restricted) and the SFA (unrestricted) model). As discussed, the SFA model specifications follow the dual variance approach, that is, σ_v^2 and σ_u^2, representing the variances of the error term and the inefficiency respectively, where the total variance is given by, $\sigma^2 = \sigma_v^2 + \sigma_u^2$. In

[31] Almanidis and Sickles (2011) show "that finding incorrect skewness does not necessarily indicate that the model is mis-specified and the only misspecification should arise from the fact that we might consider wrong distribution for inefficiency process". To the best of our knowledge no empirical study implements this approach and therefore only the proposed models showing the expected OLS skewness in their residuals are considered in this study.

[32] In the current project and for consistency, only econometric specifications that indicated positive residuals were estimated. Models including Off-Balance Sheet items and Input Distance Functions were not estimated since they showed the wrong skewness in their respective OLS residuals. For more details please see Chapter 4.

the maximization process the likelihood function is expressed in terms of the following equality[33]:

$$\gamma = \sigma_u^2/\sigma_v^2 + \sigma_u^2. \quad (3.43)$$

In the case where the model is following the normal- truncated normal distributions examined in Sections 3.4.4a and 3.4.4b, where the inefficiency effects are incorporated via the truncation of the u_i distribution on a vector of auxiliary covariates (z, equation (3.34) the absence of the inefficiency effects can be accounted for via testing of the following null hypothesis:

$$H_0: \gamma = \delta_0 = \cdots = \delta_i = 0. \quad (3.44)$$

An LR statistic can be calculated by using the following formula (Coelli et al., 2005 and Kumbhakar et al.,2015):

$$-2[L(H_0) - L(H_1)]. \quad (3.45)$$

Where $L(H_0)$ and $L(H_1)$ are the log-likelihood values of the OLS and SFA model respectively which has a mixed chi-squared distribution with degrees of freedom equal to the number of restrictions. The critical values can be obtained in table 1 of Kodde and Palm (1986). The skewness of the OLS residuals is computationally easy to perform since it only requires the estimation of the OLS model. Even though it is a useful pre-estimation test, it does not use the information provided by the distribution functions of the random error. The LR test is more precise but it can only be conducted after the maximum likelihood estimation of the Stochastic Frontier model.

[33] Different parameterizations are followed in the SFA literature. For example in Section 3.4.4 we discussed the method employed by Battese and Corra (1977), $\gamma = \sigma_u^2/\sigma_v^2 + \sigma_u^2$. A different parameterization commonly employed for in the literature is $\theta = (\alpha, \beta', \sigma^2, \lambda)'$, where $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\lambda = \sigma_u/\sigma_v$. The current project is presenting both the γ and the λ parameterizations.

3.4.6c The Gamma Parameter

One statistic reported as a post estimation test is the gamma parameter (as expressed by equation (3.35). Battese and Corra (1977) used this parameterization in the formulation of the maximization process; since the ratio is restricted between 0 and 1, it provides a useful tool in restricting the search for the maximizing value within that space. For a model where the inefficiency component is assumed to follow a half-normal distribution, a hypothesis test of $\gamma = 0$ can also serve as test for the existence of the one-sided error term. However, Kumbhakar et al., (2015) prove that the ratio should not be interpreted as the share of the total variation attributable to the inefficiency variation; the observation specific inefficiency variance $var(u) \approx 0.36338\sigma_u^2$. In the case of more complex models, such the panel data models described in Section 3.4.4, the gamma parameter conveys no useful information regarding the presence of the inefficient component of the composed error term. Therefore, preference is given to the Likelihood Test instead[34].

3.4.7 Functional form specifications

When applying the parametric frontier approach, choosing the functional form is one of the first decisions to be made. Some of the most common functional forms used are the Linear, the Cobb-Douglas (CD), the Quadratic, the Normalised quadratic, the Transcendental Logarithmic (translog), the Generalised Leontief Function (GLF), the Constant Elasticity of Substitution (CES) and the Fourier-Flexible functional Form (FFF) (Coelli at al, 2005). The choice of the functional form is dependent on the following three conditions:

- Flexibility
- Easy to calculate (parsimonious)
- Permit the imposition of homogeneity

The CD function, which has been popular in the production analysis, even though it satisfies the first two conditions, does not meet the requirements under the final

[34] It is important to note that σ_u^2 is not the variance if the firm specific inefficiency but the variance of the untrucated normal random variable whose probability density function is truncated. Hence, λ^2 does not represent the ratio of the variance of the inefficiency effects to the variance of the composed error term.

condition because of its restrictive elasticity of substitution and scale properties (Coelli and Parelman, 1999). A typical multi input/output cost Cobb Douglas function expressed in logarithmic terms is given by the following equation (3.46),

$$lnTC_{it} = \alpha_n + \sum_{i=1}^{k} \alpha_i lnQ_i + \sum_{j=1}^{l} \beta_j lnP_j + \varepsilon_{it}. \quad (3.46)$$

Where, $lnTC_{it}$ represents the measure used to total cost of production, lnP_j represents the input prices and lnQ_i represent the output quantities and ε_{it} follows the structure of the composed error term as described in equation (3.26). All variables are expressed in natural logarithms. However, as Greene (2005b) notes "the output or cost measure is usually specified in natural logs, at least for small deviations, the inefficiency effect u_{it}, can be interpreted as the percentage deviation of the observed performance from the firm's own frontier (p271)". Furthermore, the logarithmic transformation helps reduce the scale of the variables and therefore helps address any potential problems with respect to outlier observations.

As Kumbhakar and Lovell (2003) note, Hasenkamp (1976) was the first to propose that a frontier having the CD form cannot accommodate multiple outputs without violating the requisite curvature properties in output space. Furthermore, if the true structure of (single-output) production technology is more complex than it's the representation offered by the CD function, then the unmodelled complexity will show up in the error term, perhaps leading to biased estimates of the cost of inefficiency. As an alternative, the translog functional form has several advantages: (i) it accommodates multiple outputs without necessarily violating curvature conditions; (ii) it is flexible, in the sense that it provides a second- order approximation to any well-behaved underlying cost frontier at the mean of the data; and (iii) it forms the basis on much of the empirical estimation and decomposition of cost efficiency based on a system of equations (Kumbhakar and Lovell, 2003). The translog cost function can be expressed as in equation (3.47),

$$lnTC_{it} = \alpha_n + \sum_{i=1}^{k} \alpha_i lnQ_i + \sum_{j=1}^{l} \beta_j lnP_j + \frac{1}{2}\left[\sum_{i=1}^{k}\sum_{j=1}^{k} \gamma_{ij} lnQ_i lnQ_j + \sum_{i=1}^{l}\sum_{j=1}^{l} \delta_{ij} lnP_i lnP_j\right] + \sum_{i=1}^{k}\sum_{j=1}^{l} \zeta_{ij} lnQ_i lnP_j + \varepsilon_{it}. \quad (3.47)$$

Linear homogeneity of first degree on factor prices is imposed by the following restrictions:

$$\sum_{j=1}^{l} \beta_j = 1 \; and \; \sum_{j=1}^{l} \delta_j = 0 \; and \; \sum_{j=1}^{l} \zeta_j = 0 \quad (3.48)$$

That is, a proportional increase in all input prices must increase cost by the same proportion, holding output constant, effectively imposing constant economies of scale. Linear homogeneity ensures that the cost-minimizing bundle does not change if all prices are multiplied by the same positive scalar. Whereas symmetry implies that: $\gamma_{\iota j} = \gamma_{j\iota}$ and $\delta_{\iota j} = \delta_{j\iota}$. That is, an effect of increases in the price of factor j on the demand for factor i is the same as the effect of a rise in the price of factor i on the demand for factor j.

Despite the fact that the flexibility offered by the translog functional form does not come without a cost as the inclusion of many parameters raises issues of multicollinearity, the specification seems to dominate the frontier analysis literature (Fried et al, 2008). This has been employed in a number of studies both in the US and European banking systems (see for example, Dietsch and Lozano-vivas, 2000; Fan and Shaffer, 2004; Clark et al., 2007; Lozano-Vivas, 2009; Fiordelisi et al., 2011; Molyneux and Williams, 2013; Akinci et al., 2013; Goddard et al., 2014).

Finally, the FFF has also been used in when studying bank efficiency, introducing even more flexibility into the estimation process by including trigonometric transformations

that allows for a global approximation of the underlying cost function over the entire range of data and the standard translog functional form (Berger and DeYoung, 1997). This is a theoretical improvement on the translog form, which is a local approximation which may perform poorly for observations far from the sample means. The FFF can be represented as follows:

$$
\begin{aligned}
lnTC_{it} = \ & \alpha_n + \sum_{i=1}^{k} \alpha_i lnQ_i + \sum_{j=1}^{l} \beta_j lnP_j \\
& + \frac{1}{2}\left[\sum_{i=1}^{k}\sum_{j=1}^{k} \gamma_{ij} lnQ_i lnQ_j + \sum_{i=1}^{l}\sum_{j=1}^{l} \delta_{ij} lnP_i lnP_j\right] \\
& + \sum_{i=1}^{k}\sum_{j=1}^{l} \zeta_{ij} lnQ_i lnP_j \\
& + \sum_{i=1}^{k} [A_i \cos(z_i) + B_i \sin(z_i)] \\
& + \sum_{i=1}^{m}\sum_{j=1}^{m} [A_{ij} \cos(z_i + z_j) + B_{ij} \sin(z_i + z_j)] \\
& + \varepsilon_{it}.
\end{aligned}
\tag{3.49}
$$

Where z_i and z_j represent the ith scaled output quantity. The remaining notations are the same as in equation (3.46).

However, one drawback of the FFF is that it lacks any economic interpretation of the sines and cosines and the additional interaction terms add to the problem of multicollinearity. Examples utilizing the FFF include amongst others; McAllister and McManus (1993); Berger and Mester (1997); Berger and DeYoung (1997); DeYoung et al., (1998); Feng and Serletis, (2008); Girardone et al., (2009); Beccalli and Frantz, (2009); Yu et al., (2011) and Huang et al., (2011). However, as Akinci et al., (2013) note "[….] Altunbaş and Chakravarty (2001) identify some problems associated with more flexible functional forms like the Fourier (Mitchell and Onvural, 1996) when dealing with heterogeneous data sets. Secondly, (Berger and Mester, 1997) observe that the translog and the Fourier-flexible are equivalent from an economic viewpoint and both rank individual bank efficiency in almost the same order (page 274)". Indeed,

Altunbaş and Chakravarty (2001) find evidence that the Fourier form underperforms at the top end of the data (the upper quartile consisting of the largest banks).

3.5 Choice of variables

In bank efficiency studies the choice of the proxies that are used as input and output variables is an important consideration for researchers. This choice is heavily formulated by the purpose of the research, the nature of the questions addressed, and data availability. The bank efficiency literature has been influenced by four approaches that are considered to be seminal within the literature. Each modelling methodology has a different view of the role of the bank, the financial services industry and its interconnectedness with the economy. The following section discusses the key characteristics of the modelling methodologies, focusing on their theoretical underpinnings influencing the choice of inputs and outputs proxies.

3.5.1 The Production Approach

Benston and Smith (1976) view the role of the financial firm as an institution that creates specialized financial commodities. As in any other industry, these commodities are only created when they can be sold at a price that covers both direct and opportunity costs. In their model they treat financial institutions as firms and therefore adopt the same tools that would be used when analysing other industries. However, a basic problem in the analysis of financial intermediaries is the lack of an appropriate analytical framework within which to analyse the demand for the financial commodities produced by intermediaries (Benston and Smith, 1976).

That is, the demand for the commodities produced by financial intermediaries, in general is derived from the consumer's ability to achieve a higher level of utility by incurring lower levels of transaction costs. More specifically, demand for financial products, i.e., deposits and loans, derives from an individual's demand to affect their own intra-temporal consumption. The main argument of the production approach is that financial intermediaries supply consumers with units of generalized purchasing power that can be converted into goods and services at minimal transaction costs. The

production of financial commodities, like the production of any other good, requires the use of various forms of labour and capital goods. In the production of financial commodities, these inputs are more extensively employed in tasks of documentation, information and monitoring (Benston and Smith 1976: 215–231). Examples using the production approach include Ferrier and Lovell (1990), Fried et al., (1993) and more recently Sturm and Williams (2008)

3.5.2 The Value-Added Approach

An additional methodology proposed by Berger and Humphrey (1991) specifies physical operating costs, interest costs on produced deposits and interest costs on purchased funds as the main three types of bank costs. The choice of which bank products to include as an output is based on value added. That is, banking functions which are associated with a substantial labour or physical capital expenditure to produce a (noninterest) flow of banking services are identified as important outputs. Under this premise the methodology defines outputs as produced deposits (demand and retail time, and savings deposits) and loans (real estate, commercial and industrial, and instalment loans). On the other hand, labour, physical capital and purchased funds, are identified as inputs, taking into account the duality of deposits, both as having input and output characteristics.

Since the manner that produced deposits and purchased funds are raised is different, these two inflows are treated in a varied way. That is, produced deposits are treated as outputs due to the fact that they are paid for in large part by the provision of liquidity, transactions, and payments services to depositors, thus assuming substantial physical capital or labour expenditure. In contrast, purchased funds are paid for almost exclusively with interest payments rather than produced services. Recent examples in the literature include Clark (1996), Dietsch and Lozano-vivas (2000), Tortosa-Ausina (2002) and Pasiouras et al., (2009).

3.5.3 The Profit Approach

Berger and Mester (1997) in their seminal paper discuss two different profit approaches, namely the standard profit function and the alternative profit function. The standard

profit approach takes output prices as given and assumes that the bank can sell as much output as it wishes without having to lower its prices. The standard profit function specifies variable profits in place of variable costs and takes variable output prices as given (exogenous), rather than holding all output quantities statistically fixed at their observed, possibly inefficient, levels. This implies that it is prone to scale bias as it essentially treats all large and small banks the same, assuming that they should have the same variable outputs when facing the same input and output prices. On the other hand, the alternative profit functions measures how close a bank comes to earning maximum profits given its output levels rather than its output prices, holding variable output fixed and letting prices fluctuate. This attribute of the alternative profit method can help reduce scale bias since it can facilitate banks with below efficient output which might need to reduce their prices in an attempt to increase output.

They also point out the merits of the alternative profit efficiency when one or more of the following conditions hold:

- There are substantial unmeasured differences in the quality of banking services;
- outputs are not completely variable, so that a bank cannot achieve every output scale and product mix;
- Output markets are not perfectly competitive, so that banks have some market power over the prices they charge; and
- Output prices are not accurately measured (as is likely given the available banking data) so they do not provide accurate guides to opportunities to earn revenues and profits in the standard profit function

Finally, under conditions of market power, it may be appropriate to consider output levels as relatively fixed in the short run and allow for efficiency differences in the setting of prices and service quality.

3.5.4 The Intermediation Approach

A popular approach in the bank efficiency literature is the intermediation approach first proposed by Sealey and Lindley (1977); for examples see Mester, (1994) Noulas (1997), Avkiran (1999, 2000), Casu and Molyneux (2003), Drake et al., (2009) and

Hadad et al., (2012). Sealey and Lindley (1977) develop a model in which the role of production and cost was analysed and the behaviour of the financial firms understood within the context of a profit maximizing producer rather than a rational investor, as viewed from a portfolio approach. When a discussion for a production and cost model takes place, it is important to clearly define the inputs and outputs of the financial institution. As the authors argue, one of the major confusions in the theory of the financial firms arises over the lack of agreement concerning the appropriate measures for inputs and outputs. That is, financial intermediation can be defined as the borrowing of funds from surplus spending units and lending those funds to deficit spending units. Therefore, the output of financial firms (namely commercial banks), in a technical sense, is a set of services offered to depositors and borrowers. These services can be categorized as following: (i) administration of payments for demand deposit customers, (ii) Intermediation services to depositors and borrowers and (iii) Other services like portfolio advisory services.

However, the outputs discussed above do not necessarily constitute economic outputs (outputs that are more highly valued than the input used). Specifically, because of institutional arrangements and market conditions under which financial firms operate, only those services which are associated with the acquisition of earning assets are products which are more highly valued in the market than the original inputs (Sealey and Lindley 1977). Since commercial banking institutions incur positive costs without directly yielding any revenue from providing the services mentioned previously to their customers, it is clear that those services can be associated with the acquisition of economic inputs. As a result, the production process of a financial firm is a multistage production process. Loanable funds, borrowed from depositors and serviced by the firm with the use of capital, labour and material inputs, are used in the production of earning assets (i.e., loans etc.)

3.5.5 Concluding remarks

Each of the previously discussed approaches has strengths and weaknesses. A key point in the analysis is that the intermediation approach is designed in way as to use stock variables as inputs/output. This can be considered as an inherent weakness since stock variables only capture the total amount of input/output use at a certain point in

time rather the constant flow of the input/output mix. As Benston et al., (1982) observe, the production approach solves this problem by using flow variables (the number of accounts but it is difficult to weigh the different types of accounts and their contribution to total cost and output[35]. On the other hand, data availability remains a significant limitation to the model selection process. Miller and Noulas, (1996) state that the choice of the model depends on the availability of the data. When analysing the intermediation and the profit approaches, Drake et al, (2006) point out that the profit approach captures the full impact of any adverse environmental factors on revenues as well as costs, while the intermediation approach tends to focus on the technical efficiency of the financial intermediation approach. Furthermore, Berger and Mester (2003) additionally argue that the employment of the profit approach may help take into account unmeasured changes in the quality of banking services by including higher revenues paid for the improved quality, and may help capture the profit maximisation goal by including both the costs and revenues.

Finally, Berger and Humphrey (1997) have shown, various efficiency methods do not necessarily yield consistent results. Depending on the frontier selected, and the measure of financial output chosen, efficiency estimates and rankings may differ. For example, Tortosa-Ausina (2002) find that application of the intermediation approach generally gives lower overall efficiency scores than the value added approach. However, within model variation is limited, since once the frontier estimate is adopted and the input/output mix is considered, efficiency estimates are fairly stable from year to year. It is with respect to the above arguments and the inherent data limitations of Greek banks, we follow the intermediation approach. A full explanation of the data and models estimated are presented in Chapter 4.

[35] Data on the number of accounts are not only difficult to obtain, but can also prove to be biased as they may not fully reflect banks' practises. For example, recently, concerns were raised with respect to the quality of such data as regulators subpoenaed Wells Fargo (an international banking and financial services holding company) for opening 1.5 million bank accounts, in order to meet sales targets (http://ftalphaville.ft.com/2016/09/16/2175200/bank-account-fiddling-as-cultural-bridge/). In addition, out of 240 million accounts opened in India since 2014, regulators found over 10 million one-rupee accounts were found at 34 banks, again indicating towards potential problems with such data.

3.6 Conclusion

In recent years studies have used frontier techniques to examine the efficiency of banks and other financial institutions in an attempt to answer questions in relation to their operations. One attractive feature of efficiency analysis is that it can summarize the performance of banks in one single indicator while taking into account various aspects of banks' operations simultaneously. This feature makes is possible to assess a bank while taking into account for example its loan portfolio, the illiquid assets and the relationship between short-term liabilities. Such attributes offer an advantage over the traditional financial indicators that may lead into conflicting results, as seen in Section 3.3.

Furthermore, this Chapter presented the main efficiency concepts used and the various econometric techniques used in estimating them. Both distribution free and parametric approaches were presented and despite the wealth of frontier estimation methods in the literature, preference is given to SFA as the main technique used in the Thesis. In addition, the main decisions that a researcher must take when using SFA (for example, the distributional assumptions, pre/post estimation tests, the choice of the functional form and the choice of the input/output mix) were also addressed.

Chapter 4

Bank Performance Estimation

4.1 Chapter Summary

This current Chapter contributes to the European Union banking literature by providing recent findings regarding the performance of the Greek banking system. This analysis is both timely and warranted to examine the majority of recent efficiency studies concerning Greek banks that utilize non-parametric Data Envelopment Analysis. And as such, the methodology analysed in the previous Chapter is followed and stochastic frontier cost efficiency scores are estimated for commercial banks operating in the Greek financial sector (table 9.1 in Appendix provides an overview of studies examining efficiency in the Greek banking market).

> It should be noted that our theory of the inclusion of xefficiency estimates in LLP modelling has been accepted in the literature by publication using Vietnamese data – see Bryce C., **Dadoukis A**., Hall M., Nguyen L., and Simper R., (2015). This paper's publication is associated and forms part of this Thesis, but unlike Bryce C., Dadoukis A., Hall M., Nguyen L., and Simper R., (2015), the current research utilises an inclusive analysis through the Bauer et al., (1998) consistency conditions and hence advances the said publication. It should be noted that this Thesis advances the theory of cost efficiency inclusion in LLP modelling theory and as such can be thought of as the 'original' staring point concerning cost efficiency and LLP joint modelling methodologies. The aforementioned published paper was completed during my PhD research, however the current chapter on estimating cost efficiencies to utilise as modelling the theory in risk management in LLP constitutes the introduction and starting point of this work.

To recap, it should be noted that the cost efficiency scores are used as a potential indicator variable in bank risk management behaviour. As previously stipulated, this inclusion of LLP modelling structures constitutes an addition to the literature (on LLP). We believe therefore that this constitutes a comprehensive re-analysis of modelling within this construct.

In line with Leamer (1994) and Bauer et al., (1998), who emphasise the importance of assessing the fragility of econometric results, our advancement to analysing the Greek banking sector, constitutes a strategic estimation of 15 different SFA frontiers. Thus, we incorporate econometric modelling specifications taking into account the adverse macroeconomic environment effects into the estimation process covering 8 years and hence constituting a diverse set of SFA frontiers. Finally, in order to control and filter the estimated scores that will be used in the Loan Loss Provisioning panel data models in the subsequent Chapter, the measured efficiency scores derived from the alternative approaches are checked for compliance with the consistency conditions proposed by Bauer et al., (1998).

The remaining of Chapter 4 is structured as follows; Section 4.3 provides a literature review of recent banking efficiency studies examining the Greek banking system. Section 4.4 describes the proposed methodology, the data and variables chosen and the empirical model specifications estimated. Section 4.5 offers a discussion on the empirical results under the context of the consistency conditions proposed by (Bauer et al., 1998) together with an additional condition that further disentangles the suitability of the estimated cost functions. Section 4.6 discusses in greater detail the behaviour of the core banks operating in Greece. Finally, Section 4.7 concludes.

4.2 Introduction

The banking industry plays a central role in the economy providing capital allocation, finance for innovation and infrastructure, facilitation and acceleration of capital flows and has been the focus of a significant body of research both from the academic community and regulators. Building on the banking efficiency literature, this study provides an overview of the Greek banking system, assessing the levels and consistency of cost efficiency estimates in a highly volatile banking landscape. The Greek banking industry has changed dramatically since the country's introduction into the Economic Monetary Union in 2001. From a heavily regulated industry it moved towards an outward looking financial services industry attracting foreign competition into the domestic market. Indeed, the period between 2001 and before the global financial crisis can be characterized by economic development and expansion of Greek banks into foreign markets. However, the Greek banking sector was not able to remain unaffected by the recent economic developments, due to the financial crisis and the Greek sovereign debt crisis. That is, the industry was severely hit by the combined effects of:

- The cut-off from international markets and deposit outflows
- Adverse economic conditions, which resulted in deteriorating asset quality and
- The restructuring of the Greek sovereign debt through the PSI (Bank of Greece, 2012).

As a result, these factors put a great strain on Greek banks liquidity thus threatening the stability of the banking sector and the long-term sustainability of the financial services industry. Indeed, it is well established in the literature that the efficiency of financial intermediation affects economic growth and that bank insolvencies can result in systemic crises that can have a severe impact on an economy as a whole (Fethi and Pasiouras 2010). Therefore, assessing bank performance and efficiency has been the focus of various stakeholders, including, customers, investors and regulators. The aim of this Chapter is to investigate the cost efficiency of banks operating in Greece and to assess the stability of such estimates during a highly volatile period for the Greek economy.

4.3 Literature Review

Despite the fact that efficiency studies analysing banking systems are a well-established field of research for European countries, findings regarding the efficiency of the Greek banking industry are rather scarce. That is, even though empirical studies analysing Greek banks date back to the early 1990's (for example Giokas, 1991 and Boufounou, 1995), they mainly follow two distinct methodologies. These include focusing on the measurement of efficiency concerning bank branches (Tsolas and Giokas, 2012; Tsolas, 2010; Gaganis et al, 2009; Noulas et al, 2008), while the second strand exhibits a limitation regarding the data sets used, mostly employing data up to the Global Financial Crisis (see Chatzoglou et al., 2010, Chortareas et al., 2009, and Pasiouras, 2008a).

In an early study analysing the efficiency and productivity of Greek banks, Noulas (1997), by using the Malmquist index and employing the intermediation approach, estimated productivity growth and made comparisons between state owned and private institutions. Noulas' (1997) focus was on the early period after deregulation of the banking industry in the early 1990's (the sample used data for two years, 1991 and 1992). The results show a different source for state owned and private banks' productivity growth. That is, while private banks show an increased efficiency, the increase in productivity of state institutions could be attributed to technological change. Examining a similar sample, Christopoulos et al., (2002), again follow the intermediation approach and estimate cost efficiencies (for the period 1993-1998), find that the largest are less efficient than smaller ones. More specifically, small and medium sized banks exhibited average cost efficiency indices over the 1993–1998 period of almost 100%, while large banks efficiency ranged from 60 to 95%[36]. Furthermore, for the larger banks in the sample, efficiency was found to be inversely proportional with size in terms of assets. However, conflicting results were reported by Spathis et al., (2002) and Halkos and Salamouris (2004). For example, Spathis et al., (2002) using a similar data set covering the period between 1990-1999 and through the adoption of a multi criteria methodology, investigated the differences of profitability and efficiency between small and large banks, finding that large asset sized

[36] The term X-efficiency was coined by Leibenstein (1966) and relates to efficiencies brought about by superior management and technology.

banks were more efficient than small asset sized banks. In addition, consistent results were produced by Halkos and Salamouris (2004), who measured the performance of the Greek banking sector and explored the efficiency of Greek banks with the use of a number of suggested financial efficiency ratios as an output measure covering 1997–1999. They find that the average banks' efficiency increased from 78% in 1997 to 83% in 1999 with a decrease in 1998 to 71%. Additional results from this study suggest a positive relationship between total assets and high efficiency estimates. Moreover, a wide variation in performance was identified and shows that the increase in efficiency is accompanied with a reduction in the number of small asset sized banks due to mergers and acquisitions. Finally, a non-systematic relationship between the transfer of ownership and last period's performance was established.

In addition to efficiency studies, non-parametric techniques have been used to estimate Total Factor Productivity (TFP) growth including Tsionas et al., (2003) who analyse Greek banks in the early 1990's . The authors find that the majority of the Greek banks operate close to the frontier and best market practices, with efficiencies greater than 90%. Finally, the association of the changes in TFP was addressed, showing a link between an efficiency improvement and TFP for the medium asset sized banks and technical change improvements for larger asset sized banks. Furthermore, Rezitis (2006) investigated the productivity growth and technical efficiency of Greek banks covering the 1982-1997 period. By using a very small sample size of six banks, and employing the intermediation approach, he found that TFP was higher for the years after the market liberalization and reports cost efficiencies higher than 90% for the sampled banks. Next, Asimakopoulos et al (2008) investigated the evolution of Greek bank efficiency, covering 1994–2006 and found that banks efficiency gradually improved from 1999 onward. The authors also find that medium sized banks appear to be less efficient than smaller and larger ones while they attribute this improvement in efficiency to better input management strategies, also supported by stability conditions prevailing in the period examined. Similar findings were also reported by Athanasoglou et al., (2009) when assessing the evolution of output and productivity in the Greek banking industry for the period 1990–2006. Results show that bank output and labour productivity outpaced Greek GDP growth and labour productivity. Finally, since 1999 and due to the structural changes that took place during that period, capital and total factor productivity have shown an improvement.

In an analysis that has employed a recent dataset; Pasiouras (2008a) estimated the efficiency of the Greek banking industry over the period 2000-2004, taking into account the effects of credit risk exposure and Off-Balance Sheet (OBS) items on efficiency. According to Pasiouras (2008a), the inclusion of loan loss provisions as an input increases efficiency scores but OBS items do not have a significant impact. In addition, Greek banking institutions that operate abroad exhibit higher technical efficiency than those operating only domestically. In line with this study but with a slightly expanded period (1998-2003), Chortareas et al., (2009) reported average cost efficiencies that range from 8.6% to 91.1% and which increased by 4.3% from 1998-2003. In addition, banks show relatively high profit efficiency, on average 75%, increasing by 93% over 1998–2003. Furthermore, the results do not show any role of Off Balance Sheet activities in Greek banks' efficiencies, similar to Pasiouras, (2008a).

The above studies were concerned with commercial banks but, in an interesting study employing both the intermediation and the production approach on small dataset of 78 observations (13 banks covering the 2000-2005 period), Pasiouras and Sifodaskalakis (2010) estimated TFP of Greek cooperative banks. The first model (intermediation approach) estimated indicated a small decrease of 3% in TFP, while the second model (production approach) exhibited an increase of 6%. Finally, the authors found that TFP growth was higher for smaller banks on average, over the complete sample period under consideration, without however, having a robust relationship across the years. Hence, we can see that there are differences between the two sectors and as we have analysed before, only one sector should be analysed. That is, in Chapter 2 we find co-operative banks are different to commercial institutions, following different business practises. That is, inclusion of both types of financial institutions in the same sample would mean that the key assumption of technological and production homogeneity under SFA could be violated, and therefore, compromise the cost efficiency scores estimated.

Indeed, it is also important to determine if efficiency of banks has an effect in their listed vs. non-listed status. To analyse this aim, Pasiouras et al., (2008) considered the association between the efficiency of Greek banks and their share price performance, for the years 2001-2005. In the first stage of the analysis two models were estimated assuming under constant and variables returns to scale. In their first specification, the

average Technical Efficiency (TE) reported is 0.931 (TE range, 0.88 - 0.96) and increased to 0.977 under variable returns to scale (TE range, 0.966 - 0.988), resulting in a scale efficiency of 0.953. In the second model, results indicated a positive and statistically significant relationship between annual changes in technical efficiency and stock returns, while changes in scale efficiency have had no impact on stock returns. The results indicate the necessity of determining if operating efficiency is reflected in better stock performance.

In a change to the aforementioned studies, Chatzoglou et al (2010) focused on the productivity of the Greek banking sector for the time period of 2004-2006. In this study, standard ratio measures of bank financial performance as output measures in a DEA model, in combination with efficiency ratios' analysis, were employed. They find that Greek bank efficiency remained relatively constant throughout the period under observation, while, on average, the largest asset sized banks performed better than medium and interestingly the small asset sized banks (the reported efficiencies range from 0.73 to 0.77 with an average of 0.74).

Recently, after the financial crisis, the Greek banking sector has seen Mergers and Acquisitions (M&A), for example see Chapter 2. Focusing on this area, Rezitis (2008) contributed to the efficiency literature of Greek banks and examined the effects of M&A on efficiency and TFP for the years 1993-2004. These results show that banks which engaged in merging experienced a decline in Technical Efficiency (TE) and TFP. Specifically, a decrease of 15%, on average was estimated for TE while TFP change decreased from 3.17% before the M&A to 0.63% period after. They also find that the decline of TFP could be attributed to increased inefficiency levels. Similar results were reported by Liargovas and Repousis (2011), when using a similar dataset (1996-2009) studied the impact of M&A on the performance of the Greek banking sector. Overall, bank M&A have had no impact in creating new wealth and by estimating different financial ratios operating performance presented no improvement, following M&A. It is therefore interesting to note that the need to re-examine the efficiency of the Greek banking sector under the prism of M&A's has become relevant due to the impact of the Greek crisis.

That is, in the first years of the debt crisis, banks did not take action and merger initiatives were avoided. However, due to the erosion of bank capital bases due to the imposition of the Private Sector Involvement (PSI), the subsequent necessity to restructure and strengthen the sector became imperative. This therefore, led to a significant number of mergers; resolution measures; and recapitalisation strategies (see Chapter 2, Section 2.5). Indeed, as of 2013, foreign banks started to reduce their presence in Greece. This was mainly due to problems faced by parent companies as a result of the international crisis, and the re-orientation of their strategies (Bank of Greece, 2014b)

4.4 Stochastic Frontier Analysis - The Methodology

4.4.1 Data Description

The sample in this study consists of an unbalanced panel of 16 commercial banks operating in Greece over 2005-2012. The initial period has been carefully chosen as it covers the adoption of the International Financial Reporting Standards (IFRS) in Greece in 2005[37]. All data for the COLS, MOLS and SFA estimation regarding the input/output variables were collected from Bankscope by Bureau Van Dijk database[38]. Additionally, spot checks were conducted with the financial statements of credit institutions to confirm the quality of the data and identify possible disparities. The data for the auxiliary variables introduced in the SFA models were collected from three databases, namely The World Bank, European Central Bank and Eurostat database.

[37] As it was discussed in Chapter 2, 2005 was a seminal year which saw many changes to Greek banks' reporting system. It is therefore difficult to justify using data before 2005 as the values were reported under a different accounting system and therefore lack continuity and stability. Similarly, the end period of the sample was also chosen as to prevent the use of data that may introduce noise into the sample. More specifically, in January 2012, the Bank of Greece conducted the capital needs assessment exercise with the objective of conservatively estimating the capital needs of all banks. The exercise was completed in March 2012 and became publically available in late December. Under the new EU/IMF-adjustment programme, the amount of €50 billion was deemed necessary, for the recapitalization of the Greek banking system - a process that was completed mid-2013. Given this artificial inflow of resources that may not necessarily be discern from the actual inputs used by management, extending the sample period beyond 2012 could have potentially distorted the quality of the data used.

[38] Bankscope offers a wide range of banking data for 32,000 banks worldwide. The information provided by the database, includes among others, comprehensive financial statements with a wide range of other banking intelligence including ratings, bank structures, news, AML documentation and banking research. The SNL database was also considered, but the quality of information provided compromised the sample size, as it offered information for a smaller number of banks, therefore reducing the number of observations used and therefore the interpretative strength of our analysis

Even though the sample size may be considered small, we believe it does not differ significantly from several studies that have already examined efficiency in banking (see for example Tanna et al., 2011 who examine 17 banking institutions, Pasiouras et al., 2008 who analyse 10 banks, Rezitis, 2006 and Apergis and Rezitis 2004, both examining six banks)[39]. Indeed, our sample covers approximately 80% of the Total Assets of the top five banks which constitute 180% of GDP, as of 2012. Therefore, the chosen period and banks selected offer a sample in which to review the industry, constituting a timely and warranted aim of the Thesis research interests.

The next step is to define the choice of the input and output mix. The banking efficiency literature has been dominated by an on-going debate relative to the proper definition of the inputs and outputs employed. However, there is little consensus on what constitutes the inputs and outputs of a bank (see for example Casu and Girardone, 2002, Sathye, 2003). Two of the most dominating modelling theories are the production approach, first proposed by Benston and Smith (1976) and the intermediation approach, first coined by Sealey and Lindley (1977). The former assumes that banking institutions produce loans and deposit services by using inputs including labour, capital, and the number and type of accounts. Since, such detailed transaction flow data not generally available, data on the stock of the number of deposit or loan accounts serviced is used instead (see Berger and Humphrey, 1997). On the other hand, the latter approach assumes a more complex view of the role of credit institutions. That is, Sealey and Lindley (1977), consider credit institutions as financial intermediaries that facilitate the transfer of money from surplus spending to deficit spending units. Hence, this intermediation is achieved through the collection of purchased funds and the use of labour and capital to transform economic values into loans. Berger and Humphrey (1997), commenting on the nature of including these modelling approaches, argue that neither approach is perfect when examining credit institutions, since neither is able to fully capture the dual role of banks a provider of transaction/document processing service and as a financial intermediator that transfers fund from savers to investors. However, they note that the intermediation approach is better when evaluating the

[39] Additional studies include Chu and Lim (1998) examining as few as six banks while in a UK study, Drake (2001) examines only nine banks.

efficiency of entire financial institutions while the production approach is superior when examining bank branch efficiency.

In the case of the current research study, the choice of inputs and outputs is driven by European and Greek legislation and prior studies and data availability. A rationale for following the intermediation approach for Greek banks concerns in the Greek banking legislation relating to pursuit of the business of credit institutions. That is, according to Article 2 of the Hellenic Law 3601/2007 (in accordance to Directive 2006/48/EC), a credit institution is an undertaking whose business is to receive deposits or other repayable funds from the public and to grant loans or other credit for its own account. Therefore, following recent studies, a variation of the traditional intermediation approach serves as the basis of our analysis (in parenthesis we include examples of studies that have used the same inputs/outputs)[40]. Namely, the following inputs/outputs mix is selected: P_1: Price of Total Customer Deposits (estimated, as Total Interest Expenses/Total customer deposits) (Kumbhakar and Tsionas, 2005 and Beccalli and Frantz, 2009), P_2: Price of Labour (estimated as Personnel Expenses/Fixed Assets) (Bos and Schmiedel, 2007 and Tsionas et al., 2015) and, P_3: Price of Capital (estimated as Other Operating Expenses/Fixed Assets) (Kumbhakar and Tsionas, 2008 and Tsionas et al., 2015), Y_1: Gross Loans (Fries and Taci, 2005; Bos and Schmiedel, 2007; Fukuyama and Matousek, 2011 and Akinci et al., 2013), Y_2: Other Earning Assets (Berger and Humphrey, 1997; Goddard et al., 2001; Pasiouras, 2008a and Hughes and Mester, 2009), Y_3: Loans and Advances to banks (Sturm and Williams, 2008 and Wheelock and Wilson, 2012 follow a similar decomposition of loans into different categories) and Y_4: Non-interest income (net fee and commission and other operating income) (Vander Vennet, 2002 and Kenjegalieva et al., 2009) as output quantities (detailed discussion of the base mode is presented in the subsequent section)[41]. Total costs were defined operating costs, interest paid on deposits and labour expenses.

In addition to the choice of inputs and outputs, when analysing the efficiency of banking systems, it is vital to incorporate a variable that takes into account the risk profile, loan quality and hence the risk management control behaviour of banks. For example,

[40] Table 9.2 in Appendix B summarises the various input/output specifications.
[41] Hunter and Timme (1995) and Rogers (1998) include total non-interest income as a proxy for other bank output.

Altunbas et al., (2000) and Drake and Hall (2003) find that failure to adequately account for risk and problem loans respectively, can have a significant impact on relative efficiency scores. Similarly, Yildirim and Philippatos (2007) stress that equity capital should be included in efficiency model specifications for a variety of reasons. They propose that in order to absorb financial shocks, risk-averse managers might hold higher levels of equity than an optimal cost minimizing level. Therefore, not accounting for managerial risk preference might suggest that an otherwise efficient credit institution does not operate close or on the efficiency frontier. Thus, inclusion of equity controls for managerial risk preferences by solving maximization and minimization problems. Furthermore, given the reality of high insolvency risks due to significant non-performing loans, and the effect that a high level of equity has to the cost and profit function of a bank through the impact on defaults risk premium that a bank pays for borrowing (via lower default risk implications), inclusion of equity becomes important. In addition to providing a cushion against losses, financial capital can also be used to fund loans as a substitute for deposits or other borrowed funds, affecting both costs and profits. That is, financing assets through equity carries an increased cost, therefore omitting the level of equity will lead to biased efficiency estimates in favour of bank with reliance on equity (see, for example, Yildirim and Philippatos, 2007).

Furthermore, Berger and Mester (1997) also note that the inclusion of equity in any analysis may account for the scale bias arising from differences in bank dependence on borrowed funds since large banks usually depend more on borrowed funds. Similarly, Akhigbe and McNulty (2003), trying to control, in a very rough fashion for the potential increased cost of funds due to financial risk, include equity capital (as defined at the bank level). Finally, Mester (1996) concludes that financial capital should be accounted for in the cost function and at the "level" rather than the price of financial capital, since there is good reason to believe that cost-minimization does not fully explain a bank's capital level (i.e., regulations set minimum capital-to-asset ratios and bank managers may be risk-averse). These arguments are also consistent with Yildirim and Philippatos (2007), Koutsomanoli-Filippaki and Mamatzakis (2010), who when discussing risk preferences, note that if financial capital is ignored, the efficiency of banks that may be more risk averse than others and may hold a higher level of financial capital that could be mismeasured, even though they are behaving optimally given their risk preferences.

Furthermore, they argue that equity also accounts for different risk preferences of banks and controls for bank insolvency risk.

However, with respect to equity inclusion in the cost function as a risk control variable, opposing views have been put forward by both Laeven and Majnoni (2003) and Drake et al., (2006). The former they propose that the incorporation of risk into efficiency analysis should be taken into account through the inclusion of LLP. That is, to make the distinction between economic capital and LLP and by arguing that the former should be tailored in such a way as to cope with unexpected losses while loss loan reserves should act as a buffer for the expected component of the loss distribution. Therefore, as Laeven and Majnoni (2003) argue, all loan loss provisions required to build the necessary loan loss reserves should be treated as a cost that will be faced with certainty over time but that is uncertain as to when it will materialise. On the other hand, the resources required to build up capital, which serves as a buffer against truly unexpected events, should not be dealt with as a cost but only as post-tax earnings. Thus, accommodating these two strands of literature, our research includes both LLP and equity capital in the specifications. More specifically, Models 2 and 3 (further analysed in the coming sections) incorporate to the translog function the aforementioned variables. Model 2 incorporates the natural logarithm of Common Equity (Akinci et al., 2013 use equity as a fixed input) and its second order term, and model 3 includes this in a similar manner LLP.

It is interesting to note that in our modelling methodology, a commonly used variable, Off-Balance Sheet (OBS) items was also deemed necessary. The rationale for its inclusion is that Greek banks have taken steps forward in expanding their product/service portfolio to include activities such as insurance, brokerage and asset management and at the same time increased their OBS operations (Pasiouras, 2008). This trend has been acknowledged by prior research and OBS activity has been incorporated on previous efficiency studies (see for example, Altunbaş and Chakravarty, 2001; Altunbaş et al., 2001; Bos and Kolari, 2005; Isik and Hassan, 2003a; Isik and Hassan, 2003b; Pasiouras, 2008; Rao, 2005). The importance of including OBS activities in an efficiency study has been acknowledged by researchers in past studies (Clark and Siems, 2002; Lieu et al, 2005) since exclusion of this item can create downward bias in efficiency estimates. That is, when examining the

technical efficiency of Greek commercial banks Pasiouras (2008a) examined the effect of OBS activity on efficiency via the inclusion of the OBS items as an output. In the same study, the impact of credit risk in efficiency was taken into account with including LLP as an additional input in the estimation of the frontier. In a similar way, Sturm and Williams (2008) analysed foreign banks in Australia using a comparable model specification. Finally, Lozano-Vivas and Pasiouras (2013) offer similar results in cross-country studies of 84 countries. Finding that, following similar model specifications OBS items were also included in a variation of the baseline model (for more details please see models 4, 5 and 6 presented in Table 9-2 in Appendix B) of the current study and failed to pass the skewness of OLS residuals test (all three models exhibited positive but insignificant residuals) and were not therefore estimated under the SFA framework for consistency purposes.

Finally, taking into account the severity of the debt crisis; the impact of the adverse economic conditions in Greece; we control the inclusion of a vector of auxiliary variables at the macroeconomic level. Specifically, these variables are[42]:

- GDP per capita growth (%) as a proxy of the overall level of economic development and wealth. An increase in the per capita GDP signals growth in the economy and tends to translate as an increase in productivity. The data were collected from the World Bank.
- Concentration Ratio of assets for the top five banking institutions to control for the effects of industry concentration on costs. The data were collected from the European Central Bank.
- Domestic credit to private sector (% of GDP); it is utilised as a measure of financial deepening and it refers to financial resources provided to the private sector by financial firms, such as via loans, purchases of non-equity securities and trade and other accounts receivable, that establish a claim for repayment. Levine (2005) suggests a high ratio indicates a strengthening of the corporate governance of banks. Indeed, as Goddard et al., (2014) note "incremental credit provision requires further screening, raising monitoring costs for banks in a

[42] Prior literature has also utilized similar variables (i.e. Goddard et al 2014; Liadaki and Gaganis 2010; Pasiouras et al., 2008; Kasman and Yildirim, 2006).

manner that could reduce cost efficiency (page 141)". The data were collected from the World Bank

- Finally, to capture the crisis, Gross Domestic Product growth is included, representing business cycle effects; inflation rate and unemployment rate[43]. The data for GDP growth and inflation were collected from the World Bank. Data on the unemployment rate were collected from Eurostat.

Table 4.1. Summary Statistics - Inputs/Outputs Mix

	Observations	Mean	Standard Deviation	Minimum	Maximum
TC	116	1129.09	1457.92	17.4	6017.91
X_1	116	672.48	952.79	3.2	4604.80
X_2	116	260.36	332.43	4.8	1395.13
X_3	116	196.23	232.53	7.96	879.54
Y_1	116	15904.1	18882.86	51.1	70491.8
Y_2	116	5532.48	1549.64	100	11308.79
Y_3	116	1355.98	1456.50	27.45	6031.41
Y_4	116	276.17	191.17	100	1000.09
Equity	116	3741.44	1889.74	100	12641.79
LLP	116	539.67	1562.17	1.46	12967.12
P_1	116	.053	.04	.01	.36
P_2	116	1.17	.96	.31	9.57
P_3	116	1.05	.83	.25	7.07

All values are expressed in millions of Euros (€)
Where, X_1: Total Interest Expenses, X_2: Personnel Expenses, X_3: Other Operating Expenses, $TC=X_1+X_2+X_3$, P_1: Price of Total Customer Deposits (estimated as Total Interest Expenses/Total customer deposits), P_2: Price of Labour (estimated as Personnel Expenses/Fixed Assets) and, P_3: Price of Capital (estimated as Other Operating Expenses/Fixed Assets), Y_1: Gross Loans, Y_2: Other Earning Assets, Y_3: Loans and Advances to banks and Y_4: Non-interest income. Equity: Total Common Equity and LLP: Loan Loss Provisions.

Table 4.1 presents the summary statistics of the translog terms for the sample, where we have 116 observations overall and include the following banks (16 in total): Agricultural Bank of Greece, Alpha Bank AE, Attica Bank SA-Bank of Attica SA, Emporiki Bank of Greece SA, Eurobank Ergasias SA, FBB First Business Bank SA, General Bank of Greece SA, Marfin Egnatia Bank SA, Millennium Bank SA, National Bank of Greece SA, PRObank SA-PRObank Bank Societe Anonyme, Panellinia Bank

[43] Provopoulos (2013) stresses the significance of changes in GDP as it shrank the denominator in the debt-to-GDP ratio, thus resulting to the debt dynamics becoming more severe, and the crisis to obtain self-reinforcing characteristics.

Piraeus Bank SA, Proton Bank S.A., T Bank S.A, TT Hellenic Postbank S.A. Specifically, National Bank of Greece SA is the largest institution in our sample with Average Total Assets of €87602.41 million. The corresponding small asset group bank is Panellinia Bank, with a respective value of €686.7518 million. Furthermore, Eurobank Ergasias SA 2008 reports the highest total costs (€6017.916 million), with input values of X_1: €4604.802 million, X_2: €747.1636 million and X_3: €665.9502 million. The respective minimum is reported by Proton Bank S.A. in 2005, with inputs of X_1: €3.2 million, X_2: €5 million and X_3: €9.2 million. Interestingly, during the sample period, National Bank of Greece SA reports the highest amount of gross loans (Y_1) in 2010 and as expected, the maximum provisions for bad loans for the equivalent year (€1264.908 millions). The same trend is also apparent for LLP, where National Bank of Greece SA reports the maximum value for our sample in 2011 (€12967.12 million) and at the same time also registers the highest gross loans (€67854.05), for the same year.

4.4.2 Stochastic Cost Function Specifications

In order to estimate efficiency score indicators, the SFA method discussed in Chapter 3 is employed. More specifically, bank specific efficiency estimates are estimated via the use of the traditional stochastic cost frontier[44]. Building on equation (3.9), and in line with Berger and Mester (2003), the cost minimization concept assumes that banks minimize variables costs subject to exogenously driven input prices, quantities of outputs/netputs, macroeconomic conditions, their own managerial inefficiency and a random error[45]. Thus, the cost minimization behaviour can be modelled via a cost

[44] The cost minimization behaviour of banks and hence the adoption of the stochastic cost function, is a popular assumption in empirical research. For example, as discussed in greater detail in Section 3.4.4b, the same model specification were also applied in Molyneux and Williams (2013), Goddard et al., (2014) and Lensink and Meesters (2014).

[45] The transformation function expressed in equation (4.1) describes the relationship between the variable costs, output and the exogenous business environment. By assuming perfect competition, we effectively assume that all the production happens on the frontier and that all the producers are fully efficient. However, in reality, the perfect competition assumption does not always hold. In the context of a banking system, a competitive monopoly is a much better proposition than perfect competition; which amongst others assumes no barriers to entry or exit (which can never happen in banking due to stringent regulation). It is worth noting that the assumption of true, unconstrained cost minimisation may also be open to criticism. Due to the regulatory framework (i.e. the Basel capital requirements), banks are forced to hold more cash and equity than they optimally would wish to hold. In other words, given the heavily regulated nature of the banking business environment, banks may be better described as following relative rather than absolute true cost minimisation behaviour, subject to various regulatory constraints.

function that relates variable costs to exogenous factors, given input prices, (assuming banks choose an input mix to minimise costs). Hence, the general estimated cost function can be expressed as in equation (4.1),

$$TC_{it} = C(y_{it}, w_{it}; \beta) + u_{it} + v_{it}. \quad (4.1)$$

Where TC_{it} is a measure of the total costs faced by bank *i* at time *t*, and $C(y_{it}, w_{it}; \beta)$ represents the cost frontier and u_{it}, v_{it} represent the bank specific inefficiency and noise respectively. The model postulated is estimating efficiency relative to the sample global best practice frontier implicitly assuming a common banking technology. Through the application of either regression techniques or Maximum Likelihood Estimation, cost efficiency is estimated as the proximity of a bank's cost to the best practice bank's cost in producing the same output bundle under the same production setting. Estimation of equation (4.1) and follows the SFA panel data models presented in Chapter 3, namely the Battese and Coelli (1995) and Greene (2005a, 2005b) specifications, thus allowing us to take into account the severity of the economic crisis in an one-step estimation process.

Further developing the econometric model specifications and following the discussion in Chapter 3, the functional form of preference is the translog function which allows us to accommodate multiple inputs/outputs (see, for example, Fiorentino et al, 2006; Clark et al., 2007; Lozano-Vivas, 2009; Fiordelisi et al., 2011; Molyneux and Williams, 2013; Akinci et al., 2013; Goddard et al., 2014). In the case of a multi-product cost frontier, the translog takes the following form, as presented in equation (4.2),

In relation to Greece, we favour a cost minimization behaviour given the contracting economic environment and the heavy restructuring process that the Greek banking system is undergoing.

$$lnTC_{it} = \beta_0 + \sum_{k=1}^{n} \alpha_k lny_{k,it} + \sum_{j=1}^{m} \beta_{j,it} lnp_{j,it} + \frac{1}{2}\left[\sum_{k=1}^{n}\sum_{j=1}^{n} \eta_{kj,it} lny_{k,it} lny_{j,it} + \sum_{k=1}^{m}\sum_{j=1}^{m} \theta_{kj,it} lnp_{k,it} lnp_{j,it}\right] + \sum_{k=1}^{n}\sum_{j=1}^{m} \zeta_{kj,it} lny_{k,it} lnp_{j,it} + v_{it} + u_{it}. \quad (4.2)$$

Where TC_{it} is a measure of total costs, $y_{i,it}$ (i = 1....4) are the output quantities and $p_{j,it}$ (i = 1....3) are the input prices. Linear homogeneity in factor prices is imposed by the following restrictions, equation (4.3),

$$\sum_{j=1}^{3} \beta_j = 1 \; and \; \sum_{j=1}^{3} \theta_j = 0 \; and \; \sum_{j=1}^{3} \zeta_j = 0 \quad (4.3)$$

Whereas, symmetry implies that: $\eta_{\iota j} = \eta_{j\iota}$ and $\theta_{\iota j} = \theta_{j\iota}$.

Based on the aforementioned analysis, following (Kumbhakar and Lozano-Vivas 2004 and Beccalli et al., 2006;) we impose price homogeneity restrictions by normalising the translog and we divide the response variable and the right hand side price covariates by p_3, the baseline estimated translog function (TVM1) is defined as follows:

$$
\begin{aligned}
ln(TC_{it}^{*}) = {} & \beta_0 + \alpha_1 lny_{1,it} + \alpha_2 lny_{2,it} + \alpha_3 lny_{3,it} + \alpha_4 lny_{4,it} \\
& + \alpha_{11}\frac{1}{2}\left(lny_{1,it}\right)^2 + \alpha_{22}\frac{1}{2}\left(lny_{2,it}\right)^2 \\
& + \alpha_{33}\frac{1}{2}\left(lny_{3,it}\right)^2 + \alpha_{44}\frac{1}{2}\left(lny_{4,it}\right)^2 \\
& + \alpha_{12} lny_{1,it} lny_{2,it} + \alpha_{13} lny_{1,it} lny_{3,it} \\
& + \alpha_{14} lny_{1,it} lny_{4,it} + \alpha_{23} lny_{2,it} lny_{3,it} \\
& + \alpha_{24} lny_{2,it} lny_{4,it} + \alpha_{34} lny_{3,it} lny_{4,it} + \beta_1 lnp_{1,it}^{*} \\
& + \beta_2 lnp_{2,it}^{*} + \beta_{11}\frac{1}{2}\left(p_{1,it}^{*}\right)^2 + \beta_{22}\frac{1}{2}\left(p_{2,it}^{*}\right)^2 \\
& + \beta_{12} lnp_{1,it}^{*} lnp_{2,it}^{*} + \zeta_{11} lny_{1,it} lnp_{1,it}^{*} \\
& + \zeta_{12} lny_{1,it} lnp_{2,it}^{*} + \zeta_{21} lny_{2,it} lnp_{1,it}^{*} \\
& + \zeta_{22} lny_{2,it} lnp_{2,it}^{*} + \zeta_{31} lny_{3,it} lnp_{1,it}^{*} \\
& + \zeta_{32} lny_{3,it} lnp_{2,it}^{*} + \zeta_{41} lny_{4,it} lnp_{1,it}^{*} \\
& + \zeta_{41} lny_{4,it} lnp_{1,it}^{*} + \zeta_{43} lny_{4,it} lnp_{3,it}^{*} + v_{it} + u_{it}.
\end{aligned}
\tag{4.4}
$$

Where $TC_{it}^{*} = {}^{TC_{it}}/_{p_{3,it}}$, $p_{1,it}^{*} = {}^{p_{1,it}}/_{p_{3,it}}$ and $p_{2it}^{*} = {}^{p_{2,it}}/_{p_{3,it}}$.

The models, which include netputs, Equity and LLP (TVM2 and TVM3 respectively), are defined as in equation (4.5):

$$
\begin{aligned}
ln(TC_{it}^{*}) = {} & \beta_0 + \alpha_1 lny_{1,it} + \alpha_2 lny_{2,it} + \alpha_3 lny_{3,it} + \alpha_4 lny_{4,it} \\
& + \alpha_{11}\frac{1}{2}\left(lny_{1,it}\right)^2 + \alpha_{22}\frac{1}{2}\left(lny_{2,it}\right)^2 \\
& + \alpha_{33}\frac{1}{2}\left(lny_{3,it}\right)^2 + \alpha_{44}\frac{1}{2}\left(lny_{4,it}\right)^2 \\
& + \alpha_{12} lny_{1,it} lny_{2,it} + \alpha_{13} lny_{1,it} lny_{3,it} \\
& + \alpha_{14} lny_{1,it} lny_{4,it} + \alpha_{23} lny_{2,it} lny_{3,it} \\
& + \alpha_{24} lny_{2,it} lny_{4,it} + \alpha_{34} lny_{3,it} lny_{4,it} + \beta_1 lnp_{1,it}^{*} \\
& + \beta_2 lnp_{2,it}^{*} + \beta_{11}\frac{1}{2}\left(p_{1,it}^{*}\right)^2 + \beta_{22}\frac{1}{2}\left(p_{2,it}^{*}\right)^2 \\
& + \beta_{12} lnp_{1,it}^{*} lnp_{2,it}^{*} + \zeta_{11} lny_{1,it} lnp_{1,it}^{*} \\
& + \zeta_{12} lny_{1,it} lnp_{2,it}^{*} + \zeta_{21} lny_{2,it} lnp_{1,it}^{*} \\
& + \zeta_{22} lny_{2,it} lnp_{2,it}^{*} + \zeta_{31} lny_{3,it} lnp_{1,it}^{*} \\
& + \zeta_{32} lny_{3,it} lnp_{2,it}^{*} + \zeta_{41} lny_{4,it} lnp_{1,it}^{*} \\
& + \zeta_{41} lny_{4,it} lnp_{1,it}^{*} + \zeta_{43} lny_{4,it} lnp_{3,it}^{*} + \kappa_1 lnR_{it} \\
& + \kappa_{11}\frac{1}{2}(lnR_{it})^2 + v_{it} + u_{it}.
\end{aligned}
\tag{4.5}
$$

Where $\ln R_{i,t}$ represents the risk variable of choice, common equity and Loan Loss Provisions for models 2 and 3 respectively[46].

In addition, Stochastic Input Distance Functions (IDF) were also estimated with the same inputs/outputs mix, however pre estimation testing of the OLS skewness of the residuals indicated that input oriented technical efficiency were unable to be expunged. That is, the residuals indicated a positive but statistically insignificant skewness and the estimated cost functions under Models 1, 2 and 3 all indicate a positive and statistically significant skewness; indicating the presence of the one sided error term. Furthermore, in all cases, the Coelli (1995) M3T statistic supports rejection of the null hypothesis of no skewness in the OLS residuals at the 5% and 10% levels (Table 4.2).

[46] Table 9-2 in Appendix B is presenting the descriptive statistics of the estimated cost functions.

Table 4.2. M3T Statistic - Ordinary Least Squares Residuals

Model	M3T
TVM1	1.85*
TVM2	1.97**
TVM3	1.72*

**Statistically significant at the 10% level*
*** Statistically significant at the 5% level*
**** Statistically significant at the 1% level*
Critical values: 1.96 and 1.645 at the 5% and 10% respectively

Under all model specifications, the random error component is assumed to be i.i.d. following a normal distribution, $N(0, \sigma_v^2)$ and is independent of the inefficiency term u_{it}. That is, the cost inefficiency effect, u_{it} follows a Normal distribution truncated at mean, $N(m_{it}, \sigma_u^2)$. Furthermore, following equation (3.34), the linear function of the auxiliary variables z can be further expressed as in equation (4.6)[47]:

$$m_{i,t} = \delta_0 + \delta_1 GDPgr + \delta_2 UN + \delta_3 Inf + \delta_4 CapGr + \delta_5 Credit + \delta_6 CR5 + W_{i,t}. \quad (4.6)$$

Where $GDPgr$ represents the annual growth of Gross Domestic Product (% change), UN represents the annual unemployment rate (% change), Inf represents annual inflation rate (% change) in Greece, $CapGr$ represents the GDP per capita growth (% change), $Credit$ represents the Domestic credit to private sector (% of GDP), $CR5$ represents the top five Concentration Ratio and W_{it} represents the error term. Inclusion of the constant term, δ_0 in equation (4.6) is important as excluding it may result in biased $\hat{\delta}$ parameters associated with the auxiliary variables and lead to a restricted shape of the inefficiency distribution (see Battese and Coelli 1995, p 327). Thus, equation (4.6) is represents an inclusive model and to the best of our knowledge, in the banking efficiency literature prior research has mainly used a similar set of macroeconomic indicators. However, there is little discussion as to the appropriate choice of the auxiliary variables and/or as to which auxiliary variables could be seen as the "optimal

[47] For notation purposes, TVM1 will be noted as TVM1-3Z when estimated using only 3 auxiliary variables. A similar notation is followed for TVM2 and TVM3. Similarly, TFE1, TFE2 and TFE3 represent the True Fixed Effects models estimated without a netput and with equity and LLP as netputs respectively.

set". In this respect, under the TVM model specification a stepwise approach was followed starting with the estimation of the cost function including 3 auxiliary variables, thus introducing each additional macro indicator into the inefficiency distribution equation, while controlling for any significant changes into the estimated efficiency scores. Under the TFE models, only the specification including 6 macro variables was estimated as convergence failed in all other cases. For more details on the econometric specification of the auxiliary variable's functional form defining the truncation point of the distribution, see Table 9.3 in Appendix B.

Table 4.3. Descriptive Statistics of Auxiliary Variables

	Mean	Standard Deviation	Minimum	Maximum
GDP Growth	-.876	4.437	-7.105	5.507
Unemployment	11.65	4.867	7.8	24.5
Inflation	3.13	1.12	1.21	4.71
CapGr	-1.49	4.518	-8.616	5.482
Credit	97.30	16.070	77.147	122.334
CR5	69.51	3.645	65.6	79.47

GDP Growth: Annual change of Gross Domestic Product (%), Unemployment: Unemployment rate, Inflation: Annual inflation rate (%), CapGr: GDP per capita growth (%), Credit: Domestic credit to private sector, CR5: Concentration Ratio of assets for the top five banking institutions.
Sources: World Bank, the European Central Bank and Eurostat database

A closer examination of the macroeconomic and market specific indicators reveal some interesting findings. For example, Greece's macroeconomic deterioration is reflected in the GDP growth trend, starting from a maximum of 5.5% in 2006 and reaching a minimum value of -7.10 in 2011 (turning negative for the first time in 2008). This reflects a deeper structural problems in the economy, whereby unemployment rate follows a downward trend for the year 2005-2008, reaching a minimum of 7.8% in 2008, only to increase after the global financial crisis (an 2% increase) and even more so after the manifestation of the debt crisis (an unemployment rate of 12.7% for 2010, 17.9 for 2011 and 24.5 for 2012). Surprisingly, the credit expansion continued, despite the worsening of the economic environment. That is reflected in the progression of domestic credit to the private sector. For example, in 2007 it averaged at 77.14% of the Greek GDP reaching a maximum of 93.82% in 2008. After a small reduction, of

approximately 2% for the coming year the financial deepening was maintained, reaching a maximum of 122.33% in 2011.

Given the specifications presented above, the Stochastic Frontier was estimated in two sequential steps, first the cost function and equation (4.6) were estimated simultaneously via Maximum Likelihood Estimation and estimates of the model parameters were obtained by maximizing the log-likelihood *ℓ(θ)*, where $\theta = (\alpha, \beta', \sigma_v^2, \sigma_u^2)'$, α representing the constant term, β a vector of the parameters to be estimated and σ_v^2 and σ_u^2 the variance of the error term and inefficiency term respectively. In the second step, point estimates of inefficiency were obtained via the Battese and Coelli, (1988) technique, and observation specific *cost efficiency* estimates using the mean of the distribution of $E[\exp(-u_i|e_i]$, $\varepsilon_{it} = u_{it} + v_{it}$. The final estimates have a value between 0 and 1 (where 1 indicates a fully efficient firm)[48].

The estimated translog coefficients for the TVM models are statistically significant for the most part. Under the TFE specifications however, most of the estimated parameters turn insignificant – however, the main focus of the analysis concerns the decomposition of the error term into the inefficiency component and the random noise component. The γ, λ, σ_u and σ_v components are all statistically significant at the 5% level, with the exception of the TFE3 specifications[49]. However, we view these results with scepticism as Coelli et al., (2005) raise concerns regarding the validity of both the standard t and $F-tests$ for hypothesis testing concerning translog parameters as the two tests have poor finite sample properties because of the non-normality of the composed error term. The focus of our estimation is to predict the cost efficiency performance index for Greek banks, and not to interpret the estimated parameters as a cost driver for realised total costs. We are therefore more interested in controlling for the presence of the one-way error component in our specifications.

Taking advantage of the MLE method an alternative is the z statistic, which can be estimated as in equation (4.8),

[48] For a more detailed discussion on the cost efficiency estimators, see Section 3.4.5b.
[49] For brevity, the tables with the estimated coefficients are presented in Tables 9.5 to 9.8 in Appendix B.

$$z = \frac{\tilde{\lambda}}{se(\tilde{\lambda})} \sim N(0,1). \quad (4.7)$$

Where $\tilde{\lambda}$ is the Maximum Likelihood estimated parameter of λ and $se(\tilde{\lambda})$ is the standard error. However, Coelli (1995) provides Monte Carlo simulation evidence that the test tends to incorrectly reject the hull hypothesis, underlining poor small sample bias properties of the statistic. That is, for the above stated reasons and following the discussion presented in Section 3.4.6.2, a generalized Likelihood Ratio test was performed in all the estimated models. In all cases, the following null hypothesis of no inefficiency effects was tested:

$$H_0: \gamma = \delta_0 = \cdots = \delta_6 = 0. \quad (4.8)$$

Tables 4.4 to 4.7 present the results of the Likelihood Ratio test for the estimated models. Under all models the LR test indicates a strong rejection of the null hypotheses concerning the absence of the one-sided inefficiency effects. Therefore, inclusion of the inefficiency effects via the mean of the inefficiency distribution is supported by the sampled data.

Table 4.4. Generalized Likelihood Ratio Test, Time Varying Model 1

Model	Log-Likelihood	Test statistic
TVM1-3Z	59.86	35.25***
TVM1-4Z	18.88	61.04***
TVM1-5Z	18.83	60.93***
TVM1-6Z	19.24	61.77***

The critical value at the 5% significant level is obtained from the Table 1 from Kodde and Palm (1986).
TVM1-3Z, critical value at the 5%, 10.371
TVM1-4Z, critical value at the 5%, 11.911
TVM1-5Z, critical value at the 5%, 13.401
TVM1-6Z, critical value at the 5%, 14.853

Table 4.5. Generalized Likelihood Ratio Test, Time Varying Model 2

Model	Log-Likelihood	Test statistic
TVM2-3Z	77.90	36.77***
TVM2-4Z	21.66	64.52***
TVM2-5Z	21.40	64.00***
TVM2-6Z	22.23	65.65***

The critical value at the 5% significant level is obtained from the Table 1 from Kodde and Palm (1986).
TVM1-3Z, critical value at the 5%, 10.371
TVM1-4Z, critical value at the 5%, 11.911
TVM1-5Z, critical value at the 5%, 13.401
TVM1-6Z, critical value at the 5%, 14.853

Table 4.6. Generalized Likelihood Ratio Test, Time Varying Model 3

Model	Log-Likelihood	Test statistic
TVM3-3Z	65.04	34.56***
TVM3-4Z	18.83	59.21***
TVM3-5Z	18.90	59.35***
TVM3-6Z	19.57	60.71***

The critical value at the 5% significant level is obtained from the Table 1 from Kodde and Palm (1986).
TVM1-3Z, critical value at the 5%, 10.371
TVM1-4Z, critical value at the 5%, 11.911
TVM1-5Z, critical value at the 5%, 13.401
TVM1-6Z, critical value at the 5%, 14.853

Table 4.7. Generalized Likelihood Ratio Test, True Fixed Effects

Model	Log-Likelihood	Test statistic
TFE1	151.78614	326.851***
TFE2	152.1755	325.541***
TFE3	146.7125	314.976***

The critical value at the 5% significant level is obtained from the Table 1 from Kodde and Palm (1986).
TVM1-3Z, critical value at the 5%, 10.371
TVM1-4Z, critical value at the 5%, 11.911
TVM1-5Z, critical value at the 5%, 13.401
TVM1-6Z, critical value at the 5%, 14.853

To recap, the above results have found that all our estimated cost functions satisfy both pre-estimation tests (i.e., skewness of the OLS residuals and M3T statistic) but even more importantly the Likelihood Ratio test of the presence of the one-sided error component. In all cases, the null hypotheses of an insignificant inefficiency component was strongly rejected, thus indicating that inclusion of the aforementioned macroeconomic variables was supported. The latter confirms our assumption that the inclusion of economic conditions in Greece, in a one-step estimation process, was correctly specified. We now turn to the next step in our analysis, which is to determine the preferred model.

4.5 Discussion of Results

It is a well-established fact within the banking efficiency literature efficiency scores depend heavily on, and are sensitive, to the choice of input/output mix. For example, Tortosa-Ausina (2002) found that application of the intermediation approach generally gives lower overall efficiency scores than the value added approach. However, within-model variation is limited, since once the frontier estimate is adopted and the input/output mix is considered, efficiency estimates are stable. Indeed, as Berger and Humphrey (1997) have shown, various efficiency methods do not necessarily yield consistent results, therefore, Bauer et al., (1998) proposed a set of consistency criteria that efficiency estimates should meet, in order to be most useful for regulatory authorities, academics and practitioners. Accordingly, it is not necessary to have a consensus on which approach is better on measuring efficiency but instead frontier results should meet the following criteria in order to accommodate useful information, these include:

- Comparisons of efficiency distributions: The efficiency scores generated by means of frontier estimation should have comparable means, standard deviations and other distributional characteristics.
- Rank order correlations of the efficiency distributions: The different approaches should rank the institutions in an approximately similar manner.
- Identification of 'best/worst practice' banks: All the methods should be able to identify the same banks as the ones operating close to the optimal frontier (i.e.,

best practice banks), or the banks operating at low efficiency levels, with respect to their counterpart (i.e., worst practice banks)[50].

- Stability of measured efficiency over time: The estimated efficiency scores should exhibit reasonable inter-temporal stability. More specifically, they should identify that the same banks are cost efficient and cost inefficient in respective years.
- Consistency with market competitive conditions: The efficiency scores should be reasonably related to the competitive market conditions in the banks sector, and, finally;
- Consistency with non-frontier performance measures: That is, efficiency estimates should be consistent with standard non-frontier performance indicators.

The next section discusses the different cost efficiency estimates generated via the Battese and Coelli (1995) and Greene (2005a, 2005b) model specifications under the prism of the Bauer et al (1998) conditions. These conditions were employed as a filtering mechanism that allow an evaluation of the behaviour of the various estimates and provided guidance as to which set of results is more appropriate to be utilised in LLP second stage analysis.

It should be noted at this stage that the following constitutes a coherent and robust modelling strategy testing procedure. Therefore, we are only interested in determining the fit of the models and not, as yet, concerned with a detailed interpretation of the results. The latter, of course, should only be considered if the models and tests now presented have been accepted following the Bauer et al., (1998) consistency conditions.

[50] Even though the terms best/worst practice do not reflect econometric rigour, both expressions have been used in past research to describe the performance of banks relative to their counterparts (for example see Bauer et al., 1998 and Chortareas et al., 2009).

4.5.1 Condition 1 - Comparisons of Efficiency Distributions

Tables 4.8 to 4.11 report a number of distributional characteristics of the efficiency estimates for the various cost functions estimated using both the TVM and TFE[51]. As presented in Tables 4.8 to 4.10 the models estimated under the assumptions of TVM produce similar mean efficiencies, ranging between 0.75-0.82. That is, the cost functions which include equity (TVM2) as the risk produces the lowest mean score (0.75), whereas TVM1 (where no risk variable is included) and model TVM3 (which includes LLP) have almost the same mean score (0.82 and 0.81 respectively). The mean efficiency scores for the three TVM models including 6 auxiliary variables (TVM-6Z) is 0.793 with a mean standard deviation of 0.18. The less inclusive models also produce similar results. That is, TVM-3Z, on average produces a mean efficiency score equal to 0.81, with a mean standard deviation equal to 0.15, TVM-4Z produces a mean efficiency equal to 0.80 and a mean standard deviation equal to 0.18, and finally, TVM-5Z report an average efficiency score of 0.81 with a standard deviation of 0.18. Further, the skewness test for normality is rejected at the 1% level for all the values reported, whereas, the kurtosis test for normality failed to reject the null hypothesis for all the values, except in two cases (TVM2-6Z (p-value=0.04) and TVM3-6Z (p-value=0.08)).

[51] Similar results were obtained for the cost efficiencies estimated using COLS/MOLS but for brevity only the SFA results are analysed in this section.

Table 4.8. Comparisons of Efficiency Distributions: Time Varying Model 1

	TVM1			
	3Z	*4Z*	*5Z*	*6Z*
Mean	0.81	0.81	0.82	0.82
Median	0.87	0.92	0.91	0.93
Minimum	0.35	0.32	0.34	0.33
Maximum	0.97	0.97	0.97	0.97
Standard Deviation	0.15	0.18	0.18	0.19
Skewness	-1.09	-1.12	-1.03	-0.98
Kurtosis	3.22	2.83	2.60	2.46
Observations	116	116	116	116

Where TVM1: Time Varying Model 1, without a risk metric.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.9. Comparisons of Efficiency Distributions: Time Varying Model 2

	TVM2			
	3Z	*4Z*	*5Z*	*6Z*
Mean	0.81	0.80	0.81	0.75
Median	0.87	0.90	0.91	0.82
Minimum	0.34	0.31	0.34	0.31
Maximum	0.97	0.97	0.98	0.98
Standard Deviation	0.15	0.18	0.18	0.18
Skewness	-1.15	-1.03	-1.01	-0.70
Kurtosis	3.41	2.70	2.56	2.31
Observations	116	116	116	116

Where TVM2: Time Varying Model 2, with Total Equity as netput.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.10. Comparisons of Efficiency Distributions: Time Varying Model 3

	TVM3			
	3Z	*4Z*	*5Z*	*6Z*
Mean	0.81	0.81	0.81	0.81
Median	0.87	0.91	0.92	0.94
Minimum	0.34	0.32	0.34	0.33
Maximum	0.97	0.97	0.98	0.97
Standard Deviation	0.15	0.18	0.19	0.19
Skewness	-1.05	-1.09	-0.98	-0.95
Kurtosis	3.11	2.78	2.49	2.38
Observations	116	116	116	116

Where TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

In Table 4.11, the key distributional characteristic of the TFE models are presented. The mean efficiency from the three SFA parametric models averaged 0.876 with a mean standard deviation of 0.11. The null of normal skewness was rejected in all cases, indicating consistency across the TFE cost efficiency distributions. It is also worth noting that as expected, despite the same distributional assumption for the inefficiency terms, all three TFE models yielded on average higher cost efficiencies than the respective TVM models (Kumbhakar et al., 2014 present similar findings). The reason for the higher efficiencies observed under the TFE models can be explained by its methodological specification. As discussed in Section 3.4.4, the TFE specifications take into account any firm-specific heterogeneities present in the data (a_i, equation (3.45)). Thus, by construction the TFE model may over compensate for the effect of any time-invariant heterogeneities since the firm specific intercept will inevitably capture time-invariant inefficiency effects present in the data; thus considering a bank-specific, time-invariant effect as persistent inefficiency. That is, even though the model can move some of the time-invariant heterogeneities out of the inefficiency component, there is no way that these effects can be distinguished from any time-invariant inefficiency. Therefore, if there is a time-persistent inefficiency, it will be absorbed by the constant rather than the one sided error term component where it truly belongs – implying that only time-varying inefficiency has been measured. This inherent feature

of the TFE model overcompensates for the heterogeneity effects, underestimating inefficiency in the process – thereby overestimating any efficiency. Even though there is no *a priori* economic reasoning as to whether bank specific effect not be considered part of the inefficiency component, as Greene (20005a) notes, "[…] it is clear that ignoring the possibility of unit specific heterogeneity in u_i is likewise restrictive (page 29)". Finally, as mentioned above, the inclusion of loan loss provisions in the TVM models for the most part, yields equal or higher efficiency estimates; a finding supported by prior research in Greek banking (see for example, Pasiouras et al., 2008a) – however this is not supported by the TFE specification (TFE3 mean efficiency 0.83).

Table 4.11. Comparisons of Efficiency Distributions: True Fixed Effects

	TFE1	*TFE2*	*TFE3*
Mean	0.90	0.90	0.83
Median	0.97	0.96	0.86
Minimum	0.53	0.56	0.67
Maximum	0.99	0.99	0.94
Standard Deviation	0.13	0.12	0.08
Skewness	-1.28	-1.29	-0.76
Kurtosis	3.31	3.43	2.24
Observations	*116*	*116*	*116*

Where TFE1: Time Varying Model 1, without a risk metric, TFE2: Time Varying Model 2, with Total Equity as netput, TFE3: Time Varying Model 3, with Loan Loss Provisions as netput.
The skewness test for normality rejected the null hypothesis at the 1% level for all the values reported. The kurtosis test for normality failed to reject the null hypothesis for all the values reported, except in the case of TFE3 (p-value=0.01).

Therefore, when examining consistency condition 1, we have shown that all the TVM specifications estimated show significant stability in their distributional properties and across models (that is, across TVM1, TVM2 and TVM3), and within models (for example, TVM1-3Z, TVM1-4Z, TVM1-5Z and TVM1-6Z). Hence, it is evident that all the examined frontier estimates share similar and in some cases identical statistical properties (for example, mean, standard deviation and negative skewness). Regarding the true SFA specifications, based on the theoretical properties of the models, and following our expectations, on average, all TFE models produced greater efficiency estimates. Finally, similar to the TVM specifications, all the TFE models, for the most part, share similar distributional properties (only TFE3 produced less dispersed cost

efficiency estimates (min: 0.67, max: 0.83) than its counterparts). The data therefore suggest that the estimated SF models are consistent with one another in terms of the distributions of the efficiencies generated, thus satisfying the first set of the conditions under examination.

4.5.2 Condition 2 - Rank Order Correlations of Efficiency Distributions

The efficiency estimates produced by the means of SFA are sensitive to distributional assumptions and to the input/output mix. However, even though estimates of the levels of the efficiency estimated by the various models are different across the sample, the rankings generated by the techniques should be similar across the frontier. That is, if the methods do not rank institutions in a similar manner, then policy conclusions will be fragile and model dependant. Table 4.12 presents the pooled Spearman's rank order correlation test for each estimated model. The rationale for estimating the Spearman's rank correlation coefficient is that the test is a nonparametric (distribution-free) rank statistic, proposed as a measure of the strength of the association between two variables. It is a measure of a monotone association that is used when the distribution of data makes the Pearson's correlation coefficient undesirable or misleading (Hauke and Kossowski, 2011). The test assesses how well an arbitrary monotonic function can describe the relationship between two variables, without making any assumptions concerning the frequency distribution of the variables. Furthermore, the main difference between the Spearman's and the Pearson's product-moment correlation coefficient is that in the former it does not demand the restrictive assumption of a linear relationship between the two variables.

In consideration of the results presented in Table 4.12, the rankings are reasonably consistent as the rank-order correlation measured as Spearman's ρ, are all positive and statistically significant at the 1% level, thus indicating a strong correlation across both the TVM models and the TFE estimated frontiers, and the correlations range from a minimum of 0.676 (TFE2 – TVM2) to a maximum of 0.999 (TVM1 – TVM3).

Table 4.12. Across Models Spearman's rank order correlations

	TVM1	*TVM2*	*TVM3*	*TFE1*	*TFE2*	*TFE3*
TVM1	1.000					
TVM2	0.860***	1.000				
TVM3	0.999***	0.865***	1.000			
TFE1	0.941***	0.756***	0.938***	1.000		
TFE2	0.881***	0.676***	0.876***	0.946***	1.000	
TFE3	0.734***	0.679***	0.728***	0.781***	0.861***	1.000
Observations	116	116	116	116	116	116

** Correlation is statistically significantly different from zero at the 10% level*
*** Correlation is statistically significantly different from zero at the 5% level*
**** Correlation is statistically significantly different from zero at the 1% level*
Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput, TFE1: True Fixed Effects Model 1, without a risk metric, TFE2: True Fixed Effects Model 2, with Total Equity as netput, TFE3: True Fixed Effects Model 3, with Loan Loss Provisions as netput.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

A more detailed analysis indicates that the results are consistent with the theory as within model Spearman rank-order correlations also show 'strong' positive correlation between each family of model specifications for the pooled sample (Table 4.13). Additional within model Spearman rank correlations tests were also performed for both the TVM and the TFE models on annual data. Under the TVM specifications all models produced Spearman's $\boldsymbol{\rho}$ values that were found to be statistically significantly different from zero at the 1% level. The test presented in Table 4.13 is not applicable to the TVM specifications as only models including 6 auxiliary variables were estimated under the FEM approach. The TFE rankings produced similar results. That is, for the most part the Spearman $\boldsymbol{\rho}$, values were statistically significant at the 1% level, with only few exceptions, where the null hypothesis was rejected at the 10% critical level. Finally, in one case we fail to reject the null hypothesis, that is for 2012 for the TFE3 and TFE9 (Table 4.21).

Table 4.13. Within Model Correlations - Full Sample

		TVM1		
	3Z	*4Z*	*5Z*	*6Z*
3Z	1.000			
4Z	0.828***	1.000		
5Z	0.682***	0.914***	1.000	
6Z	0.661***	0.896***	0.971***	1.000
		TVM2		
	3Z	*4Z*	*5Z*	*6Z*
3Z	1.000			
4Z	0.743*	1.000		
5Z	0.678*	0.971*	1.000	
6Z	0.784***	0.970***	0.936***	1.000
		TVM3		
	3Z	*4Z*	*5Z*	*6Z*
3Z	1.000			
4Z	0.865***	1.000		
5Z	0.692***	0.894***	1.000	
6Z	0.668***	0.879***	0.967***	1.000
Observations	*116*	*116*	*116*	*116*

** Correlation is statistically significantly different from zero at the 10% level*
*** Correlation is statistically significantly different from zero at the 5% level*
**** Correlation is statistically significantly different from zero at the 1% level*
Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput, TFE1: True Fixed Effects Model 1, without a risk metric, TFE2: True Fixed Effects Model 2, with Total Equity as netput, TFE3: True Fixed Effects Model 3, with Loan Loss Provisions as netput.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

As an additional test we next present the annual Spearman's rank order correlation tests, shown in Tables 4.14 to 4.21. For the years 2005 and 2006 (Table 4.14 and 4.15), the test indicates a strong positive and statistically significant correlation both within and across the TVM/TFE models, ranging from a minimum value of ρ of 0.511 (TVM2 correlated to TFE2, 2006) to a maximum of 0.991 (TVM1 correlated to TVM3). For 2007 and 2008 only within correlations are positive and significant, with the TVM models exhibiting much stronger ρ values that the TFE respective ones (for 2007, Tables 4.16). Surprisingly, for 2008 (Table 4.17), the TFE rankings exhibit for the first time a negative but insignificant correlation with their TVM counterparts (a notable exception is the negative and statistically significant at the 10% level correlation

between TFE1 and TVM1). The same trend is observed for 2010 (Table 4.19), where the within correlations remain positive and statistically significant at either the 1% or 10% level, whereas TFE3 is negatively correlated with the respective TVM specifications. Finally, for 2009, 2011 and 2012, the Spearman ρ values return to a positive range, with a minimum of 0.473 and a maximum ρ value of 0.991 (Tables 4.20 and 4.21).

Table 4.14. Annual Spearman's rank order correlations - 2005 (6 Macroeconomic indicators)

	TVM1	*TVM2*	*TVM3*	*TFE1*	*TFE2*	*TFE3*
TVM1	1.000					
TVM2	0.964***	1.000				
TVM3	0.985***	0.975***	1.000			
TFE1	0.810***	0.857***	0.800***	1.000		
TFE2	0.825***	0.867***	0.814***	0.985***	1.000	
TFE3	0.825***	0.771***	0.725***	0.882*	0.864***	1.000
Observations	*15*	*15*	*15*	*15*	*15*	*15*

** Correlation is statistically significantly different from zero at the 10% level*
*** Correlation is statistically significantly different from zero at the 5% level*
**** Correlation is statistically significantly different from zero at the 1% level*
Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput, TFE1: True Fixed Effects Model 1, without a risk metric, TFE2: True Fixed Effects Model 2, with Total Equity as netput, TFE3: True Fixed Effects Model 3, with Loan Loss Provisions as netput.
Where, 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.15. Annual Spearman's rank order correlations - 2006 (6 Macroeconomic indicators)

	TVM1	*TVM2*	*TVM3*	*TFE1*	*TFE2*	*TFE3*
TVM1	1.0000					
TVM2	0.964***	1.000				
TVM3	0.991***	0.9706***	1.000			
TFE1	0.608**	0.494*	0.532**	1.000		
TFE2	0.644***	0.511**	0.567**	0.970***	1.000	
TFE3	0.661***	0.5471**	0.600**	0.926***	0.914***	1.000
Observations	16	16	16	16	16	16

** Correlation is statistically significantly different from zero at the 10% level*
*** Correlation is statistically significantly different from zero at the 5% level*
**** Correlation is statistically significantly different from zero at the 1% level*
Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput, TFE1: True Fixed Effects Model 1, without a risk metric, TFE2: True Fixed Effects Model 2, with Total Equity as netput, TFE3: True Fixed Effects Model 3, with Loan Loss Provisions as netput.
Where, 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.16. Annual Spearman's rank order correlations - 2007 (6 Macroeconomic indicators)

	TVM1	*TVM2*	*TVM3*	*TFE1*	*TFE2*	*TFE3*
TVM1	1.00					
TVM2	0.967***	1.000				
TVM3	0.988***	0.964*	1.000			
TFE1	0.332	0.255	0.297	1.000		
TFE2	0.397	0.341	0.367	0.967***	1.000	
TFE3	0.144	0.229	0.205	0.485*	0.555**	1.000
Observations	16	16	16	16	16	16

** Correlation is statistically significantly different from zero at the 10% level*
*** Correlation is statistically significantly different from zero at the 5% level*
**** Correlation is statistically significantly different from zero at the 1% level*
Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput, TFE1: Time Varying Model 1, without a risk metric, TFE2: Time Varying Model 2, with Total Equity as netput, TFE3: Time Varying Model 3, with Loan Loss Provisions as netput.
Where, 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.17. Annual Spearman's rank order correlations - 2008 (6 Macroeconomic indicators)

	TVM1	*TVM2*	*TVM3*	*TFE1*	*TFE2*	*TFE3*
TVM1	1.000					
TVM2	0.914***	1.000				
TVM3	0.994***	0.923***	1.000			
TFE1	-0.432*	-0.314	-0.414	1.000		
TFE2	-0.350	-0.270	-0.329	0.982***	1.000	
TFE3	-0.205	-0.100	-0.179	0.935*	0.932*	1.000
Observations	16	16	16	16	16	16

** Correlation is statistically significantly different from zero at the 10% level*
*** Correlation is statistically significantly different from zero at the 5% level*
**** Correlation is statistically significantly different from zero at the 1% level*
Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput, TFE1: True Fixed Effects Model 1, without a risk metric, TFE2: True Fixed Effects Model 2, with Total Equity as netput, TFE3: True Fixed Effects Model 3, with Loan Loss Provisions as netput.
Where, 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.18. Annual Spearman's rank order correlations - 2009 (6 Macroeconomic indicators)

	TVM1	*TVM2*	*TVM3*	*TFE1*	*TFE2*	*TFE3*
TVM1	1.000					
TVM2	0.979*	1.000				
TVM3	0.991*	0.970***	1.000			
TFE1	0.458*	0.458*	0.455*	1.000		
TFE2	0.473**	0.473*	0.476*	0.973***	1.000	
TFE3	0.241	0.258	0.220	0.794***	0.791***	1.000
Observations	*16*	*16*	*16*	*16*	*16*	*16*

** Correlation is statistically significantly different from zero at the 10% level*
*** Correlation is statistically significantly different from zero at the 5% level*
**** Correlation is statistically significantly different from zero at the 1% level*
Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput, TFE1: True Fixed Effects Model 1, without a risk metric, TFE2: True Fixed Effects Model 2, with Total Equity as netput, TFE3: True Fixed Effects Model 3, with Loan Loss Provisions as netput.
Where, 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.19. Annual Spearman's rank order correlations - 2010 (6 Macroeconomic indicators)

	TVM1	*TVM2*	*TVM3*	*TFE1*	*TFE2*	*TFE3*
TVM1	1.000					
TVM2	0.952***	1.000				
TVM3	1.000***	0.952*	1.000			
TFE1	-0.091	-0.032	-0.091	1.000		
TFE2	-0.100	-0.047	-0.100	0.964***	1.000	
TFE3	-0.470*	-0.426*	-0.470*	0.5382*	0.438*	1.000
Observations	*16*	*16*	*16*	*16*	*16*	*16*

** Correlation is statistically significantly different from zero at the 10% level*
*** Correlation is statistically significantly different from zero at the 5% level*
**** Correlation is statistically significantly different from zero at the 1% level*
Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput, TFE1: True Fixed Effects Model 1, without a risk metric, TFE2: True Fixed Effects Model 2, with Total Equity as netput, TFE3: True Fixed Effects Model 3, with Loan Loss Provisions as netput.
Where, 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.20. Annual Spearman's rank order correlations - 2011 (6 Macroeconomic indicators)

	TVM1	*TVM2*	*TVM3*	*TFE1*	*TFE2*	*TFE3*
TVM1	1.000					
TVM2	0.881***	1.000				
TVM3	0.990***	0.872***	1.000			
TFE1	0.736***	0.600*	0.754***	1.000		
TFE2	0.772***	0.672**	0.790***	0.872***	1.000	
TFE3	0.409	0.290	0.418	0.790***	0.727**	1.000
Observations	*11*	*11*	*11*	*11*	*11*	*11*

** Correlation is statistically significantly different from zero at the 10% level*
*** Correlation is statistically significantly different from zero at the 5% level*
**** Correlation is statistically significantly different from zero at the 1% level*
Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput, TFE1: True Fixed Effects Model 1, without a risk metric, TFE2: True Fixed Effects Model 2, with Total Equity as netput, TFE3: True Fixed Effects Model 3, with Loan Loss Provisions as netput.
Where, 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.21. Annual Spearman's rank order correlations - 2012 (6 Macroeconomic indicators)

	TVM1	*TVM2*	*TVM3*	*TFE1*	*TFE2*	*TFE3*
TVM1	1.000					
TVM2	0.927***	1.000				
TVM3	0.975***	0.878***	1.000			
TFE1	0.709**	0.818***	0.672**	1.000		
TFE2	0.660*	0.769***	0.672*	0.975*	1.000	
TFE3	0.187	0.309	0.103	0.515	0.660**	1.000
Observations	*10*	*10*	*10*	*10*	*10*	*10*

** Correlation is statistically significantly different from zero at the 10% level*
*** Correlation is statistically significantly different from zero at the 5% level*
**** Correlation is statistically significantly different from zero at the 1% level*
Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput, TFE1: True Fixed Effects Model 1, without a risk metric, TFE2: True Fixed Effects Model 2, with Total Equity as netput, TFE3: True Fixed Effects Model 3, with Loan Loss Provisions as netput.
Where, 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Interestingly, for the two periods where the crises hit Greece, 2008 and 2010, the across model correlations indicate some inconsistencies when compared to the theoretical predictions. That is, as noted above, for 2008, the rankings produced from the true SF results are negative, yet insignificantly correlated to the TVM rankings (with only the exception noted above). The within TFE specifications remain positively and strongly correlated. Interestingly, in 2010 (Table 4.19), the same pattern re-emerges. In this case the across model correlations for TFE1 and TFE2 are insignificant, with values ranging from -0.032 (TFE1 with TVM2-6Z) to -0.1 (TFE2 with TVM1 and TVM3-6Z). TVM1-6Z, TVM2-6Z and TVM3-6Z are negatively correlated with TFE3, with respective values of -0.470 -0.426 and -0.470 (10% level). Whereas, the within TFE correlations with respect to TFE3 have also been significantly weakened with ρ values of 0.538 and 0.438, at the 10% level. Treating the weak within TFE model correlations, and the across models very low negative and insignificant correlation for TFE1 and TFE2 as a benchmark, our results indicate a reduction in the predictive power of TFE3 with respect to both its TFE and TVM counterparts.

Therefore, the results arising from examining consistency condition 2, point out that for the most part all the cost frontiers are reliable to generate consistent rankings for Greek

banks. With regards to the TVM rankings, it is evident that all estimated models perform in a consistent manner indicating that all models identify and rank Greek banks in a similar manner – a finding which is consistent with the theoretical properties of the econometric specifications and our expectation. Similarly, the TFE models also produce rankings that are generally consistent both across and within models. However, the integrity of the cost estimates may be compromised as in 2007, the within Spearman rank order correlation test, resulted in an unexpectedly lower correlation than in previous and successive years. We treat this finding as a sign for concern with regards the stability of the TFE specifications. Further examination is also conducted in the following consistency conditions.

4.5.3 Condition 3 - Identification of Best/Worst Practice Banks

Even if the various models do not always rank the banking institution identically, they can still provide some useful information to regulatory authorities as long as they can consistently identify the best and worst practice banks in the sector. Table 4.22 summarizes the correspondence of best and worst practice banks across the more inclusive 6Z based models and the cost efficiencies and rankings for each of the model specifications estimated. Closer examination of Table 4.22 shows good correspondence of identifying the extreme performers in the industry. The upper left part of the table reports for each pair of model specifications the proportion of banks that have been identified simultaneously by both models to exhibit efficiency scores in the upper quartile. For example, with respect to banks that were identified in the upper quartile of the sample by TVM2, 75% of them were also identified as top performers by TVM1 (i.e., also present in the top quartile). Respectively, the lower part of the table reports the correspondence for the lower quartile. Random chance would yield an expected value of 25% and perfect correspondence would give a value of 100%. The correspondence values estimated range from as low as 25% to perfect correspondence (100%), indicating consistency across the various SFA models. Interestingly, within model correspondence is higher than across model correspondence for the top 25% performing banks. Within TVM models the correspondence rates range between 75%-100%, whereas, across models the respective rate ranges between 25% and 50%. For the worst 25% performers, all models share similar correspondence rates, ranging between 50%-100.

Table 4.22. Correspondence of best/worst practice banks across models

	TVM1-6Z	*TVM2-6Z*	*TVM3-6Z*	*TFE1*	*TFE2*	*TFE3*
TVM1-6Z		75%	75%	50%	50%	25%
TVM2-6Z	75%		100%	50%	25%	25%
TVM3-6Z	75%	100%		50%	25%	25%
TFE1	100%	75%	75%		75%	25%
TFE2	75%	75%	75%	75%		25%
TFE3	75%	75%	75%	75%	50%	

The upper right triangle shows best practice and lower left triangle shows worst practice.
To reduce noise, the average efficiency of each bank was estimated over the sample years.
Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput, TFE1: Time Varying Model 1, without a risk metric, TFE2: Time Varying Model 2, with Total Equity as netput, TFE1: True Fixed Effects Model 1, without a risk metric, TFE2: True Fixed Effects Model 2, with Total Equity as netput, TFE3: True Fixed Effects Model 3, with Loan Loss Provisions as netput.
Where, 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Extending our analysis further, similar results are also presented when examining the correspondence of best/worst performers across macroeconomic variables for the TVM specifications (Table 4-23, Table 4-24 and Table 4-25). That is, there is very good consistency among the various TVM specifications when examined per macroeconomic variable set, with correspondence rate ranging from 75% to 100%. Tables 4.26 to 4.28 present essentially the same findings as the results above – there is good consistency in the estimated results via the stepwise inclusion of additional macroeconomic indicators in the estimation process (ranging from 75%-100%).

Table 4.23. Correspondence of best/worst practice banks - Time Varying Models

	3Z			*4Z*		
	TVM1	*TVM2*	*TVM3*	*TVM1*	*TVM2*	*TVM3*
TVM1		100%	100%		100%	100%
TVM2	100%		100%	100%		100%
TVM3	75%	75%		100%	100%	

The upper right triangle shows best practice and lower left triangle shows worst practice.
To reduce noise, the average efficiency of each bank was estimated over the sample years.
Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio

Table 4.24. Correspondence of best/worst practice banks - Time Varying Models

	4Z			*5Z*		
	TVM1	*TVM2*	*TVM3*	*TVM1*	*TVM2*	*TVM3*
TVM1		100%	100%		100%	100%
TVM2	100%		100%	100%		100%
TVM3	100%	100%		100%	100%	

The upper right triangle shows best practice and lower left triangle shows worst practice.
To reduce noise, the average efficiency of each bank was estimated over the sample years.
Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.
Where, 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP).

Table 4.25. Correspondence of best/worst practice banks - Time Varying Models

	5Z			*6Z*		
	TVM1	*TVM2*	*TVM3*	*TVM1*	*TVM2*	*TVM3*
TVM1		100%	100%		75%	75%
TVM2	100%		100%	75%		100%
TVM3	100%	100%		75%	100%	

The upper right triangle shows best practice and lower left triangle shows worst practice.
To reduce noise, the average efficiency of each bank was estimated over the sample years.
Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.
Where, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.26. Correspondence of best/worst practice banks - Time Varying Model 1

	3Z	*4Z*	*5Z*	*6Z*
3Z		75%	75%	75%
4Z	75%		100%	100%
5Z	75%	100%		100%
6Z	75%	75%	75%	

The upper right triangle shows best practice and lower left triangle shows worst practice.
To reduce noise, the average efficiency of each bank was estimated over the sample years.
Where TVM1: Time Varying Model 1, without a risk metric.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.27. Correspondence of best/worst practice banks - Time Varying Model 2

	3Z	*4Z*	*5Z*	*6Z*
3Z		75%	75%	100%
4Z	75%		100%	75%
5Z	75%	100%		75%
6Z	75%	100%	100%	

The upper right triangle shows best practice and lower left triangle shows worst practice.
To reduce noise, the average efficiency of each bank was estimated over the sample years.
Where, TVM2: Time Varying Model 2, with Total Equity as netput.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.28. Correspondence of best/worst practice banks - Time Varying Model 3

	3Z	*4Z*	*5Z*	*6Z*
3Z		75%	75%	100%
4Z	100%		100%	75%
5Z	100%	100%		75%
6Z	100%	100%	100%	

The upper right triangle shows best practice and lower left triangle shows worst practice.
To reduce noise, the average efficiency of each bank was estimated over the sample years.
Where, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.29 distinguishes banking institutions based on their financial importance to the Greek banking sector. More specifically, in August 2011, the Bank of Greece engaged BlackRock Solutions to conduct a Diagnostic Assessment of the loan portfolios of a select group of Greek commercial banks as of 30 June 2011. Based on this assessment (Blackrock Solutions, 2011), the Greek government identified four core banking institutions (National Bank of Greece SA, Eurobank Ergasias SA, Alpha Bank SA, and Piraeus Bank SA) which were deemed suitable candidates for recapitalization and ‘‘non-core banks’’ that would need to be recapitalized by the private sect, as end April 2013 (Bank of Greece, 2012). To reduce noise, the rankings where constructed based on the average efficiency of each model for each individual bank.

The estimated efficiencies on average generate similar rankings. All three TVM models identify the same institutions as best performers; a fact that remains unaffected by the fact that TVM2-6Z is consistently generating lower cost efficiencies. More specifically, when examining the rankings of the four core banks in Greece (Table 4.29), all the models rank them almost identically. Alpha Bank and National Bank of Greece (NBoG) are ranked very closely and in a consistent manner by all three models, interchanging positions between themselves. That is, the former is ranked 8th under two model specifications (TVM1-6Z TVM3-6Z), whereas TVM2-6Z positions the bank in the 9th place. Similarly, NBoG is ranked 9th by TVM1-6Z and TVM3-6Z and 8th by model TVM2-6Z. Whereas, Eurobank Ergasias SA and Piraeus Bank SA are consistently ranked in the top 30% of the sample (the former is 3rd across all models when the latter is 4th (TVM1-6Z) and 5th under TVM2-6Z and TVM3-6Z).

For the most part, the True Fixed Effect models also tell the same story regarding the core institutions; TFE1 and TFE2 exhibit similar behaviour in their rankings. However, surprisingly, TFE3 in the case of the National Bank of Greece is classifying the bank in the top three (3rd position) efficient banks in the industry, when all the other five models rank the bank at a lower rank position (ranging from 8th – 12th place). The results presented in this section essentially confirm the results from the rank order correlation tests presented before; generally, there is good consistency among the various cost frontiers estimated. However, despite some anomalies presented regarding specific banking institutions and their rankings, this is only limited within the models estimated under the TFE specifications. Finally, Table 4.30 provides an overview of the TVM rankings based on the cost functions estimated over the various macroeconomic specifications. Close examination reveals that across the various models and the different macroeconomic indicators chosen, all rankings remain consistent, with the exception of only minor discrepancies (i.e., banks that change their rankings by one place based on the version of the models used). For example, Alpha Bank AE is ranked 9th under the TVM2-4Z/5Z/6Z and 8th under the TVM1-4Z/5Z/6Z and TVM3-4Z/5Z/6Z. With the exception of such minor changes, the remaining of the banks retain the same rankings. The changes in the rankings for the individual banks are denoted in bold italics.

In conclusion, although the TVM models tended to identify the same banks as efficient and inefficient, both internally and across models, the TFE's did not perform as consistent as expected. That is, internal stability of the rankings is weakened in more than one occasion, for example, two systemically important banks; Eurobank Ergasias SA and National Bank of Greece SA exhibit significant differences in the way they are ranked across the three models. In addition, similar differences are also present in the case of other financial institutions (for example, Emporiki Bank of Greece SA, FBB First Business Bank SA, General Bank of Greece SA, Millennium Bank SA and T Bank S,A). This leads us to tentatively accept as the 'preferred' model TVM – based on the "best/worst" characteristics ranking under the Bauer et al., (1998) conditions. However, in order to determine the coherence and stability of this result we have three more tests in our arsenal.

Table 4.29. Time Varying Mean efficiency and rankings - 6 Macroeconomic indicators

Bank	*TVM1-6Z*	*TVM2-6Z*	*TVM3-6Z*	*TFE1*	*TFE2*	*TFE3*
Alpha Bank AE	0,834 (8)	0,762 (9)	0,829 (8)	0,832 (8)	0,932 (6)	0,931 (6)
Eurobank Ergasias SA	0,858 (3)	0,801 (3)	0,857 (3)	0,832 (9)	0,936 (2)	0,932 (4)
National Bank of Greece SA	0,831 (9)	0,786 (8)	0,825 (9)	0,832 (3)	0,87 (12)	0,871 (11)
Piraeus Bank SA	0,85 (4)	0,796 (5)	0,845 (5)	0,832 (7)	0,933 (4)	0,932 (5)
Agricultural Bank of Greece	0,738 (15)	0,646 (15)	0,73 (15)	0,821 (14)	0,838 (16)	0,842 (16)
Attica Bank SA-Bank of Attica SA	0,846 (5)	0,8 (4)	0,846 (4)	0,832 (10)	0,924 (7)	0,923 (7)
Emporiki Bank of Greece SA	0,84 (7)	0,792 (6)	0,837 (6)	0,832 (5)	0,888 (10)	0,883 (10)
FBB First Business Bank SA	0,877 (1)	0,814 (2)	0,871 (2)	0,827 (11)	0,933 (5)	0,935 (3)
General Bank of Greece SA	0,818 (11)	0,755 (10)	0,815 (11)	0,832 (2)	0,87 (13)	0,869 (12)
Marfin Egnatia Bank SA	0,785 (13)	0,737 (11)	0,779 (12)	0,82 (15)	0,871 (11)	0,866 (13)
Millennium Bank SA	0,875 (2)	0,842 (1)	0,871 (1)	0,832 (4)	0,897 (9)	0,898 (9)
PRObank SA-PRObank Bank Societe Anonyme	0,822 (10)	0,713 (12)	0,82 (10)	0,854 (1)	0,934 (3)	0,954 (1)
Panellinia Bank	0,842 (6)	0,791 (7)	0,835 (7)	0,832 (6)	0,916 (8)	0,912 (8)
Proton Bank S,A,	0,753 (14)	0,657 (14)	0,741 (14)	0,821 (12)	0,852 (14)	0,845 (14)
T Bank S,A	0,788 (12)	0,678 (13)	0,77 (13)	0,82 (16)	0,947 (1)	0,947 (2)
TT Hellenic Postbank S,A	0,713 (16)	0,602 (16)	0,707 (16)	0,821 (13)	0,839 (15)	0,843 (15)

Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput, TFE1: True Fixed Effects Model 1, without a risk metric, TFE2: True Fixed Effects Model 2, with Total Equity as netput, TFE3: True Fixed Effects Model 3, with Loan Loss Provisions as netput.

Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

The core banks include: Alpha Bank AE, Eurobank Ergasias SA, National Bank of Greece SA and Piraeus Bank SA.

Table 4.30. Rankings across Models - Time Varying Models

Bank	*TVM1*				*TVM2*				*TVM3*			
Macroeconomic indicators	*3Z*	*4 Z*	*5 Z*	*6 Z*	*3 Z*	*4 Z*	*5 Z*	*6 Z*	*3 Z*	*4 Z*	*5 Z*	*6 Z*
Alpha Bank AE	(8)	(8)	(8)	(8)	(8)	***(9)***	***(9)***	***(9)***	(8)	(8)	(8)	(8)
Eurobank Ergasias SA	(3)	(3)	(3)	(3)	(3)	(3)	(3)	3)	(3)	(3)	(3)	(3)
National Bank of Greece SA	(9)	(9)	(9)	(9)	***(10)***	***(8)***	***(8)***	***(8)***	(9)	(9)	(9)	(9)
Piraeus Bank SA	(5)	(4)	(4)	***(4)***	(5)	(4)	(4)	(5)	(5)	(4)	(4)	(5)
Agricultural Bank of Greece	(15)	(15)	(15)	(15)	(15)	(15)	(15)	(15)	(15)	(15)	(15)	(15)
Attica Bank SA-Bank of Attica SA	(4)	(5)	(5)	***(5)***	(4)	(5)	(5)	(4)	(4)	(5)	(5)	(4)
Emporiki Bank of Greece SA	(7)	(6)	(7)	***(7)***	(7)	***(7)***	(7)	(6)	(7)	(6)	(7)	(6)
FBB First Business Bank SA	(2)	***(1)***	***(1)***	***(1)***	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)
General Bank of Greece SA	(11)	(10)	(11)	(11)	(11)	***(10)***	(10)	***(10)***	(11)	(10)	(11)	(11)
Marfin Egnatia Bank SA	(10)	(12)	(12)	***(13)***	***(9)***	(12)	(12)	***(11)***	(10)	(12)	(12)	***(12)***
Millennium Bank SA	(1)	***(2)***	***(2)***	***(2)***	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)
PRObank SA-PRObank Bank Societe Anonyme	(13)	(11)	(10)	(10)	(13)	(11)	***(11)***	***(12)***	***(12)***	(11)	(10)	(10)
Panellinia Bank	(6)	(7)	(6)	***(6)***	(6)	***(6)***	(6)	(7)	(6)	(7)	(6)	(7)
Proton Bank S,A,	(14)	(14)	(14)	(14)	(14)	(14)	(14)	(14)	(14)	(14)	(14)	(14)
T Bank S,A	(12)	(13)	(13)	***(12)***	(12)	(13)	(13)	(13)	***(13)***	(13)	(13)	(13)
TT Hellenic Postbank S,A	(16)	(16)	(16)	(16)	(16)	(16)	(16)	(16)	(16)	(16)	(16)	(16)

Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.

Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

The core banks include: Alpha Bank AE, Eurobank Ergasias SA, National Bank of Greece SA and Piraeus Bank SA.

Table 4.31. Mean efficiency and rankings - 3Z Macroeconomic indicators

Bank	*TVM1*	*TVM2*	*TVM3*
Alpha Bank AE	0.825 (8)	0.826 (8)	0.821 (8)
Eurobank Ergasias SA	0.854 (3)	0.858 (3)	0.855 (3)
National Bank of Greece SA	0.823 (9)	0.826 (10)	0.819 (9)
Piraeus Bank SA	0.842 (5)	0.848 (5)	0.837 (5)
Agricultural Bank of Greece	0.743 (15)	0.748 (15)	0.730 (15)
Attica Bank SA-Bank of Attica SA	0.846 (4)	0.852 (4)	0.846 (4)
Emporiki Bank of Greece SA	0.833 (7)	0.828 (7)	0.830 (7)
FBB First Business Bank SA	0.871 (2)	0.875 (2)	0.862 (2)
General Bank of Greece SA	0.790 (11)	0.791 (11)	0.788 (11)
Marfin Egnatia Bank SA	0.816 (10)	0.826 (9)	0.814 (10)
Millennium Bank SA	0.875 (1)	0.876 (1)	0.873 (1)
PRObank SA-PRObank Bank Societe Anonyme	0.783 (13)	0.783 (13)	0.783 (12)
Panellinia Bank	0.839 (6)	0.842 (6)	0.836 (6)
Proton Bank S.A.	0.773 (14)	0.777 (14)	0.765 (14)
T Bank S.A	0.783 (12)	0.783 (12)	0.766 (13)
TT Hellenic Postbank S.A	0.685 (16)	0.685 (16)	0.678 (16)

Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change).
The core banks include: Alpha Bank AE, Eurobank Ergasias SA, National Bank of Greece SA and Piraeus Bank SA.

Table 4.32. Mean efficiency and rankings - 4Z Macroeconomic indicators

Bank	*TVM1*	*TVM2*	*TVM3*
Alpha Bank AE	0.827 (8)	0.813 (9)	0.827 (8)
Eurobank Ergasias SA	0.862 (3)	0.853 (3)	0.862 (3)
National Bank of Greece SA	0.825 (9)	0.820 (8)	0.825 (9)
Piraeus Bank SA	0.853 (4)	0.845 (4)	0.850 (4)
Agricultural Bank of Greece	0.729 (15)	0.715 (15)	0.722 (15)
Attica Bank SA-Bank of Attica SA	0.849 (5)	0.842 (5)	0.847 (5)
Emporiki Bank of Greece SA	0.838 (6)	0.824 (7)	0.836 (6)
FBB First Business Bank SA	0.874 (1)	0.866 (2)	0.868 (2)
General Bank of Greece SA	0.810 (10)	0.805 (10)	0.808 (10)
Marfin Egnatia Bank SA	0.795 (12)	0.788 (12)	0.792 (12)
Millennium Bank SA	0.874 (2)	0.868 (1)	0.870 (1)
PRObank SA-PRObank Bank Societe Anonyme	0.806 (11)	0.788 (11)	0.802 (11)
Panellinia Bank	0.838 (7)	0.831 (6)	0.835 (7)
Proton Bank S.A.	0.747 (14)	0.729 (14)	0.742 (14)
T Bank S.A	0.783 (13)	0.764 (13)	0.769 (13)
TT Hellenic Postbank S.A	0.693 (16)	0.680 (16)	0.689 (16)

Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.
Where, 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio.
The core banks include: Alpha Bank AE, Eurobank Ergasias SA, National Bank of Greece SA and Piraeus Bank SA.

Table 4.33. Mean efficiency and rankings - 5Z Macroeconomic indicators

Bank	*TVM1*	*TVM2*	*TVM3*
Alpha Bank AE	0.835 (8)	0.827 (9)	0.832 (8)
Eurobank Ergasias SA	0.864 (3)	0.859 (3)	0.858 (3)
National Bank of Greece SA	0.833 (9)	0.833 (8)	0.830 (9)
Piraeus Bank SA	0.853 (4)	0.851 (4)	0.848 (4)
Agricultural Bank of Greece	0.735 (15)	0.735 (15)	0.728 (15)
Attica Bank SA-Bank of Attica SA	0.850 (5)	0.847 (5)	0.847 (5)
Emporiki Bank of Greece SA	0.843 (7)	0.833 (7)	0.839 (7)
FBB First Business Bank SA	0.877 (1)	0.871 (2)	0.870 (2)
General Bank of Greece SA	0.821 (11)	0.820 (10)	0.817 (11)
Marfin Egnatia Bank SA	0.792 (12)	0.792 (12)	0.785 (12)
Millennium Bank SA	0.876 (2)	0.872 (1)	0.871 (1)
PRObank SA-PRObank Bank Societe Anonyme	0.821 (10)	0.816 (11)	0.821 (10)
Panellinia Bank	0.846 (6)	0.841 (6)	0.840 (6)
Proton Bank S.A.	0.750 (14)	0.744 (14)	0.743 (14)
T Bank S.A	0.788 (13)	0.780 (13)	0.774 (13)
TT Hellenic Postbank S.A	0.707 (16)	0.707 (16)	0.704 (16)

Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.

Where, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP).

The core banks include: Alpha Bank AE, Eurobank Ergasias SA, National Bank of Greece SA and Piraeus Bank SA.

Table 4.34. Time Varying Model 1 Mean Cost Efficiency

Bank	*3Z*	*4Z*	*5Z*	*6Z*
Alpha Bank AE	0.825 (8)	0.827 (8)	0.835 (8)	0.834 (8)
Eurobank Ergasias SA	0.854 (3)	0.862 (3)	0.864 (3)	0.858 (3)
National Bank of Greece SA	0.823 (9)	0.825 (9)	0.833 (9)	0.831 (9)
Piraeus Bank SA	0.842 (5)	0.853 (4)	0.853 (4)	0.850 (4)
Agricultural Bank of Greece	0.743 (15)	0.729 (15)	0.735 (15)	0.738 (15)
Attica Bank SA-Bank of Attica SA	0.846 (4)	0.849 (5)	0.850 (5)	0.846 (5)
Emporiki Bank of Greece SA	0.833 (7)	0.838 (6)	0.843 (7)	0.840 (7)
FBB First Business Bank SA	0.871 (2)	0.874 (1)	0.877 (1)	0.877 (1)
General Bank of Greece SA	0.790 (11)	0.810 (10)	0.821 (11)	0.818 (11)
Marfin Egnatia Bank SA	0.816 (10)	0.795 (12)	0.792 (12)	0.785 (13)
Millennium Bank SA	0.875 (1)	0.874 (2)	0.876 (2)	0.875 (2)
PRObank SA-PRObank Bank Societe Anonyme	0.783 (13)	0.806 (11)	0.821 (10)	0.822 (10)
Panellinia Bank	0.839 (6)	0.838 (7)	0.846 (6)	0.842 (6)
Proton Bank S.A.	0.773 (14)	0.747 (14)	0.750 (14)	0.753 (14)
T Bank S.A	0.783 (12)	0.783 (13)	0.788 (13)	0.788 (12)
TT Hellenic Postbank S.A	0.685 (16)	0.693 (16)	0.707 (16)	0.713 (16)

Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).
The core banks include: Alpha Bank AE, Eurobank Ergasias SA, National Bank of Greece SA and Piraeus Bank SA.

Table 4.35. Time Varying Model 2 Mean Cost Efficiency

Bank	*3z*	*4z*	*5z*	*6z*
Alpha Bank AE	0.826 (8)	0.813 (9)	0.827 (9)	0.762 (9)
Eurobank Ergasias SA	0.858 (3)	0.853 (3)	0.859 (3)	0.801 (3)
National Bank of Greece SA	0.826 (10)	0.820 (8)	0.833 (8)	0.786 (8)
Piraeus Bank SA	0.848 (5)	0.845 (4)	0.851 (4)	0.796 (5)
Agricultural Bank of Greece	0.748 (15)	0.715 (15)	0.735 (15)	0.646 (15)
Attica Bank SA-Bank of Attica SA	0.852 (4)	0.842 (5)	0.847 (5)	0.800 (4)
Emporiki Bank of Greece SA	0.828 (7)	0.824 (7)	0.833 (7)	0.792 (6)
FBB First Business Bank SA	0.875 (2)	0.866 (2)	0.871 (2)	0.814 (2)
General Bank of Greece SA	0.791 (11)	0.805 (10)	0.820 (10)	0.755 (10)
Marfin Egnatia Bank SA	0.826 (9)	0.788 (12)	0.792 (12)	0.737 (11)
Millennium Bank SA	0.876 (1)	0.868 (1)	0.872 (1)	0.842 (1)
PRObank SA-PRObank Bank Societe Anonyme	0.783 (13)	0.788 (11)	0.816 (11)	0.713 (12)
Panellinia Bank	0.842 (6)	0.831 (6)	0.841 (6)	0.791 (7)
Proton Bank S.A.	0.777 (14)	0.729 (14)	0.744 (14)	0.657 (14)
T Bank S.A	0.783 (12)	0.764 (13)	0.780 (13)	0.678 (13)
TT Hellenic Postbank S.A	0.685 (16)	0.680 (16)	0.707 (16)	0.602 (16)

Where, TVM2: Time Varying Model 2, with Total Equity as netput.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).
The core banks include: Alpha Bank AE, Eurobank Ergasias SA, National Bank of Greece SA and Piraeus Bank SA.

Table 4.36. Time Varying Model 3 Mean Cost Efficiency

Bank	*3z*	*4z*	*5z*	*6z*
Alpha Bank AE	0.821 (8)	0.827 (8)	0.832 (8)	0.829 (8)
Eurobank Ergasias SA	0.855 (3)	0.862 (3)	0.858 (3)	0.857 (3)
National Bank of Greece SA	0.819 (9)	0.825 (9)	0.830 (9)	0.825 (9)
Piraeus Bank SA	0.837 (5)	0.850 (4)	0.848 (4)	0.845 (5)
Agricultural Bank of Greece	0.730 (15)	0.722 (15)	0.728 (15)	0.730 (15)
Attica Bank SA-Bank of Attica SA	0.846 (4)	0.847 (5)	0.847 (5)	0.846 (4)
Emporiki Bank of Greece SA	0.830 (7)	0.836 (6)	0.839 (7)	0.837 (6)
FBB First Business Bank SA	0.862 (2)	0.868 (2)	0.870 (2)	0.871 (2)
General Bank of Greece SA	0.788 (11)	0.808 (10)	0.817 (11)	0.815 (11)
Marfin Egnatia Bank SA	0.814 (10)	0.792 (12)	0.785 (12)	0.779 (12)
Millennium Bank SA	0.873 (1)	0.870 (1)	0.871 (1)	0.871 (1)
PRObank SA-PRObank Bank Societe Anonyme	0.783 (12)	0.802 (11)	0.821 (10)	0.820 (10)
Panellinia Bank	0.836 (6)	0.835 (7)	0.840 (6)	0.835 (7)
Proton Bank S.A.	0.765 (14)	0.742 (14)	0.743 (14)	0.741 (14)
T Bank S.A	0.766 (13)	0.769 (13)	0.774 (13)	0.770 (13)
TT Hellenic Postbank S.A	0.678 (16)	0.689 (16)	0.704 (16)	0.707 (16)

Where, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).
The core banks include: Alpha Bank AE, Eurobank Ergasias SA, National Bank of Greece SA and Piraeus Bank SA.

4.5.4 Condition 4 - Stability of Measured Efficiency over time

For regulatory purposes, rankings produced by the means of SFA techniques should demonstrate a relative stability over time without any significant variation from one year to the next. Even though some banking institutions might improve over short periods of time, it is unlikely that a very efficient bank that is ranked in the top performing tier for one year to be ranked in the lower performing tier for the next year only to return in the top tier the following year. Measuring cost efficiencies by comparable approaches should produce estimates that are relatively stable over time and regulatory policies targeted specifically at either very efficient or very inefficient banks should hit their mark after normal policy and implementation lags (Bauer et al., 1998). Even though in recent years and especially after 2008 the Greek banking system has undergone significant structural changes, the expectation remains that the rankings of the bank should not exhibit large changes in the short run. The year-to-year stability of rankings is further analysed by the implementation of Spearman's rank-order correlation between each pair of years, following Bauer et al.,'s (1998) proposed consistency criterion 4. That is, for TVM1, the rank-order correlation test between cost efficiency estimates in each year *i*, *i*= 2006 to 2009 is estimated and for years *j*, *j* = 2007 to 2010 with *j*>*i*. The same process was repeated for the remaining five models. The next step is to estimate the rank-order correlations for the Two-Year-Apart, Three-Year-Apart and Four-Year-Apart periods. Due to the unbalanced structure of the data set, additional correlations including the years 2005, 2011 and 2012 could not be calculated as those years do not share the same length of observations with the estimated in this test[52].

Tables 4.37 to 4.40 summarize the results for the estimated models. Overall, the TVM models are more stable over time, exhibiting positive and statistically significant correlations. The One-Year, Two-Year and Three-Year-Apart correlations are statistically significant from zero in all cases, with notable exceptions for the Two-Year-Apart correlation starting in 2006 and 2008 (i.e., 2006-2008 and 2008-2010). Our results indicate that the models exhibit short/medium term stability characteristics. On the other hand, the TFE models (Table 4.40), even though they exhibit some positive

[52] Years 2005, 2011 and 2012 have 15, 11 and 10 observations respectively, not allowing correlation tests with the remaining sample years.

and significant correlations, the results are rather worrying since significant negative correlations are also present. This suggests that banks which can be identified as cost efficient in one year, are subsequently identified as highly cost inefficient in the following year (the negative ρ values range from -0.56 to -0.77). Although such results are scarce, they indicate a more unstable behaviour over time since it is highly unlikely that efficient banks operating close to the frontier would become very inefficient in the next one, only to return to high efficiency in the following year. This behaviour of the TFE model specifications does not look promising given the sample and the period under investigation (even for Greek banks!).

As noted before, the efficiency rankings are fairly stable over time. However, it is clear that the competitive and dynamic nature of the banking industry is evident in the correlations that concern the Four-Year-Apart period. The singular difference is that only TVM2 presents significant Four-Year-Apart Spearman ρ, whereas TVM1 and TVM3 show insignificant results. A similar pattern is also present in the TFE cost efficiencies. Finally, it is safe to say that even though most of the pair correlations yield significant results in the short-term lags, the pair correlations concerning the Four-Year-Apart period suggest that a policy strategy that has a four year implementation target might prove unsuccessful as it will not effectively target the intended banks. That is, based on the sample size employed our results suggest that short and medium term policies could potentially be more effective in their intended purpose. Finally, further analysis along similar lines with an extended, balanced sample size could offer more conclusive results in the case of Greece. Although, December 2016 data limitations become apparent as Bankscope collapses sample years to only the previous 5 year window (SNL Financial will offer little help on data as their current sample size is significantly poorer in terms of the number of banks – of course, creating a lot of interesting degrees of freedom problems).

In conclusion, is it again apparent that overall, the TVM estimates confirm our expectations and remain stable over time, consistently identifying the same banks as either best or worst performers. Examination of the estimates produced by the true SF specifications raise concerns as the results do not hold up to scrutiny, indicating severe instability in many cases. However, before we determine if the TVM's correctly model the data, another test is conducted on Greek bank efficiencies.

Table 4.37. Stability of Measured Efficiency over time - TVM1 Mean Cost Efficiency

		3Z		
Year	*2006*	*2007*	*2008*	*2009*
2007	0.773***			
2008	0.402	0.735***		
2009	0.558**	0.773***	0.629***	
2010	0.358	0.550**	0.373	0.829***
		4Z		
2007	0.826***			
2008	0.311	0.644***		
2009	0.588**	0.667***	0.623***	
2010	0.411	0.476*	0.352	0.811***
		5Z		
2007	0.817***			
2008	0.394	0.655***		
2009	0.520**	0.638***	0.644***	
2010	0.367	0.476*	0.358	0.791***
		6Z		
2007	0.826***			
2008	0.335	0.602**		
2009	0.561**	0.652***	0.614**	
2010	0.373	0.441*	0.317	0.800***

**Correlation is statistically significantly different from zero at the 10% level*
***Correlation is statistically significantly different from zero at the 5% level*
****Correlation is statistically significantly different from zero at the 1% level*
Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.38. Stability of Measured Efficiency over time - TVM2 Mean Cost Efficiency

		3Z		
Year	*2006*	*2007*	*2008*	*2009*
2007	0.832***			
2008	0.291	0.647***		
2009	0.564**	0.788***	0.697***	
2010	0.447*	0.602**	0.355	0.779***
		4Z		
2007	0.870***			
2008	0.344	0.632***		
2009	0.561**	0.752***	0.673***	
2010	0.376	0.532**	0.282	0.702***
		5Z		
2007	0.882***			
2008	0.344	0.605**		
2009	0.567**	0.744***	0.647***	
2010	0.394	0.567**	0.341	0.741**
		6Z		
2007	0.870***			
2008	0.252	0.491**		
2009	0.588**	0.764***	0.600**	
2010	0.447*	0.623***	0.311	0.767***

**Correlation is statistically significantly different from zero at the 10% level*
***Correlation is statistically significantly different from zero at the 5% level*
****Correlation is statistically significantly different from zero at the 1% level*
Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.39. Stability of Measured Efficiency over time - TVM3 Mean Cost Efficiency

		3Z		
Year	*2006*	*2007*	*2008*	*2009*
2007	0.794***			
2008	0.385	0.711***		
2009	0.582**	0.726***	0.579**	
2010	0.394	0.505**	0.379	0.779***
		4Z		
2007	0.835***			
2008	0.311	0.638***		
2009	0.579**	0.667***	0.620**	0.811***
2010	0.420	0.476**	0.350	
		5Z		
2007	0.841****			
2008	0.373	0.632***		
2009	0.570**	0.679***	0.620**	
2010	0.379	0.476*	0.320	0.817*
		6Z		
2007	0.814***			
2008	0.388	0.658***		
2009	0.597**	0.676***	0.600**	
2010	0.388	0.482*	0.326	0.800***

**Correlation is statistically significantly different from zero at the 10% level*
***Correlation is statistically significantly different from zero at the 5% level*
****Correlation is statistically significantly different from zero at the 1% level*
Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.40. Stability of Measured Efficiency over time - True Fixed Effects

			TFE1	
Year	*2006*	*2007*	*2008*	*2009*
2007	0.702***			
2008	-0.561**	-0.326		
2009	0.282	-0.108	-0.732***	
2010	-0.423	-0.561**	0.335	-0.138
			TFE2	
2007	0.597**			
2008	-0.714***	-0.338		
2009	0.397	-0.076	-0.770***	
2010	-0.461	-0.441*	0.297	-0.244
			TFE3	
2007	-0.091			
2008	-0.741***	0.055		
2009	-0.173	-0.229	-0.270	
2010	-0.464	-0.070	0.685***	0.070

**Correlation is statistically significantly different from zero at the 10% level*
***Correlation is statistically significantly different from zero at the 5% level*
****Correlation is statistically significantly different from zero at the 1% level*
Where TFE1: True Fixed Effects Model 1, without a risk metric, TFE2: True Fixed Effects Model 2, with Total Equity as netput, TFE3: True Fixed Effects Model 3, with Loan Loss Provisions as netput.
Where, 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

4.5.5 Condition 5 - Consistency with market competitive conditions

This test will allow us to determine whether efficiencies generated by the different specifications are consistent with reality and the market conditions in Greece. As it is summarized in Table 4.41 and Table 4.42, all the parametric 6Z models yield similar estimates of cost efficiency. Strikingly, the results suggest low levels of cost efficiency for the early years of the sample (2005-2006), with efficiency levels ranging from 0.464 to 0.496 for 2005 and 2006 respectively for the TVM models and from 0.675 to 0.691 for the three TFE models. Low efficiency estimates remain consistent across all models, suggesting that Greek banks on average, before the outbreak of the global financial crisis and the Greek debt crisis, did not exercise rigorous control on inputs. The TFE models have produced higher efficiency estimates than the respective TVM ones. That is, in Table 4-42 we observe that from the three TFE models, TFE3 yields lower estimates that the remaining two; in contrast to the TVM model specifications where TVM2 yielded the lowest scores. All TFE applications exhibit an increase in the mean cost efficiency from 2005 to 2008 and similar to the TVM ones, they show a decrease for the next year; ranging from -8.6% (TFE3) to -3.3% (TFE1). The upward trend continues again for one year (2010) and for the remaining two years of the sample all three models remain relatively stable. In contrast to the TVM models, for the years 2010 -2011 the TFE models follow the opposite behaviour, TFE2 mean efficiency marginally decreases by -0.7% (the equivalent TVM model increases by 11.5%) and the TFE3 shows a minor increase of 0.2% (-1.2% drop in the TVM3 model). Even though the extent of the phenomenon is not very strong, the TFE specifications capture the change in the risk variables in an opposite manner than the respective TVM models. Further analysis is required in order to disentangle the reasons behind this change in the cost efficiencies and the possible link to the internal risk function of Greek banks.

To determine and examine these results, Figure 4.1 shows the progress of both common equity and loan loss provision though the sample period. For the years in question the two risk variables follow an opposite trend (Table 4.43 and Table 4.44); average common equity for the whole sample drops from €1576.1 million in 2010 to €-147.1 million in 2011. Loan loss provisions, for these years exhibit a sharp increase; from €372.9 million in year 2010 to €3132.8 million in 2011. Closer examination reveals that the drop (increase) in the common equity (loan loss provisions) is driven by the core banks (that is, Alpha Bank AE, Eurobank Ergasias SA, National Bank of Greece

SA and Piraeus Bank SA). More specifically, in the case of common equity, the four core institutions experience a massive reduction amounting to €6014.1 million when at the same time, the remaining non-core banks show a reduction of only €1326.4 million. The core banks also drive the increase of the average loan loss provisions in the sample. For example, provisions increase from €936.274 in year 2010 million to €7832.665 million for 2011 for the core banks – when the provisions for the non-core banks only show a moderate increase from €185.1107 million to €447.3132 million.

Table 4.41. Time Varying Mean cost efficiency – 6Z

Year	*TVM1*	*TVM2*	*TVM3*
2005	0.496	0.464	0.486
2006	0.578 (16.53%)	0.531 (14.44%)	0.561 (15.43%)
2007	0.784 (35.64%)	0.736 (38.61%)	0.769 (37.08%)
2008	0.958 (22.19%)	0.879 (19.43%)	0.957 (24.45%)
2009	0.928 (-3.13%)	0.818 (-6.94%)	0.933 (-2.51%)
2010	0.973 (4.85%)	0.828 (1.22%)	0.972 (4.18%)
2011	0.961 (-1.23%)	0.924 (11.59%)	0.96 (-1.23%)
2012	0.97 (0.94%)	0.976 (5.63%)	0.97 (1.04%)

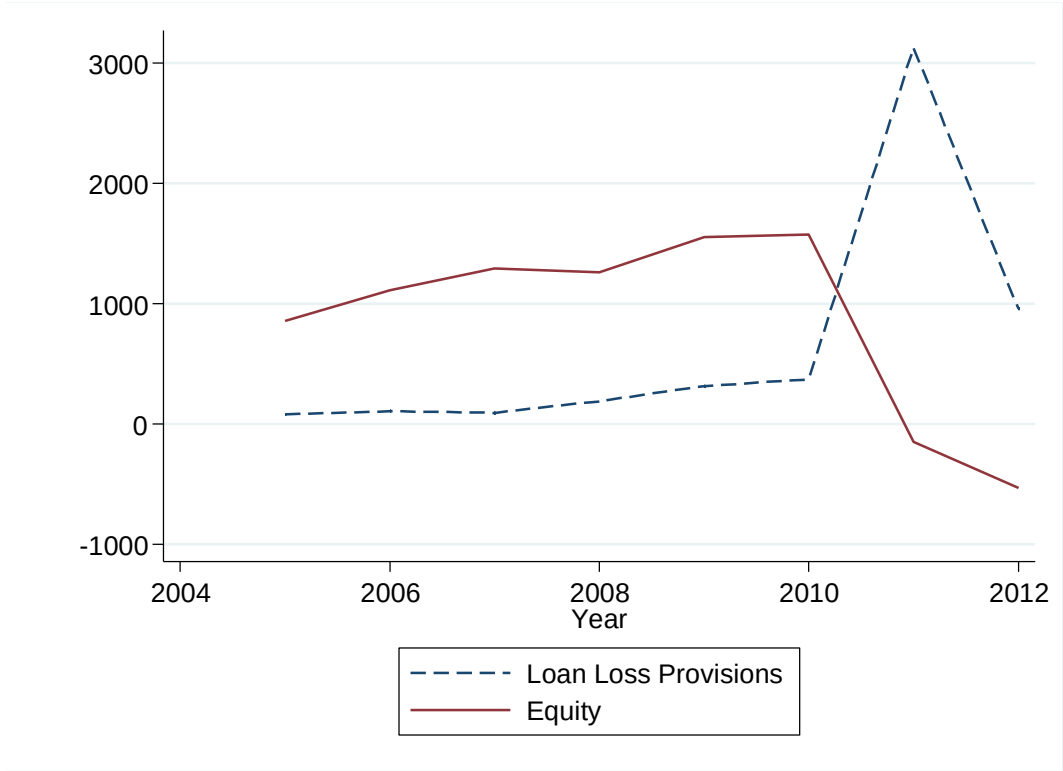
The percentage change is included in the parenthesis.
Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.
Where, 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.42. True Fixed Effects Mean cost efficiency – 6Z

Year	*TFE1*	*TFE2*	*TFE3*
2005	0.675	0.691	0.676
2006	0.749 (10.96%)	0.756 (9.41%)	0.718 (6.21%)
2007	0.893 (19.23%)	0.897 (18.65%)	0.864 (20.33%)
2008	0.993 (11.20%)	0.995 (10.93%)	0.938 (8.56%)
2009	0.96 (-3.32%)	0.955 (-4.02%)	0.857 (-8.64%)
2010	0.996 (3.1%)	0.996 (4.29%)	0.867 (1.17%)
2011	0.994 (0.14%)	0.988 (-0.80%)	0.869 (0.23%)
2012	0.994 (0.00%)	0.959 (-2.94%)	0.863 (-0.69%)

The percentage change is included in the parenthesis.
Where TFE1: True Fixed Effects Model 1, without a risk metric, TFE2: True Fixed Effect Model 2, with Total Equity as netput, TFE3: True Fixed Model 3, with Loan Loss Provisions as netput.
Where, 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Figure 4.1. Mean Common Equity and Loan Loss Provisions over time



Author's own calculations.

Table 4.43. Mean Common Equity

	Common Equity		
Year	*Core Banks*	*Non-Core Banks*	*Average*
2005	2244.35	355.2182	858.9867
2006	3263.915	395.4671	1112.579
2007	3974.731	397.4164	1291.745
2008	4109.152	314.5893	1263.23
2009	4956.104	423.4171	1556.589
2010	5193.094	370.5194	1576.163
2011	-821.034	237.8733	-147.1839
2012	-1873.413	361.3477	-532.5564

All values are expressed in millions of euros (€). Author's own calculations

Table 4.44. Mean Loan Loss Provisions

Loan Loss Provisions			
Year	*Core Banks*	*Non-Core Banks*	*Average*
2005	217.125	35.45454	83.9
2006	229.9481	66.66647	107.4869
2007	253.5886	41.2489	94.33383
2008	525.3832	78.94247	190.5527
2009	801.9366	155.2081	316.8902
2010	936.274	185.1107	372.9016
2011	7832.665	447.3132	3132.896
2012	2012.512	252.8106	956.6911

All values are expressed in millions of euros (€). Author's own calculations

With respect to condition 5, market competition, an explanation of the findings regarding Greek banks is as follows. In recent history, the Greek banking sector has been characterized by two distinct periods. During the first period, the focus was on retail banking, with banks enlarging their products and services, improving service quality, modernizing and expanding their branch networks and alternative distribution channels, investing heavily in new technology, and improving their internal processes (Giokas and Tsolas, 2008). This expansion of the Greek banking system was accompanied by a more liberal cost minimisation approach by Greek banks. Indeed, further examination of the results suggests that even though Greek banks display significantly low cost efficiency behaviour at the beginning of our sample period, major improvements in managing their costs are evident at a later stage. This is indicated by the upward trend in the mean efficiencies between the years 2005-2008, leading towards the sample period after the financial crisis. The low cost efficiencies prior to the 2008 crisis could be an indication of the bad management hypothesis as proposed by Berger and DeYoung (1997) and found by Williams (2004) when examining a large sample of European savings banks from 1990 to 1998[53]. The hypothesis proposes that low cost efficiency scores are Granger-caused by large amounts of loan loss provisions due to an inadequate control of operating costs (translating in low cost efficiencies). Such poor managerial practices are accompanied by a lack of control over the credit monitoring process (customers are insufficiently monitored and compliance with the loan contract not ensured). Thus, leading to increases in the loan loss provisions after

[53] The econometric results presented by the author suggested that the most pressing management problem for European banks is bad management.

a lag period. In the case of our sample, this behaviour is supported by the overall upward trend of loan loss provisions between the years 2005 – 2008, which could prove to be an indication in favour of the bad management hypothesis[54]. Interestingly, recent studies which present conflicting results, include Louzis et al., (2012), who find evidence in favour of the "bad management" hypothesis in their study on determinants of Non-Performing Loans in Greece, for the years 2003 – 2009. Louzis et al., (2012) stress the importance of focusing on managerial performance as a means of detecting potential NPL increases, as performance and inefficiency measure may serve as leading indicators for future problem loans. However, more recently, Monokroussos et al., (2016) suggest that the primary cause of the sharp increase in non-performing loans following the debt crisis is mainly attributed to the economic contraction of domestic activity and an increase in the unemployment rate. Concerning the 'bad management hypothesis', the authors find no evidence indicating that aggressive lending practises by the major Greek banks in an attempt to boost earnings by extending access to credit to lower credit quality individuals. Further econometric investigation with respect to the intertemporal link between NPLs and cost efficiency follows in Chapter 5.

In the latter years of the sample, the Greek banking sector is characterized by intensified competition among Greek banks. Provopoulos (2014) notes that "a series of sovereign downgrades, beginning in late 2009, led to what initially was a liquidity problem for the banks. The sovereign downgrades generated increased uncertainty, leading to deposit withdrawals and deleveraging, which fed on each other, compounding the problems faced by the banking sector, exacerbating the economic contraction, and contributing to a rise in non-performing loans (page 244)". Further downgrades of Greek banks eventually led to their exclusion from the interbank market, effectively deteriorating their capacity to provide liquidity. After the emergence of the debt crisis and due to the adverse economic conditions, the main focus of Greek banks shifted towards cost reduction and optimization of branch network coverage and efficiency through selective branch closure[55].

[54] Exhaustive econometric testing of the aforementioned hypotheses is not within the scope of the current thesis. It is though within our intentions to further examine the econometric relationship between NPL's and cost efficiency, following a base line methodology, following Podpiera and Weill (2008), Casu and Girardone (2009) and Fiordelisi et al., (2011) in Chapter 5.

[55] Table 8.1 in Appendix A provides an overall summary of the branch network for the sample period and banks under examination.

For the two key crisis years of the sample, 2008-2009 and 2010-2011 (after the outbreak of the Global Financial Crisis but before the full manifestation of the Greek debt crisis which effectively hit Greece in late 2009), most models exhibit a drop in their mean estimated cost efficiencies. That is, more specifically, TVM1-6Z, -3.13%; TVM2-6Z, -6.93% and TVM3-6Z -2.5%; TFE1, -3.3%; TFE2, -3.9% and TFE3, -8.6% for the first crisis point [56]. In relation to the second crisis point, the decrease in cost efficiency equals: TVM1-6Z, -1.2%; TVM3-6Z, -1.2%; TFE1, -0.14%; TFE2 -0.7%. Only models TVM2-6Z and TFE3 indicate an increase, 11.5% and 0.2% respectively. A possible explanation for this reduction is again the bad luck hypothesis, according to which an exogenous shock (in the case of Greek banks this shock can be easily thought of as the sovereign debt crisis which started to materialise in 2010), increases loan loss provisions and Granger-causes a decrease in the cost efficiency. Thus, bank managers are inclined to increase operating expenses in an attempt to address this adverse situation by allocating resources to protect the quality of the existing loan portfolio and increase monitoring towards any potential future bad loans[57].

Further decomposition of our results (Tables 5.45 to 5.47) indicate that overall, all specifications, follow a similar trend, starting with low efficiency scores and then moving towards the frontier towards the end of the sample period. Interestingly, only the 4Z and 5Z specifications capture a reduction in the cost efficiencies in the aftermath of the GFC (2008-2009). That is, inclusion of the CR5 ratio and the Domestic Credit to the private sector influence the estimated scores. The small reduction in the CR5 ratio, leads, therefore, to a reduction in the mean efficiency scores estimated (all TVM1-4Z, TVM2-4Z, TVM3-4Z indicate a reduction of -1.35%, -4.80% and -0.21% respectively for the aforementioned years).

Inclusion of market concentration in Greece affects the cost efficiencies estimated as a marginally less concentrated market indicates a reduction in cost efficiencies. These specific reductions in the efficiency scores could be suggestive of the reverse of the

[56] By the spring of 2010, spreads between 10-year Greek and German sovereigns reached 1000 basis points. Following several months of negotiations, on May, 9, 2010 the Greek government reached agreement with the European Commission, the European Central Bank, and the International Monetary Fund on a 110-billion-euro adjustment program (Provopoulos, 2014).

[57] Extensive econometric testing of the 'bad luck' hypothesis extends beyond the focus of the thesis - much like the 'bad management' hypothesis previously discussed. As stated above, it is our intention to further examine the econometric relationship between NPL's and cost efficiency in Chapter 5.

quiet life hypothesis as originally proposed by Hicks (1935). That is, the reduction in competitive pressures (proxied by an increase in market concentration) in the banking industry should be translated to more inefficient banks, indicating that way a reduced effort by management to control operating efficiency and costs[58,59].

Interestingly, after the 2008-2009 period, all the TVM under 4Z and 5Z specifications exhibit an upward trend, following the upward movement of both CR5 and credit. Finally, under the TVM-5Z specifications (inclusion of domestic credit to private sector, as a percent of GDP), our results suggest the incremental credit provided by the banking sector has no effect on cost efficiency, as the mean scores remain qualitatively similar to the ones estimated under the 4Z specifications (see, Table 4.48 and Figure 4.2 for the auxiliary variables progression over time).

In conclusion, despite the lack of a clear consistent trend throughout the sample (upward or downward) in the results, it is obvious that the global financial crisis led to high cost efficiencies generally consistent with what are believed to be the competitive condition in the banking industry, especially given the restructuring process. The estimated performance indicators seem to capture the cost cutting strategies implemented by bank managers in a market where output expansion was not possible due lack of liquidity and financial resources. However, additional analysis is required in order to formally test preliminary indications of either bad management, bad luck and quiet life hypotheses in an attempt to further disentangle the reasons behind the changes in the cost efficiencies and the possible link to the internal risk functions of Greek banks.

[58] Casu and Girardone (2009), examining 5 EU countries provide findings that do not support Hick's (1935) quiet life hypothesis. Their findings indicate that an increase in banks' monopoly power does not translate into a decrease in cost efficiency.

[59] It is worth noting that rigorous econometric investigation of the presence of the "quiet life" hypothesis extends beyond the scope of the thesis. It is however our intention to further examine the link between SF cost efficiencies and market competition/concentration in future research.

Table 4.45. Time Varying Model 1 - Mean cost efficiency

Year	*3Z*	*4Z*	*5Z*	*6Z*
2005	0.609	0.510	0.506	0.496
2006	0.584 (-4.11%)	0.582 (14.12%)	0.576 (13.83%)	0.578 (16.53%)
2007	0.824 (41.10%)	0.813 (39.69%)	0.819 (42.19%)	0.784 (35.64%)
2008	0.9 (9.22%)	0.941 (15.74%)	0.949 (15.87%)	0.958 (22.19%)
2009	0.969 (7.67%)	0.928 (-1.38%)	0.897 (-5.48%)	0.928 (-3.13%)
2010	0.861 (-11.15%)	0.929 (0.11%)	0.97 (8.14%)	0.973 (4.85%)
2011	0.919 (6.74%)	0.939 (1.08%)	0.972 (0.21%)	0.961 (-1.23%)
2012	0.909 (-1.09%)	0.972 (3.51%)	0.975 (0.31%)	0.97 (0.94%)

The percentage change is included in the parenthesis. Where TVM1: Time Varying Model 1, without a risk metric.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.46. Time Varying Model 2 - Mean cost efficiency

Year	*3Z*	*4Z*	*5Z*	*6Z*
2005	0.613	0.497	0.499	0.464
2006	0.593 (-3.26%)	0.575 (15.69%)	0.574 (15.03%)	0.531 (14.44%)
2007	0.829 (39.80%)	0.79 (37.39%)	0.809 (40.94%)	0.736 (38.61%)
2008	0.901 (8.69%)	0.938 (18.73%)	0.947 (17.06%)	0.879 (19.43%)
2009	0.968 (7.44%)	0.893 (-4.80%)	0.898 (-5.17%)	0.818 (-6.94%)
2010	0.864 (-10.74%)	0.933 (4.48%)	0.964 (7.35%)	0.828 (1.22%)
2011	0.92 (6.48%)	0.939 (0.64%)	0.966 (0.21%)	0.924 (11.59%)
2012	0.905 (-1.63%)	0.973 (3.62%)	0.975 (0.93%)	0.976 (5.63%)

The percentage change is included in the parenthesis. Where, TVM2: Time Varying Model 2, with Total Equity as netput.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.47. Time Varying Model 3 - Mean cost efficiency

Year	*3Z*	*4Z*	*5Z*	*6Z*
2005	0.601	0.506	0.498	0.486
2006	0.573 (-4.66%)	0.573 (13.24%)	0.561 (12.65%)	0.561 (15.43%)
2007	0.816 (42.41%)	0.806 (40.66%)	0.806 (43.67%)	0.769 (37.08%)
2008	0.895 (9.68%)	0.936 (16.13%)	0.944 (17.12%)	0.957 (24.45%)
2009	0.969 (8.27%)	0.934 (-0.21%)	0.9 (-4.66%)	0.933 (-2.51%)
2010	0.854 (-11.87%)	0.923 (-1.18%)	0.971 (7.89%)	0.972 (4.18%)
2011	0.922 (7.96%)	0.94 (1.84%)	0.974 (0.31%)	0.96 (-1.23%)
2012	0.915 (-0.76%)	0.972 (3.40%)	0.975 (0.10%)	0.97 (1.04%)

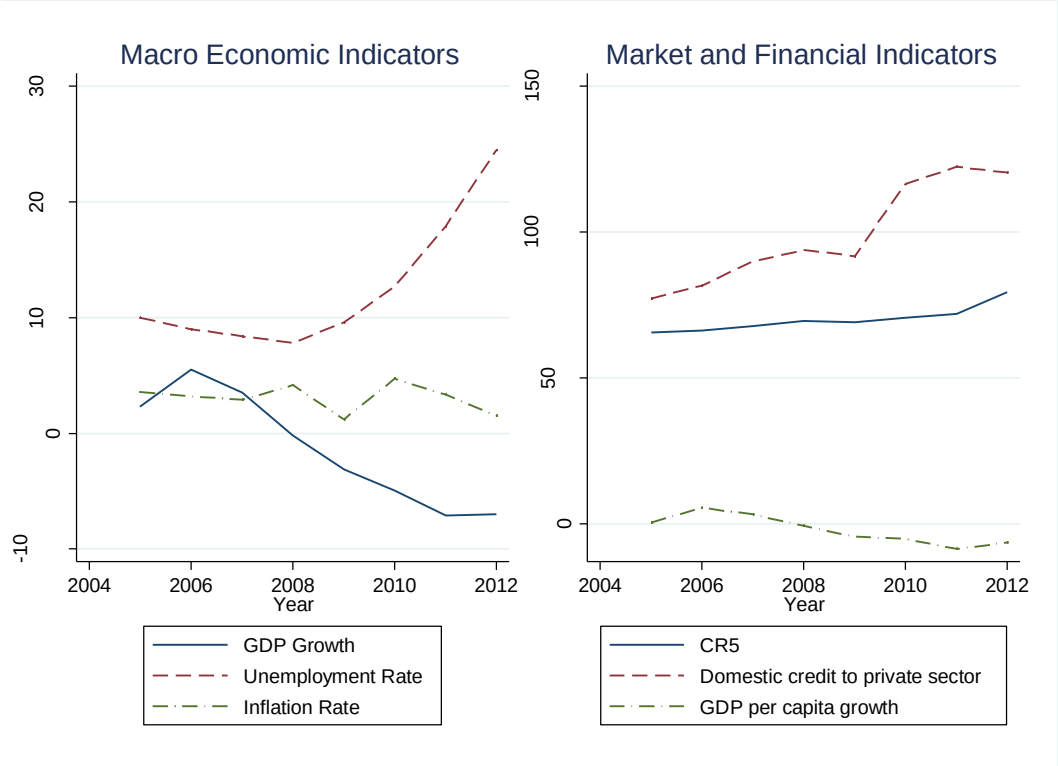
The percentage change is included in the parenthesis. Where, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.
Where, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.48. Evolution of auxiliary variables over time

Year	*GDPGR*	*UN*	*Inf*	*CR5*	*Credit*	*CapGr*
2005	2.28	10	3.545	65.6	77.147	.552
2006	5.507	9	3.195	66.3	81.639	5.482
2007	3.53	8.4	2.895	67.7	90.011	3.212
2008	-.215	7.8	4.152	69.5	93.826	-.652
2009	-3.136	9.6	1.21	69.19	91.762	-4.400
2010	-4.943	12.7	4.712	70.64	116.517	-5.163
2011	-7.105	17.9	3.329	71.99	122.334	-8.616
2012	-6.972	24.5	1.501	79.47	120.425	-6.315

Where, GDPGR: Gross Domestic Product (% change), Un: Unemployment rate (% change), Inf: Inflation rate (% change), CR5: top five Concentration Ratio, Credit: Domestic credit to private sector (% of GDP), CapGr: GDP per capita growth (% change). Author's own calculations.

Figure 4.2. Evolution of auxiliary variables over time



Author's own calculations.

4.5.6 Condition 6 - Consistency with non-frontier performance measures

The sixth consistency criterion is based on the premise that a positive relationship between the SFA efficiency estimates and the more traditional non-frontier indicators should exist, even though Bauer et al., (1998) do not expect a perfect correlation of 1.00. The underlying argument being that both types of performance measurements should be able to capture the behaviour of the banks' in a reasonably similar manner. Traditional performance measures used by bank managers and consultants to evaluate performance are based on accounting financial ratios. Indicators produced by means of SFA model specifications are subject to assumptions regarding the optimization concept (economic efficiency and technological efficiency), functional forms employed, the existence of random error, the underlying distributional assumptions imposed on both inefficiencies and random error and the shape of efficiency frontier. The intuition of this link is that 'possible' positive correlations with non-frontier measures could provide additional reassurance that the SFA estimates are not an artificial product of all the aforementioned assumptions. However, such a comparison could prove to be misleading. That is, limitations of traditional performance ratios are well documented within the efficiency literature. For example accounting financial ratios do not take into account information regarding the composition of the output produced and input prices (Berger and Humphrey, 1992; Berger et al., 2009); do not accommodate a multiple input/output mix or incorporate the impact of exogenous factor on the production/cost function; and are more relevant than in a single output single input context making it difficult to gain insight of a DMU's performance when not all of its ratios are of the same level (Thanassoulis et al., 1996).

In other words, as Thanassoulis et al., (1996) note, "given the fact that DEA measures of performance are based on simultaneous consideration of multiple inputs and outputs while each Performance Indicator (PI) measures performance in relation to one input and one output only, we would normally expect DEA and individual-PI based assessments of the performance of a unit not to agree. If several PI values are combined in some manner to gain some view of the overall performance of a unit that view may accord better with that gained using DEA as both views would be based on simultaneous consideration of multiple inputs and outputs (page 230)". Such information are present in the construction of the efficiency frontier when a cost function is estimated, hence allowing for the cost efficiency indicators to incorporate

both the vector of production and the input prices in the final efficiencies produced. For example, the cost to income ratio may increase due to increased competition, leading in higher cost to income ratio through to reduction in the interest margins. This commonly shows that a cost efficient bank is producing a high-cost output vector due to making more loans and less liquid assets or simply because it is facing higher input prices. Therefore, examination of the cost to income ratio alone might produce misleading information about how well a bank is converting its inputs into outputs and thus incorrectly identifying a bank as a poor performer.

Additionally, Spearman's correlation results examining the consistency of SFA models estimated with traditional non-frontier indicators can be subject to sample selection sensitivity. In a previous version of the study presented by Maudos et al., (2002b) , when using an extended sample of 11 European Union countries (instead of 10 used in the latter version) and over the same period (1993-1996), the authors report positive and significant correlations to the cost per unit of asset ratio, whereas in the latter version of the study they report negative rank correlations (for more details and comparisons across the two versions of the study, see Maudos et al., 2002a and 2002b). It is worth noting that in both studies the authors used the positive of the Total Costs to Assets ratio instead of a negative as in the current study, leading to contradicting results. That is, comparison accounting based performance indicators are used; Return on Average Assets (ROAA); Return on Average Equity (ROAE) and the negative of the Cost to Income Ratio (CtI). With respect to the latter, the minus sign is placed for simplicity in the interpretation of the results. These indicators capture the economic optimization function of banking institutions in terms both of cost and revenues and have been used in prior research (see, Bauer et al., 1998 and Maudos et al., 2002b).

Tables 4.49 to 4.51 show the Spearman's Rank correlation tests per year for each model specification. In the vast majority of cases the correlations for all models under examination are statistically insignificant. Whereby, the exception in this set of results concerns 2009 and 2011 were they exhibit a statistically significant negative correlation with the Cost to Income ratio. Paradoxically, given the sample employed and the choice of input/output mix, the most cost efficient banks have the highest average costs and for the year 2011 negatively correlated to ROAE (indicating a positive relationship between profitability and a reduction in cost efficiency). Furthermore, a lack of a

monotone relationship between ROAA or ROAE and cost efficiency indicates that inefficient banks translate their higher costs into higher prices and still earn positive profits, pointing towards evidence of market power within the Greek financial sector.

Overall, our results suggest that both the return indicators and the cost to income ratios fail to account for the efficiency characteristics of the Greek banking system. This fact is not surprising given that the behaviour of the correlations presented in this study are mostly in line with the arguments put forward that frontier performance measurements are superior than traditional indicators. Even though Bauer et al., (1998) and Maudos et al., (2002b) found positive Spearman rank correlations between the popular accounting ratios and frontier results (it should be noted that their estimates were only weakly correlated)[60,61]. The results presented here could potentially indicate that such ratios might be suffering from influences due to accounting and reporting rules.

In the above discussion we revisited the conditions first proposed by Bauer et al., (1998) under the context of the Greek banking system. The first three conditions determine whether the estimated models are consistent with each other in terms of efficiency levels, rankings and correspondence in identification of best and worst performers in the sector. The last three criteria determine the degree to which the scores are reasonably consistent over time, market condition, and with non-frontier performance indicators.

By filtering the efficiency scores through the proposed conditions, useful conclusions are drawn regarding both the estimates and the structure of future policy recommendations. Our findings suggest that both the TVM and TFE applications produce results that have comparable means, standard deviations and other distributional properties - a finding that also holds in the case where additional TVM models were estimated. Similarly, both models meet the second condition, yielding high and statistically significant Spearman's rank order correlations, indicating

[60] Technical and cost efficiency measures are believed to be better indicators of performance than the traditional accounting ratios.(Beccalli, et al., 2006).

[61] For example, Bauer et al., (1998) report fairly low correlations, about 10% `or less, with only one correlation approaching 20%. The ratio of labour/branch which was additionally tested in their study – showing negative correlations, due to lack of complete information was not possible to be tested in the current research project.

consistency both across models (TVM vs. TFE) and within models. Finally, with the exception of TFE3, all models did a good job of identifying the same banks as either 'best' or 'worst' performers having high correspondence rankings.

Regarding the second set of conditions, which measure the degree to which the estimated cost efficiencies are consistent with reality, TVM models show good stability over time, supported by significant Spearman's rank correlation tests. The Four-Year-Apart correlation was mostly insignificant but this is not surprising given the volatile economic environment under which Greek banks operate. The main finding of this test is the behaviour of the TFE models. Effectively, all three collapse under closer examination. With the exception of one positive and significant Spearman ρ value, all the remaining correlations are either insignificant or more importantly, negatively correlated, indicating high inter temporal volatility. Such results suggest that the TVM models, given the sample selected and the input/output mix, are better in supporting proposed policy recommendations given their behaviour over time. Of course policy design should not be based solely on one set of frontier results, however this condition, could prove to be an indication for future research. We suggest that policies with an implementation horizon of more than three years might prove to target the wrong institutions.

All models are consistent with what are arguably the competitive conditions of the Greek banking system. Both sets of results show the same trends and patterns, following the market conditions in the Greek economy. Finally, it is clear that the current research has produced inconsistent results with prior research adding evidence on the debate between the suitability of a comparison between frontier estimates and more traditional performance indicators. It is clear that the choice between TVM and TFE models for secondary analysis is not an easy one, since both exhibit reasonable stability and meet most of the conditions. A possible tie breaker that will help in this choice is condition 4 – stability over time. The TVM models showed a high degree of consistency, whereas the TFE models collapsed, indicating an unstable nature, thus rendering them unsuitable candidates for the second stage analyses of Loan Loss Provisioning modelling. In the next section we introduce Condition 7 as a tool to further examine the TVM models and to determine which set of SFA cost estimates

will serve as the main performance indicator for the LLP analysis presented in Chapter 5, which is the main focus of the Thesis.

Table 4.49. Consistency with standard non Frontier performance measures – Time Varying Model 1

				3Z				
	2005	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
ROAA	0.071	-0.026	0.110	-0.248	-0.306	0.126	0.318	-0.175
ROAE	0.207	0.158	0.241	-0.267	-0.255	0.114	0.472	
-CtI Ratio	-0.060	-0.070	0.102	-0.232	-0.344	0.235	-0.709**	-0.030
				4Z				
ROAA	-0.180	-0.038	0.189	-0.248	-0.396	0.097	0.387	-0.297
ROAE	-0.303	0.141	0.329	-0.305	-0.335	0.085	0.554*	
-CtI Ratio	-0.360	-0.108	0.123	-0.285	-0.441*	0.182	-0.718**	-0.090
				5Z				
ROAA	-0.196	-0.082	0.189	-0.254	-0.461*	0.097	0.277	-0.345
ROAE	-0.289	0.091	0.329	-0.279	-0.408	0.085	0.400	
-CtI Ratio	-0.385	-0.141	0.123	-0.244	-0.497*	0.182	-0.709**	-0.115
				6Z				
ROAA	-0.187	-0.082	0.160	-0.287	-0.409	0.102	0.305	-0.345
ROAE	-0.275	0.091	0.300	-0.300	-0.350	0.088	0.445	
-CtI Ratio	-0.389	-0.141	0.088	-0.279	-0.455*	0.194	-0.718**	-0.115
Observations	*15*	*16*	*16*	*16*	*16*	*16*	*11*	*10*

**Correlation is statistically significantly different from zero at the 10% level*
***Correlation is statistically significantly different from zero at the 5% level*
****Correlation is statistically significantly different from zero at the 1% level*
Where TVM1: Time Varying Model 1, without a risk metric, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change). ROAA = Return on Average Assets; ROAE = Return on Average Equity; -CtI = Negative of Cost to Income Ratio. The number of observations for the year 2005 is 15 since two banks, namely, Attica Bank SA-Bank of Attica SA and General Bank of Greece SA share an identical value for ROAA. The Spearman's Rank order correlation test was not performed for the year 2012 and ROAE due to incompatible length of observations in the relevant variables due to one missing value in ROAE (Eurobank Ergasias SA).

Table 4.50. Consistency with standard non Frontier performance measures – Time Varying Model 2

	2005	2006	2007	2008	2009	2010	2011	2012
				3Z				
ROAA	0.069	0.038	0.157	-0.359	-0.306	0.202	0.387	-0.381
ROAE	-0.160	0.226	0.285	-0.388	-0.255	0.188	0.554*	
-CtI Ratio	-0.078	-0.005	0.126	-0.350	-0.379	0.279	-0.718**	-0.321
				4Z				
ROAA	-0.155	0.017	0.151	-0.369	-0.396	0.185	0.451	-0.442
ROAE	-0.296	0.194	0.302	-0.391	-0.338	0.179	0.627**	
-CtI Ratio	-0.339	-0.050	0.102	-0.355	-0.476*	0.261	-0.654**	-0.333
				5Z				
ROAA	-0.182	0.023	0.175	-0.357	-0.396	0.141	0.350	-0.466
ROAE	-0.257	0.191	0.323	-0.373	-0.338	0.135	0.509	
-CtI Ratio	-0.378	-0.058	0.117	-0.350	-0.476*	0.214	-0.718**	-0.369
				6Z				
ROAA	-0.141	0.020	0.188	-0.408	-0.381	0.202	0.501	-0.381
ROAE	-0.207	0.182	0.347	-0.423	-0.329	0.197	0.636**	
-CtI Ratio	-0.353	-0.055	0.120	-0.417	-0.458*	0.267	-0.636**	-0.260
Observations	*15*	*16*	*16*	*16*	*16*	*16*	*11*	*10*

**Correlation is statistically significantly different from zero at the 10% level.*

***Correlation is statistically significantly different from zero at the 5% level.*

****Correlation is statistically significantly different from zero at the 1% level.*

Where TVM2: Time Varying Model 2, with Total Equity as netput, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change). ROAA = Return on Average Assets; ROAE = Return on Average Equity; -CtI = Negative of Cost to Income Ratio. The number of observations for the year 2005 is 15 since two banks, namely, Attica Bank SA-Bank of Attica SA and General Bank of Greece SA share an identical value for ROAA. The Spearman's Rank order correlation test was not performed for the year 2012 and ROAE due to incompatible length of observations in the relevant variables due to one missing value in ROAE (Eurobank Ergasias SA).

Table 4.51. Consistency with standard non Frontier performance measures – Time Varying Model 3

	2005	2006	2007	2008	2009	2010	2011	2012
				3Z				
ROAA	0.023	-0.023	0.128	-0.282	-0.382	0.117	0.159	-0.248
ROAE	-0.239	0.161	0.255	-0.294	-0.332	0.117	0.318	
-CtI Ratio	-0.067	-0.052	0.111	-0.270	-0.402	0.264	-0.736***	-0.066
				4Z				
ROAA	-0.148	-0.005	0.189	-0.290	-0.396	0.097	0.382	-0.175
ROAE	-0.317	0.179	0.329	-0.300	-0.335	0.085	0.554*	
-CtI Ratio	-0.275	-0.064	0.123	-0.276	-0.441*	0.182	-0.754***	-0.018
				5Z				
ROAA	-0.193	-0.058	0.189	-0.282	-0.396	0.097	0.323	-0.345
ROAE	-0.296	0.111	0.329	-0.305	-0.344	0.085	0.409	
-CtI Ratio	-0.371	-0.114	0.123	-0.282	-0.426*	0.182	-0.718**	-0.115
				6Z				
ROAA	-0.234	-0.073	0.189	-0.265	-0.394	0.102	0.223	-0.260
ROAE	-0.325	0.097	0.311	-0.288	-0.338	0.088	0.363	
-CtI Ratio	-0.385	-0.120	0.132	-0.261	-0.426*	0.194	-0.745***	-0.030
Observations	*15*	*16*	*16*	*16*	*16*	*16*	*11*	*10*

**Correlation is statistically significantly different from zero at the 10% level.*

***Correlation is statistically significantly different from zero at the 5% level.*

****Correlation is statistically significantly different from zero at the 1% level.*

Where TVM3: Time Varying Model 3, with Loan Loss Provisions as netput, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change). ROAA = Return on Average Assets; ROAE = Return on Average Equity; -CtI = Negative of Cost to Income Ratio. The number of observations for the year 2005 is 15 since two banks, namely, Attica Bank SA-Bank of Attica SA and General Bank of Greece SA share an identical value for ROAA. The Spearman's Rank order correlation test was not performed for the year 2012 and ROAE due to incompatible length of observations in the relevant variables due to one missing value in ROAE (Eurobank Ergasias SA).

Table 4.52. Consistency with standard non Frontier performance measures – True Fixed Effects

				TFE1				
	2005	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
ROAA	-0.103	-0.029	0.122	0.089	-0.412	0.241	0.132	-0.175
ROAE	-0.175	0.164	0.182	0.161	-0.335	0.244	0.290	n/a
-CtI Ratio	-0.207	-0.079	0.150	-0.017	-0.320	0.364	-0.627*	-0.066
Observations	15	16	16	16	16	16	11	9
				TFE2				
ROAA	-0.096	-0.091	0.163	0.173	-0.449*	0.329	0.132	-0.212
ROAE	-0.160	0.088	0.220	0.226	-0.376	0.320	0.281	n/a
-CtI Ratio	-0.235	-0.150	0.173	0.044	-0.358	0.432*	-0.663*	-0.090
Observations	15	16	16	16	16	16	11	10
				TFE3				
ROAA	-0.307	-0.108	0.401	-0.061	-0.192	0.217	-0.045	-0.297
ROAE	-0.328	0.097	0.444*	0.002	-0.176	0.258	0.009	n/a
-CtI Ratio	-0.307	-0.141	0.397	-0.170	-0.205	0.232	-0.345	-0.139
Observations	*15*	*16*	*16*	*16*	*16*	*16*	*11*	*10*

**Correlation is statistically significantly different from zero at the 10% level.*
***Correlation is statistically significantly different from zero at the 5% level.*
****Correlation is statistically significantly different from zero at the 1% level.*
Where TFE1: True Fixed Effects Model 1, without a risk metric, TFE2: True Fixed Effects Model 2, with Total Equity as netput, TFE3: True Fixed Effects Model 3, with Loan Loss Provisions as netput, 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change). ROAA = Return on Average Assets; ROAE = Return on Average Equity; -CtI = Negative of Cost to Income Ratio. The number of observations for the year 2005 is 15 since two banks, namely, Attica Bank SA-Bank of Attica SA and General Bank of Greece SA share an identical value for ROAA. The Spearman's Rank order correlation test was not performed for the year 2012 and ROAE due to incompatible length of observations in the relevant variables due to one missing value in ROAE (Eurobank Ergasias SA). ROAA = Return on Average Assets; ROAE = Return on Average Equity; -CtI = Negative of Cost to Income Ratio The number of observations for the year 2005 is 15 since two banks, namely, Attica Bank SA-Bank of Attica SA and General Bank of Greece SA share an identical value for ROAA. The Spearman's Rank order correlation test was not performed for the year 2012 and ROAE due to incompatible length of observations in the relevant variables due to one missing value in ROAE (Eurobank Ergasias SA).

4.5.7 Condition 7 - Goodness of Fit

In order to further analyse the TVM models and to assess the goodness of fit from the estimated cost functions, two sets of testing procedures are employed. First, given the nested nature of the within models, a series of Likelihood Ratio tests is conducted in order to identify the effect of the inclusion of the additional auxiliary variable into the frontier. More specifically, for example, TVM1-3Z is nested within TVM1-4Z and TVM1-4Z is nested within TVM1-5Z. We start therefore with estimating the LR statistic (following equation (3.45)) to test the significance of the additional regressors in equation (3.34). If we reject the null hypothesis then we proceed into estimating the LR statistic for the next set of nested models, TVM1-4Z and TVM1-5Z until we reach the last combination of models. In the case were we fail to reject the null hypothesis, we end the process at this stage and subsequently select the last chosen specification with the higher number of auxiliary variable as our preferred. We proceed in a similar manner to further examine TVM2 and TVM3.

As a second post estimation model selection tool, the goodness of fit of the estimated cost functions is evaluated via the use of a class of metrics called discrimination functions. That is, Akaike Information Criteria (AIC), Corrected Akaike Information Criteria (AICc) proposed by Hurvich and Tsai (1989), Bayesian Information Criteria (BIC) and the Hannan–Quinn Information Criterion (HQC) are constructed, as in equations (4.9), (4.10), (4.11) and (4.12) respectively[62,63],

$$AIC = -2 \times LL + 2 \times k. \tag{4.9}$$

$$AICc = AIC + \frac{2 \times k \times (k+1)}{n-k-1}. \tag{4.10}$$

[62] Akaike based his derivation on a large sample size. Hurvich and Tsai (1989) proposed a second-order bias adjustment for small, more realistic sample sizes. It is recommended that AICc be used whenever $^{n}/_{k} < 40$.

[63] A full methodological exposition of the various information criteria is beyond the scope of this discussion. Bonate (2008) notes, "Akaike's criterion and its derivations has been called by some [see Verbeke and Molenberghs (2000) for example] as a minimization function plus a penalty term for the number of parameters being estimated. As more model parameters are added to a model, $-2 \times LL$ tends to decrease but $2 \times k$ increases. Hence, AIC may decrease to a point as more parameters are added to a model but eventually the penalty term dominates the equation and AIC begins to increase. Conceptually this fits into the concept of bias-variance trade-off or the trade-off between over fitting and under fitting (page 25)".

$$BIC = -2 \times LL + k \times \ln(n). \quad (4.11)$$

$$HQC = -2 \times LL + 2 \times k \times \ln(\ln(n)). \quad (4.12)$$

Where, LL is the maximized log-likelihood of the model, k is the number of parameters estimated and n is the sample size. The model with the smallest discrimination function is superior to all other models having the same number of estimable parameters.

Turning to the results, Table 4.53 presents the findings of the aforementioned LR test. It is clear that under all TVM approaches we end the testing process in the first step. That is, introduction of the 4th macro-indicator into our auxiliary regression in equation (3.34) is supported by the data leading to the conclusion that inclusion of CR5 is supported by the data. However, in the second step of the testing process, we fail to reject the null hypothesis in all TVM specifications, thus indicating towards a rejection of the 3Z, 5Z and 6Z specifications.

Tables 4.54 to 4.56, report the estimated values for the relevant information criteria. It is clear that all discrimination functions confirm that the TVM-4Z is the preferred choice under all model specifications (that is, TVM1, TVM2 and TVM3).

Table 4.53. Likelihood Ratio Test, within specifications - Time Varying Models

	3Z-4Z	*4Z-5Z*	*5Z-6Z*
		TVM1	
LR Statistic	25.79***	-0.103	0.835
		TVM2	
LR Statistic	27.748***	-0.517	1.654
		TVM3	
LR Statistic	24.652***	0.134	1.356

The LR test has a mixed chi square distribution with degrees of freedom equal to the additional parameters estimated. The following critical values were employed for testing 3Z-4Z, 4Z-5Z, 5Z-6Z and 4Z-6Z respectively; $x^1_{0.95}$*: 2.705;* $x^2_{0.95}$*: 5.138.*

Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.54. Information Criteria – Time Varying Model 1

	AIC	*AICc*	*BIC*	*HQC*
3Z	56.027	85.410	149.649	94.032
4Z	32.236	63.736	128.612	71.359
5Z	34.339	68.061	133.469	74.580
6Z	35.504	71.555	137.387	76.862

Where TVM1: Time Varying Model 1, without a risk metric, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change

Table 4.55. Information Criteria - Time Varying Model 2

	AIC	*AICc*	*BIC*	*HQC*
3Z	56.418	90.140	155.547	96.659
4Z	30.670	66.721	132.552	72.028
5Z	33.187	71.681	137.824	75.664
6Z	33.533	74.586	140.923	77.128

Where, TVM2: Time Varying Model 2, with Total Equity as netput, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

Table 4.56. Information Criteria - Time Varying Model 3

	AIC	*AICc*	*BIC*	*HQC*
3Z	58.985	92.706	158.114	99.225
4Z	36.332	72.383	138.215	77.691
5Z	38.197	76.691	142.834	80.674
6Z	38.840	79.893	146.230	82.435

Where, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

To further disentangle the fit of the estimated cost functions, following Wagenmakers and Farrell (2004) and Bonate (2008), the Evidence Ratio (ER) between the two top performing models is also estimated, as the ratio of the two Akaike weights (w_i) between two competing models. Where, the Akaike weight is estimated by equation (4.13)

$$w_i = \frac{\exp(-{}^{1}/_{2} \times \Delta AIC_i)}{\sum_{r=1}^{j} \exp(-{}^{1}/_{2} \times \Delta AIC_r)}. \tag{4.13}$$

And

$$\Delta AIC_i = AIC_i - AIC_{min}. \tag{4.14}$$

A model with a high Akaike ratio is considered to offer the best fit and can be interpreted as the estimated probability that model i is the best model for the selected sample and estimated model specifications. Therefore, an evidence ratio of 25 (that is, ER=0.25/0.01) provides convincing evidence that the model with an Akaike weight equal to 0.25 is a better model than a model with a respective Akaike weight equal to 0.01. Table 4.57 reports the estimated weights for the three models.

Table 4.57. Akaike Weights – Based on AICc

	3Z	*4Z*	*5Z*	*6Z*
TVM1	0.000	0.880	0.101	0.017
TVM2	0.000	0.906	0.075	0.017
TVM3	0.000	0.877	0.101	0.020

Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput, 3Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, 5Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), 6Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio, Domestic credit to private sector (% of GDP), GDP per capita growth (% change).

The respective ER's for TVM1-4Z/5Z, TVM2-4Z/5Z and TVM3-4Z/5Z are estimated as follows,

$$ER_1 = \frac{w_{4Z}(AICc)}{w_{5Z}(AICc)} = 8.712$$

$$ER_2 = \frac{w_{4Z}(AICc)}{w_{5Z}(AICc)} = 12.08$$

$$ER_3 = \frac{w_{4Z}(AICc)}{w_{5Z}(AICc)} = 8.683$$

The ER value results suggest that the models including 4 auxiliary variables in the SFA estimation stage are 8.7, 12.08 and 8.6 times more likely to be the best model in terms of Kullback-Leibler discrepancy than the next best model, TVM-5Z. We therefore conclude that our preferred cost efficiency estimates that will be further adopted as an index of bank performance and managerial behaviour into the LLP econometric specifications, are those estimated from having 4 exogenous variables (Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change) and top five Concentration Ratio).

Given this finding, based on a coherent and strategic modelling methodology reducing all 15 models, we now turn to analysing the efficiency results. Again, it should be noted that the following discussion is based on the TVM-4Z models as appropriate given the

discussion presented above. That is, we discuss in detail the TMV which include 4 macroeconomic variables (Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change) and top five Concentration Ratio) without any netput and including either netput Total Equity and LLP.

4.6 Analysis of Core Banks

Thus far we have examined the stability and overall performance of the cost efficiencies estimated from all the model specifications. The highly concentrated nature of the Greek banking system with a CR5 ratio of 79.47% and 94% for 2012 and 2014 respectively, (European Central Bank, 2015) stresses even more the importance to further evaluate the performance of the systemically important institutions, leading us to the next step of our analysis, to further explore the efficiency of the core banks. Following Berger et al., (2004) and Goddard et al., (2014) we convert the estimated efficiencies into rank order from 0 to 100. For our purposes, we rank the banks based on the inefficiency component. That is, the bank with the lowest residual is ranked as the most efficient (i.e. the bank with the highest cost efficiency estimate). We create a rank ordering in each year of our sample. Following Berger et al., (2004) we convert the rankings into a uniform scale using the formula $(\mathrm{order}_{it}-1)/(n_t-1)$, where order_{it} is the place in descending order of bank i in period t based on its inefficiency component u_{it} and n_t is the number of banks in year t. Given the formulation above, the bank with the highest inefficiency component is assigned the worst rank, $0[(1-1)/(n_t-1)]$ and the bank with the lowest component will have the highest rank, $1[((n_t-1)/(n_t-1)]$. The bank $i's$ efficiency rank in year t gives the proportion of the other sample banks with lower efficiencies for the same year. For example, a score of 0.60 indicates a bank with efficiency levels better than 60% of the other banks in the same year. In that way, the rankings are further refined and become more comparable across time and in that way we obtain an index of relative performance/efficiency.

Tables 4.58 to 4.60 present the cost rankings for the core banks. A value of 0.50 indicates that core institutions are on average equally efficient with non-core banks. The four institutions are on average, across our sampled years, marginally more efficient with respect to the non-core banks (with an average equal to 0.521, 0.51 and 0.527, for TVM1-4Z, TVM2-4Z and TVM3-4Z respectively). Further decomposition indicates that the 2008 crisis led to a reduction in the performance gap between core and non-core banks. Indeed, prior to the 2008 economic crisis, the core institutions where on average more efficient than non-core banks, but subsequently declining after the global financial crisis. That can be shown by estimating the pre and post 2008

average of the mean rankings. That is, for TVM1-4Z, the pre-crisis average is equal to 0.584 when the post-crisis respective score equals 0.424. In a similar manner, under TVM2-4Z the pre and pro-crisis scores equal 0.567 and 0.453. Finally, and following the same trend as the previous SF models, the TVM3-4Z equals 0.597 and 0.458. On average, 2006 is the year that the core banks record the highest relative efficiency scores. For example, under TVM1-4Z, on average the core banks are more cost efficient that 70% of the sample banks operating that same year. Similar results are obtained under TVM2-4Z and TVM3-4Z.

In greater detail, Eurobank Ergasias SA and Piraeus Bank SA are the two top performers on average, with respective scores equal to 0.616, 0.596, and 0.633 for Eurobank Ergasias SA under the three different specifications (TVM1-4Z, TVM2-4Z and TVM3-4Z), and 0.634, 0.618 and 0.626 for Piraeus Bank SA. This finding potentially mirrors the overall quality of the management in the bank – a finding supported by the evaluation of Greek bank executives carried out by Spencer Stuart on behalf of the HFSF in 2016[64][65]. Eurobank Ergasias SA records the highest rank values prior to the 2010 debt crisis, equal to 1 – 0.928. That is, Eurobank Ergasias SA exhibits efficiency levels better than 92.8% of the other banks in the country. Its efficiency ranks deteriorate until reaching a pre-2008 crisis low equal to 26.6% under TVM1-4Z (26.6% under TVM2-4Z and 33.3% under TVM3-4Z), indicating a closing gap between the performance of Eurobank Ergasias SA and the competitors in the industry. Piraeus Bank SA also follows a similar decreasing pattern prior to the crisis. National Bank of Greece SA on the other hand starts from an opposite position, recording low ranking scores in 2005 (equal to 14.2%, 7.1% and 14.2% under TVM1-4Z, TVM2-4Z and TVM3-4Z respectively) and registering its highest values in 2007. Finally, Alpha Bank AE, similarly as National Bank of Greece SA, also records scores that indicate that in 2005 it operated on average closer to the optimal frontier than after the 2008 and 2010 crises.

[64] Spencer Stuart is an executive search and consulting firm, which was appointed by the Bank of Greece to evaluate the quality of top executives in the core banks.

[65] To the present, this study is not published and available, but reports in local news indicate that Eurobank and Alpha Bank appear to be better off than the other Greek banks and as such will require the least amount of board member changes (see http://www.hfsf.gr/files/announcement_20160428_en.pdf, http://www.tovima.gr/en/article/?aid=813859).

Focusing on the two key dates that impacted the Greek economy, 2008 and more importantly 2010, unsurprisingly, all core banks record on average marginally lower efficiency scores after the 2008 crisis. However, under TVM1-4Z only National Bank of Greece SA records a decrease, when all other core institutions either remain stable or even show increasing cost efficiencies. Under, TVM2-4Z, all banks follow the same trend and record higher deviations from the frontier, with Alpha Banks AE recording the highest drop from 0.983 to 0.872. Finally, under TVM3-4Z, results indicate mixed findings. Eurobank Ergasias SA and Piraeus Bank SA record slight increases in their respective scores, whereas National Bank of Greece SA and Alpha Bank AE report either small reductions or present stable cost efficiency scores. In all three cases, the core institutions have strengthened their position against their non-core counterparts as they report on average rank ordering scores indicating that they operate on higher cost efficiencies than 56%, 46% and 48% of the remaining sample banks for TVM1-4Z, TVM2-4Z and TVM3-4Z respectively. Irrespective of the risk metric included in the SFA estimation process, our results indicate that the Greek banking system and more specifically the core banks, have remained relatively insulated from the macroeconomic impact that the crisis has had on other EU banks. That is, it appears that the strong fundamentals of the Greek banking system (for example, high capital-adequacy ratios, low loan-to-deposit ratios, and limited exposure to the toxic assets that set-off the 2007 global financial crisis, see Table 2.1., Chapter 2 for more details) helped banks to address the potential impact of the financial crisis and maintain a high level of performance.

Further analysis of the 2010 cost efficiencies reveal that after the Greek debt crisis erupted in 2010, the core banks register a mild decrease in their efficiency scores (Table 4.58 to 4.60, efficiency scores in parenthesis). This shows a weakening of their positions relative to the rest of the banks operating in the market for that year. Despite this reduction, they still operate, on average, at higher cost efficiencies than 20% of the sampled banks. Indeed, despite the drop in the mean cost efficiencies of core banks, it is interesting to note that the upward trend in the overall mean efficiencies discussed in Section 4.5.5 is sustained by an increase in the efficiency levels of the non-core institutions. For example, in Table 4.61, we observe a -0.9% reduction on average for TVM1-4Z for 2010-2011, whereas, for the same year, the equivalent non-core mean

cost efficiency estimates increase by 2.04%. The remaining two specifications also indicate a similar trend.

It is worth noting that Eurobank Ergasias SA records the sharpest decrease in its relative cost rankings. The bank is moves from a relatively strong position in 2010 (operating in higher cost efficiencies than 66% of the remaining sampled banks) to a lowest position in the market (score of 0) only to move either close to or on the frontier in the next and final year, 2012! That reduction in cost efficiency (together with the reduction in efficiency of the remaining three core institutions) could be attributed to the disposal of NPLs and to the fact that the reduction in values of loans (in levels), will register as reduced output quantities when no change is evident in the input side of the SFA estimation. More specifically, Kumbhakar and Wang (2007) note that, "[…] improvement in the quality of assets might be caused by partial disposal of non-performing loans from the portfolio of the bank assets. Disposal of nonperforming loans will be reflected in the balance sheet as a reduction in the stock value of loans. This will lead to a decrease in total net loans with no corresponding change in the input usage, and thus will be reflected as technical inefficiency because more inputs are used without any increase in outputs. Therefore, the decline in efficiency may not necessarily imply that banks are getting worse over time (page 123)". However, the lack of bank level data does not permit us to further explore this potential link. On the other hand, one additional explanation could be that these reductions may also indicate aggregate spill-over effects from other countries where the core banks have presence. For example, Eurobank Ergasias SA has s presence in Romania, Bulgaria, Serbia, Ukraine, Cyprus, UK and Luxembourg. The remaining core banks also have strong presence in similar countries. Therefore, any potential economic upset could lead to contagion (feedback effect) into the Greek financial system via an indirect channel.

In conclusion, this section focused mainly on the performance of core banks operating in the Greek market. The highly concentrated market and the fact the resulting capital needs for all Greek commercial banks were estimated in May 2012 at €40.5 billion, of which the €27.5 billion corresponded to the four core banks, stress the importance of those institutions to the stability of the Greek financial market. On average, the core banks indicate strong performance, exceeding their respective non-core counterparts. Despite the double hit that the Greek economy suffered, Greek banks operate close to

the optimal frontier, indicating a sound financial system that was able to overcome the strain of the first two years of the Greek debt crisis. The main difficulty that Greek banks and more specifically the core banks, will have to overcome in the near future is to address the challenging issue of increasing NPLs. That is, Greek banks carry a substantial number of NPLs in their balance sheets (as of end of September 2015, Greece reported a ratio of more than 40%) and may need to sell some of those bad quality loans to third parties[66]. In interest to promote stability, Law 4354/2015 (NPL Law) presents the regulatory and legal framework for NPLs in Greece that can be managed by specialised Non-Performing Loan Asset Management Companies (NPL AMC) or to be transferred to other credit or financial institutions, in attempt to mitigate the threatening matter of NPL's in Greek banks' balance sheets[67].

[66] Monokroussos (2016) notes, "a significant portion of problem loans have been restructured in Greece over the last several years, following direct borrower-creditor negotiations to modify their terms. At the end of 2015, the outstanding amount of problem loans in domestic banks' balance sheets stood at c. €98.4bn (or 43.5 percent of total outstanding loans), while the respective level which excludes restructured loans was c. €80.5bn (or 35.6 percent of total loans). So far, loan restructuring has mostly taken the form of maturity extensions (page 2)".

[67] Law 4354/2015 on the management of NPL sets out the regulatory and legal framework for NPL in Greece either to be managed by specialized NPL AMCs or to be transferred to other credit or financial institutions. The NPL AMCs are licensed by the Bank of Greece, following a certain procedure and complying with certain criteria.

Table 4.58. Relative Cost Ranking, TVM1-4Z

	Alpha Bank AE	*Eurobank Ergasias SA*	*National Bank of Greece SA*	*Piraeus Bank SA*	*Mean*
2005	0.428	0.928	0.142	0.857	*0.589*
	(0.629)	(0.645)	(0.425)	(0.578)	
2006	0.666	0.866	0.466	0.8	*0.7*
	(0.826)	(0.701)	(0.588)	(0.645)	
2007	0.466	0.6	0.866	0.733	*0.666*
	(0.934)	(0.845)	(0.876)	(0.860)	
2008	0.2	0.266	0.733	0.333	*0.383*
	(0.914)	(0.935)	(0.950)	(0.935)	
2009	0.266	0.6	0.4	0.666	*0.483*
	(0.931)	(0.936)	(0.923)	(0.941)	
2010	0.466	0.666	0.4	0.733	*0.566*
	(0.931)	(0.941)	(0.941)	(0.945)	
2011	0.2	0	0.3	0.4	*0.225*
	(0.921)	(0.913)	(0.933)	(0.939)	
2012	0.222	1	0.444	0.555	*0.555*
	(0.970)	(0.978)	(0.972)	(0.973)	
Average	*0.364*	*0.616*	*0.469*	*0.634*	***0.521***

Where TVM1: Time Varying Model 1, without a risk metric, 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio

Table 4.59. Relative Cost Rankings TVM2-4Z

	Alpha Bank AE	*Eurobank Ergasias SA*	*National Bank of Greece SA*	*Piraeus Bank SA*	*Mean*
2005	0.357	0.928	0.071	0.857	*0.553*
	(0.612)	(0.639)	(0.385)	(0.573)	
2006	0.666	0.866	0.6	0.733	*0.716*
	(0.778)	(0.685)	(0.610)	(0.632)	
2007	0.4	0.6	0.8	0.733	*0.633*
	(0.923)	(0.815)	(0.860)	(0.843)	
2008	0.2	0.266	0.533	0.466	*0.366*
	(0.923)	(0.930)	(0.943)	(0.940)	
2009	0.266	0.666	0.4	0.533	*0.466*
	(0.872)	(0.917)	(0.903)	(0.909)	
2010	0.466	0.666	0.6	0.866	*0.65*
	(0.935)	(0.948)	(0.944)	(0.953)	
2011	0.3	0	0.4	0.2	*0.225*
	(0.934)	(0.908)	(0.936)	(0.933)	
2012	0.333	0.777	0.222	0.555	*0.472*
	(0.972)	(0.976)	(0.970)	(0.974)	
Average	*0.373*	*0.596*	*0.453*	*0.618*	*0.510*

Where, TVM2: Time Varying Model 2, with Total Equity as netput, 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio.

Table 4.60. Relative Cost Rankings TVM3-4Z

	Alpha Bank AE	*Eurobank Ergasias SA*	*National Bank of Greece SA*	*Piraeus Bank SA*	*Mean*
2005	0.428	1	0.142	0.857	*0.607*
	(0.494)	(0.647)	(0.432)	(0.576)	
2006	0.733	0.866	0.533	0.8	*0.733*
	(0.632)	(0.699)	(0.591)	(0.638)	
2007	0.466	0.6	0.866	0.733	*0.666*
	(0.821)	(0.842)	(0.874)	(0.851)	
2008	0.2	0.333	0.733	0.266	*0.383*
	(0.928)	(0.931)	(0.947)	(0.929)	
2009	0.266	0.6	0.4	0.666	*0.483*
	(0.922)	(0.942)	(0.929)	(0.944)	
2010	0.466	0.666	0.4	0.733	*0.566*
	(0.924)	(0.938)	(0.919)	(0.941)	
2011	0.1	0	0.3	0.4	*0.2*
	(0.922)	(0.913)	(0.930)	(0.942)	
2012	0.333	1	0.444	0.555	*0.583*
	(0.971)	(0.978)	(0.971)	(0.973)	
Average	*0.374*	*0.633*	*0.477*	*0.626*	*0.527*

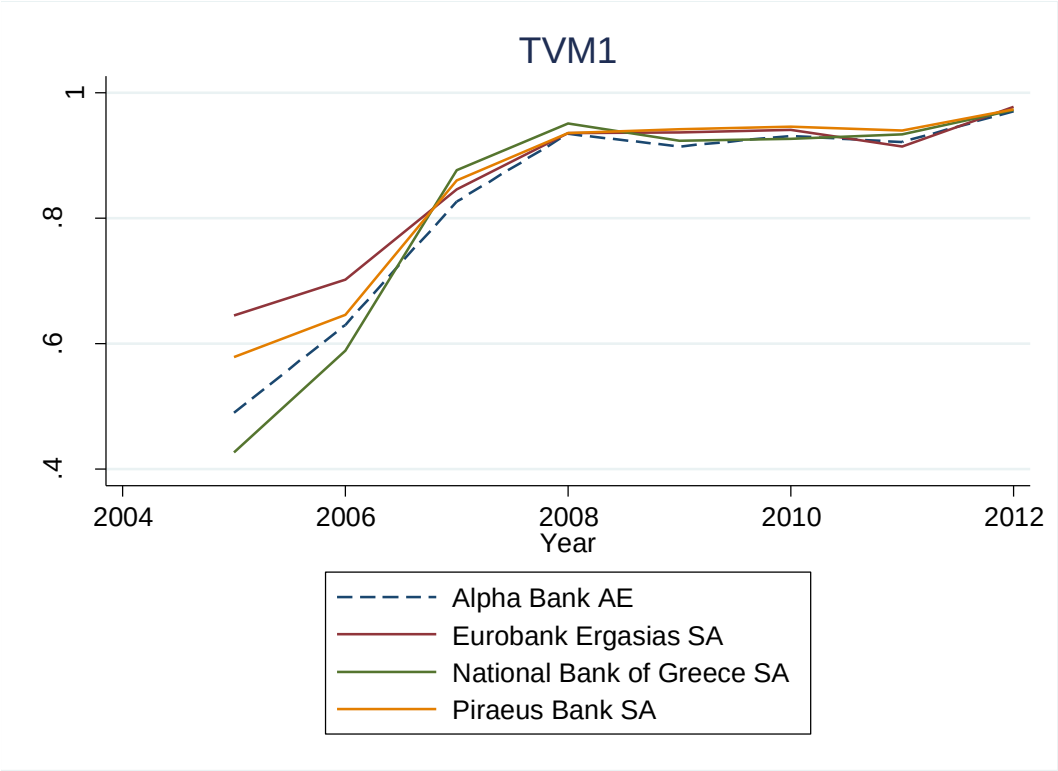
Where, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput, 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio.

Table 4.61. Time Varying Mean Cost Efficiency

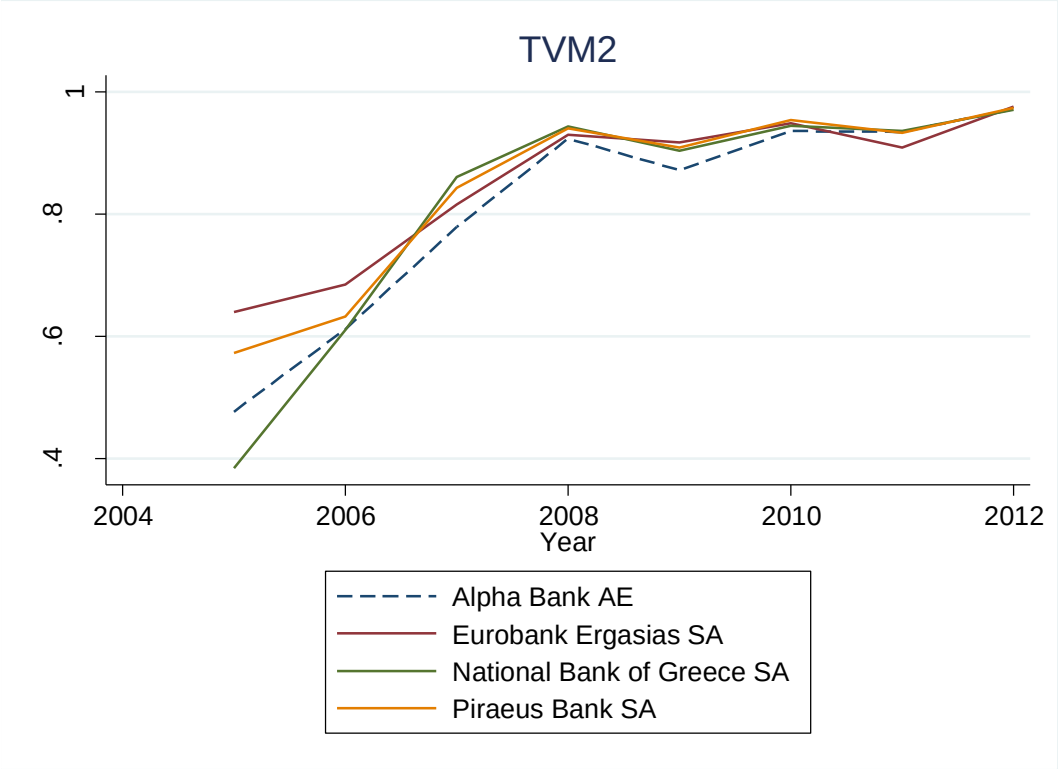
	Core			*Non-Core*		
	TVM1-4Z	*TVM2-4 Z*	*TVM3-4 Z*	*TVM1-4 Z*	*TVM2-4 Z*	*TVM3-4 Z*
2005	0.534	0.518	0.537	0.501	0.489	0.495
2006	0.641	0.635	0.640	0.562	0.555	0.551
2007	0.852	0.824	0.847	0.801	0.779	0.792
2008	0.939	0.934	0.934	0.941	0.939	0.936
2009	0.929	0.900	0.934	0.927	0.890	0.933
2010	0.936	0.945	0.931	0.927	0.929	0.921
2011	0.927	0.928	0.927	0.946	0.946	0.947
2012	0.973	0.973	0.973	0.972	0.973	0.972

Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput, 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio.

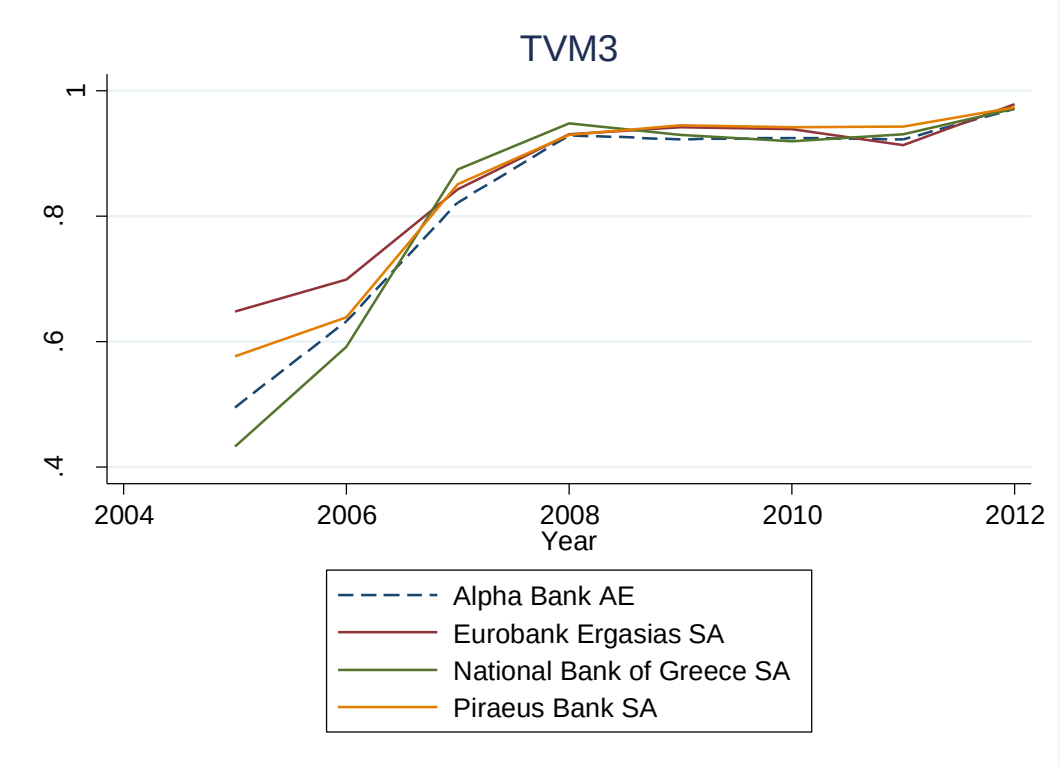
Figure 4.3. Time Varying Mean Cost Efficiency – Core Banks
Panel A



Panel B



Panel C



Where TVM1: Time Varying Model 1, without a risk metric, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.

4.7 Conclusion

This Chapter presents recent cost efficiency estimates for a panel of Greek banks via the estimation of different econometric model specifications. Using a sample covering both the 2008 global financial crisis and the beginning of the recent Greek debt crisis, two sets of cost frontiers were estimated. Following the popular intermediation approach under both the Battese and Coelli (1995) TVM model and the Greene (2005a, 2005b) TFE model specifications, bank specific cost efficiency scores were estimated. The Stochastic Frontier Analysis methodology was used where the stochastic cost function specify a two-component error term that allows for the inefficiency effects to be separated from the random error term. In this manner, the symmetric and normally distributed component captures any random variation of the cost frontier across banks, statistical noise and any measurement error present. Contrary, the other component is a one-sided error term that captures all systematic deviations for the frontier. It carries a positive sign as all inefficient banks operate above the frontier and it is drawn from a non-negative half normal distribution truncated at m_{it}, which is a linear function of a set of covariates that are assumed to be outside the control of management. This allows us to take into account the country macroeconomic factors that have in impact in the cost minimization behaviour of Greek banks.

Given the lack of consensus as to which econometric approach is optimal when estimating a cost frontier, a set of consistency conditions proposed by Bauer et al., (1998) was used in order to ensure that the generated frontier scores are not a derivative of the various distributional assumptions employed. We evaluate the extent to which all cost frontiers meet the aforementioned conditions. Our findings indicate that for the most part all SFA frontiers generated cost efficiencies that meet the conditions. The TVM models perform well under all the conditions whereas the respective TFE models indicated a more unstable performance (for example, under condition 4), thus yielding evidence that they are not suitable candidates for the implementation of the second stage analyses of Loan Loss Provisioning modelling. In order to further distinguish which set of TVM models best fit the data, we proceed evaluation criteria via a post estimation strategy (condition 7) consisting of two goodness of fit tests. That is, a Likelihood Ratio test and a set of information criteria where employed. In both cases, the post estimation tests indicate that the best models for the selected sample and estimated

model specifications are those that incorporate only four macroeconomic indicators into the inefficiency estimation process. Having identified the cost efficiency estimates that will be employed into the second stage LLP modelling strategy, we now turn to discuss the different theories surrounding the empirical LLP literature and to empirically test whether Greek banks have the ability to manage their LLP's attempting to pursue additional management objectives.

Chapter 5

Loan Loss Provisioning

5.1 Chapter Summary

This Chapter aims to advance an under-researched area concerning modelling Loan Loss Provisioning (LLP) risk management behaviour of Greek banks for the 2005-2012 period. In this aim, we jointly incorporate business cycle effects and capital management hypotheses in a combined econometric model following prior research (see, for example, Anandarajan et al., 2007; Ghosh, 2007 and Skala, 2015). In addition, and following Bryce et al., (2015), we also extend the traditional econometric specifications of Berger and DeYoung (1997) by including cost efficiency scores estimated in the previous Chapter. Thus, we begin by estimating static versions in the literature and then re-estimate these models by positing augmented regressions, which incorporate cost efficiency scores[68]. Thereby proceeding to examine the suitability of dynamic auto-regressive models in a similar manner, estimate a baseline specification, which follows prior research; and conclude with findings obtained from an advanced augmented dynamic models.

This Chapter is structured as follows. Section 5.2 discusses the contextual background for this Chapter, offering an overview of the key concepts examined. Section 5.3 provides an overview of the relevant hypothesis investigated and a literature review of the recent LLP studies. Section 5.4 describes our proposed methodologies, the data and variables chosen and the empirical model specifications estimated. Whereas, sub-sections 5.4.1 and 5.4.2 offer discussions on the empirical results for the static and dynamic models respectively. Section 5.5 discusses the recent reforms proposed under Basel III with respect to LLP. Finally, Section 5.6 concludes.

[68] Even though one might believe that estimation of static panel data models are unnecessary we undertake these as it is still common in the literature (for example, Marton and Runesson, 2016, estimate LLP models using OLS and Curcio et al., 2016 using Fixed Effects). Indeed, this strategy allows us to show that static and dynamic models can produce different results.

5.2 Introduction

In relation to accounting, Curcio and Hasan (2015) identify two rules as the conservative valuation of assets (which is central to the European accounting system) and the accurate measurement of each period's net income (strongly emphasized by the American accounting set of rules). Indeed, the underlying principles followed by banks with respect to loan loss accounting may differ significantly across the world, however, they can be considered to be well-established and are surrounded by an on-going debate with respect to their soundness (see Hasan and Wall, 2004). That is, prior research has suggested several motives for bank managers' discretionary behaviour with respect to LLP, including signalling, capital management and management compensation (see, for example, Wahlen, 1994; Collins et al., 1995; Kanagaretnam et al., 2004; and Cheng et al., 2011)[69].

That is, as LLP are one of the main accrual expenses for banks, they play a crucial role within banks financial statements as they are set aside to face any future deterioration in the credit portfolio. For example, Glen and Mondragón-Vélez (2011) note that "[….] given loan loss provisions are recognized expenses to increase loan loss reserves on the balance sheet, they provide a potentially valuable measure of bank reassessments about expected losses in their loan portfolio. Furthermore, while loan loss provisions and reserves are related to an assessment on the entire loan portfolio, not all NPLs may generate future losses (although the assigned probabilities of doing so are higher for these in the calculation of loan loss provisions and reserves) (page 151)." More specifically, the expected loan losses are represented via loan loss provisions, which are classified as an expense account and thereby identified for a specified credit risk incorporated on an individual loan. The standard practise in banking involves the setup of a portfolio of loan loss provisions that concerns individual loans based on historical data and expected losses. That is, increases in LLPs are reflected in increases in losses for impaired loans (LIC), which subsequently are reported in the financial statement as a deduction from the gross value of loans. However, this LIC component is based on

[69] LLP represents the annual net result of changes in the stock of loan loss reserves and is a flow variable reported in the income statement. Loan Loss Reserves are the stock variable reducing the value of gross loans on the balance sheet. The European Banking Authority (2013) recognises as Non-Performing Loans, exposures that satisfy at least one of the following criteria: (i) material exposures that are more than 90 days past-due; (ii) exposures present a risk of not being paid back in full without collateral realisation, regardless of the existence of any past-due amount or of the number of days past due.

discretionary and nondiscretionary risk managerial decisions and may not be linked to underlying bank risk (actual losses). Therefore, LLP may be subject to opportunistic behaviour by managers and could give a false impression as to the real state of the bank's fundamental balance income statement position which could also over/under estimate the actual 'true' value of loans in the balance sheet (Bushman and Williams 2012).

To enable an examination of this accounting interaction in the financial statements, we consider Gebhardt and Novotny-Farkas' (2011) formulation, equation (5.1),

$$LLR_t = LLR_{t-1} + LLP_t + NCO_t + Other_t. \quad (5.1)$$

Where; LLR_t represents Loan Loss Reserves in period t, LLR_{t-1} represents Loan Loss Reserves (LLR) in the beginning of period t, LLP_t represent the Loan Loss Provisions in period t, NCO_t represent the current net charge-off in period t, and $Other_t$ represent adjustments due to changes in exchange rates or adjustments due to changes in the scope of consolidation[70]. Their analysis posits that LLR is a stock variable capturing all previous and current loan provisions, in so much, that, when loans cannot be collected, they are 'charged-off' against the LLRs[71].

Interestingly, the components in equation (5.1) offer distinct information regarding the nature of loan losses. That is, LLR represents the bank managements 'estimate' of loan losses that are conditional on accounting rules, whereas, the flow $LLR_{t-1}$and 'charge-off' components incorporate changes in credit losses. Indeed, given the accounting relationship between LLR and LLP – by definition – flow across the income statement and the balance sheet, LLP can be seen as managements estimate on future expected losses that can be recognised at the balance sheet at a point in time. That is, the intention through the anticipation of the loan's expected losses by adjusting the book value of the loan. Furthermore, subsequent loan loss provisions must be compared to the expected loss (accounting rules IFRS 39 according to Basel II) and, in the case of a

[70] 'Charge-off' refers to the removal from the balance sheet of loans considered uncollectible.
[71] LLPs are an interesting accounting phenomenon in that they flow across both sides of the financial statements. For example, we can observe the following relationship: as ↑NPLs → ↓LLR (reducing equity) → ↑LLP ↔ ↑equity after LLP at the end of period goes into equity end of period.

difference, liable equity has to be adjusted. On the other hand, accounting 'charge-offs' represent losses on loans that have been identified as uncollectible. Therefore, in both LLP and charge-offs, there is a measure of subjective evaluation by the risk management of a banks across the credit portfolio.

For example, a detailed analysis of each bank's rating practices has shown that in Greece, banks do not automatically classify borrowers which are 3 months delinquent as nonperforming[72]. Instead, such a classification is often at the discretion of the 'loan or relationship officer' and therefore requires the approval of the review committee (Blackrock Solutions, 2011). Hence, the likelihood of collection on a loan is measured by the length of the period that the loan interest and principal are overdue (that is, the ability of the borrower to repay the loan is evaluated based on historical loan loss data and all current available information). However, in cases where past or current information is limited, concerning the loan portfolio, risk management judgments are necessary. This problem, most prevalent in Greece after the global financial crisis, concerns the discretionary nature of LLP, and as such, management could be free to pursue different agendas other than the alleged pictorial representation of the bank's financial position. Indeed, research has identified that income smoothing, capital management and the nature of the relationship between LLP and the macroeconomic environment are of crucial importance in financial systems (see, for example, Bikker and Metzemakers, 2005; Fonseca and González, 2008; Bouvatier and Lepetit, 2008; Leventis et al., 2010 and Skala, 2015).

[72] Loan delinquency is referring to describe a situation in which a borrower is late on a payment. Under Law 4354/2015 and in line with the European Banking Authority, loans that are more than 90 days delinquent are deemed as Non-Performing Loans.

5.3 Literature Review

5.3.1 The Economic Cycle Effect

An important aspect of loan loss provisioning is its timing with respect to the business cycle and procyclicality (an economic expansion can indicate an improved market condition with respect to bank profitability and thereby lead to a lower probability of loan defaults)[73]. Contrariwise, a recession can have an opposing effect on the real economy and as a result may lead to a deterioration of the asset base of a bank. When analysing the Greek banking industry we can find that banks reflect these cyclical effects in their own loan strategies by lowering the amount of provisions during good times, and increasing provisions during a downturn. As a result, even though economic cycles are partly caused by what economists call "deep" parameters of economic behaviour, the financial sectors' behaviour can exacerbate the amplitude of fluctuations in economic activity and amplify fluctuations through feedback leading to behaviour that creates the phenomenon of 'contagion' (Hardouvelis, 2010). More specifically, the consensus in the literature is that the relationship between LLP and the economic cycle is negative. That is, during an upturn in the economy, banks will not adjust their LLPs in such a way to cover any future expected losses that could incur during a potential economic downturn.

A closer examination of the relationship between the business cycle and procyclicality reveals that during a business cycle upward trend, firms and households become optimistic, expand investing, and hence take on more risk (Borio et al., 2001; Borio and Lowe, 2002). During this period a series of events follows. Typically, commercial banking institutions accelerate their credit expansion and competition within the sector increases; interest rate margins decrease; and, banks loosen their credit standards. The aforementioned macroeconomic expansion leads to increased asset prices thus increasing collateral price indices and thereby further accelerating lending activity. In response, the banking sector follows a similar pattern of exacerbating the business cycle (Borio 2006 and 2010), which leads to the regulatory authorities adopting a lenient

[73] According to the 2009 Annual report of the Bank for International Settlements, procyclicality refers to "[….] the fact that, over time, the dynamics of the financial system and of the real economy reinforce each other, increasing the amplitude of booms and busts and undermining stability in both the financial sector and the real economy page (125)"

behaviour. This ultimately can lead to lacking foresight to heightened risks and hence accelerating an economic upturn the business cycle (a factual position regarding Greece and explained in more details in Chapter 2). Indeed, Borio (2006, 2010) notes that due to the decreased margin-per-deal, investment banking institutions pursue more deals, increase their leverage and trading on their own account, promoting financial innovation and creating hidden and under-priced risk. The same leverage expansion behaviour is also followed by hedge funds and other financial intermediary institutions, which together with the herding behaviour experienced can destroy financial diversification, contribute to the procyclicality and increase systemic risk (Chan et al., 2005; Lo, 2009 cited in Hardouvelis, 2010).

The aforementioned macroeconomic position and link to banks and their business models can be abruptly stopped (by money markets) due to the interconnectedness of the financial sector and the hidden risks involved. That is, a consequence of a financial bust could be easily transmitted to the real economy in the downward phase of the business cycle, leading to decreased financial lending, reduced risk taking, and increased risk premia. Furthermore, the banking sector can experience increases in Non-Performing Loans (NPL) whereby, commercial banking credit expansion declines and, a flight to quality in credit extension is observed with the application of stricter credit standards. For example, in Greece, the decline in GDP during the last quarter of 2009 was accompanied by more stringent bank credit standards and an increased rejection rate for SMEs, despite a steady business loan demand (Bank of Greece, 2010); in line with past research and the "flight to quality" argument that credit flow is restricted towards borrowers subject to higher agency costs, as argued by Bernanke et al., (1996). The resultant effect on profits and retained earnings decrease capital reserves relative to assets and reduce liquidity and asset fire sales reduce prices (further exacerbating contraction in lending). Despite regulatory requirements (accounting rules and capital requirements) this could trigger a negative feed-back loop amplified by major impacts in credit markets (see, De Larosière Report, 2009).

This procyclical economic business cycle behaviour may be attributed in a number of reasons. Due to the economic policies followed by agencies, governments and

regulators[74]. The unhindered supply of loans from the financial sector to borrowers is a key prerequisite for sustainable economic activity and development. Furthermore, monetary policy can affect procyclicality through transmissions to the credit demand and supply or lending rates (ECB, 2009). Furthermore, procyclical behaviour of the banking industry has been attributed to asymmetric information or market imperfections (ECB, 2005)[75]. Indeed, Borio et al., (2001) find that a common explanation for procyclicality within the financial system has its roots in asymmetries of information between borrowers and lenders. That is, information asymmetry in a period of economic stress implies that borrowers with positive net present value projects, might find it difficult to obtain credit. Furthermore, executives and investors tend to follow the 'competition', thus, adding to overall market volatility - an issue that can be attributed to the uniformity of information[76]. Indeed, Scharfstein and Stein (1990) and Rajan (1994) observe that managers are not willing to jeopardize their reputational capital and their position by following incorrect and/or personal choices. That is, managers who are concerned about reputation have an incentive to ignore private information and mimic investment decisions made by other managers. Herd behaviour is always inefficient because managers do not utilise all available information (Scharfstein and Stein, 1990). This links to the important factor behind herding behaviour whereby structures that limit the blame in the case of a collective, as opposed to an individual failure (Borio et al., 2001). That is, in the event of financial turmoil, much like the case of the recent financial crisis, bank managers relied on government support and the collective failure shows potential shows homogenous managerial skills, making state support more likely to take place in the presence of

[74] The efficient market hypothesis was first proposed by Fama (1970), who proposed three types of efficiencies based on the context of what information sets are factored in price trends. More specifically, Fama (1970) identifies, weak-form, semi-strong form and strong-form efficiency. In weak-form, the efficiency information set reflects just historical prices and the information set can be predicted from historical price trends, thus it is impossible to profit from it. The semi-strong form requires that all public information is reflected in prices and finally, the strong-form posits that all information sets, including private information are incorporated in price trends.

[75] With respect to banking and its business cycle link, the ECB (2005) posits that procyclical behaviour may be explained by deviations from the efficient markets hypothesis. That is, market participants possess all available information and evaluate it rationally, distinguishing between temporary shocks and events with a long-lasting impact. Consequently, banks will have counter-cyclical behaviour and can appreciate the true state of the economy and reduce (increase) their loans by increasing (decreasing) loan interest rates when the economic cycle is reaching its maximum (minimum) point. Inefficient functioning of the market can be attributed to the following hypotheses: information asymmetry, principal-agent, free-riding, moral hazard, disaster myopia, cognitive dissonance and herding behaviour (Beattie et al., 1995).

[76] Gompers and Metrick (1998) and more recently Sias (2003) have both shown the herding behaviour in the context of institutional investors.

systemic risk in order to limit the spill-over effects. In this case, pressures to conform to the norm can be strong and in that way, individual managers also secure their 'reputational capital' against accusations of poor performance[77].

Therefore, an important aspect of LLP is its relation in timing with respect to the business cycle and issues of procyclicality. As discussed above, during an economic upswing, rising incomes can indicate improving conditions for banks and hence lower the probability of loan defaults. In this respect, banks are expected to lower loan loss provisions reflecting an overall optimistic economic environment. This view dictates that banks' provisioning behaviour follows a procyclical trend reinforcing the current economic state. Whereby, the opposing countercyclical view asserts that an economic expansion with higher risks (the build-up of financial imbalances) could increase the likelihood of future economic contractions. In this respect, banks should recognise that any underlying risk and provisions should be built up during the upswing of a business cycle in order to draw on during recessions - hence indicating a positive correlation between LLP and the macroeconomic environment (see, for example, Laeven and Majnoni, 2003; Bikker and Metzemakers, 2005 and Quagliariello, 2007).

The examination of the relationship between the provisioning behaviour of financial institutions and the business cycle has received considerable attention in the empirical literature. For example, Laeven and Majnoni (2003) use an extended data set of 45 countries for the period 1998-1999 and find evidence of procyclical effects. Using a similar data set modelling 8000 banks from 29 OECD countries, Bikker and Metzemakers (2005) investigate how bank provisioning behaviour is related to the business cycle. Their findings suggest that provisioning is substantially higher when GDP growth is lower, thus reflecting increased riskiness of the credit portfolio in a recession, and amplifying the risk of a credit crunch. In addition, Sorge and Virolainen (2006) estimate two different models for stress-testing purposes and find a negative relationship between LLP and lagged GDP growth; indicating that banks are more likely to make new loan loss provisions if GDP growth has slowed down three quarters in the past. More recently, and employing a panel of 186 European banks for the period

[77] Through this behaviour, they also capitalize by securing higher executive remuneration packages, since compensation tends to depend on the overall performance of the industry (Borio et al., 2001).

1992–2004, Bouvatier and Lepetit (2008) find that LLP (calculated to cover expected future loan losses, non-discretionary LLP) amplify credit fluctuations. However, their results find that the discretionary component of LLP used for managerial purposes does not affect credit fluctuations.

In a further analysis that covers the pre-crisis period of 1996-2008, Glen and Mondragón-Vélez (2011) examine the effects of business cycles on the performance of commercial bank loan portfolios across major developing economies. The authors estimate a non-linear model by including a 5^{th} order polynomial in GDP, whereby LLP and economic growth is highly non-linear only under extreme economic stress – reporting a negative relationship between the economic cycle and LLP with respect to the 5^{th} order polynomial term – also finding offsetting effects for a range of GDP growth rates[78]. More recently, Skala (2015) further analyses European banks covering the outbreak of the financial crisis and examines the cyclicality of LLP in Central European banks using data from 179 commercial banks in 11 countries over the period 2004–2012 and find that Central European banks' LLP practices are procyclical with respect to national business cycles. Therefore, during economic downturns, EU banks created extra reserves, thus further increasing the probability of a credit crunch. Their analysis posits that during periods of economic expansion (proxied by an exceptionally high GDP growth rate) bank managers did not engage in making additional provisions. Finally, Balasubramanyan et al., (2016) study the financial crisis and bank provisions in the U.S. by examining three distinct phases, the pre-crisis period, crisis period, and post-crisis period. The structure of the analysis is particularly important as LLP are driven by different factors and a negative and highly significant relationship between the real GDP growth rate and loan-loss provisioning.

The aforementioned studies show that it is therefore unclear, until estimation, of the business cycle effect on Greek banks. However, we hypothesise a procyclical behaviour of Greek banks which suggests that an improvement of the macroeconomic environment as proxied by GDP growth (unemployment rate), should be negatively or positively related to LLP. In contrast, a counter-cyclical behaviour could imply a

[78] Glen and Mondragón-Vélez (2011) define a 5th order polynomial of GPD as GDP^5, equation (5), page 158.

positive relationship with the GDP growth and a negative relationship with respect to unemployment. This gives us our first hypothesis with respect to LLP in Greek banking.

5.3.2 Capital Management

Bank capital management results from the conflicts between the exogenous cost of capital and regulatory capital requirements. That is, capital management is a process that ensures banks hold sufficient capital to absorb any unexpected losses that they may incur. However, given the exogenous cost of raising capital, a bank may tend to hold less than the optimal level required to fully account its risk exposure (holding capital reduces the probability of default and hence it mitigates the costs of failure). These capital costs may include reputational costs, compliance with existing capital requirements and bankruptcy costs. Therefore, a strong capital position can minimize the aforementioned risks and also help bolster future growth prospects. It should be noted that the process of adjusting capital positions does not come for free and apart from any transaction costs, issues of information asymmetry in capital markets also become an important contributory factor (Myers and Majluf, 1984). More specifically, raising new capital may be costly by issuing stock; the issuer has an information advantage over the buyer. Therefore, issuing stock may be perceived as a signal to the market that the bank considers market prices are above its true share value, which could increase the cost of raising the additional capital. Given the increase cost of raising capital, associated costs could be significantly higher during periods of an economic downturn. Thereby, shareholders could be reluctant to contribute additional capital to banks when they are undercapitalized as most of the benefits could accrue to creditors. Finally, new equity issuance by undercapitalized banks could convey negative information to market investors concerning its economic value, therefore, managers may be inclined to choose a different path in order to maintain the banks' capital position at a level as not to attract the regulatory authority's attention.

Of interest, this 'so called' cost of capital inadequacy could give bank managers incentives to manipulate capital upward in order to maintain a minimum capital requirements using general LLP - an effort that may be intensified in the case of poorly capitalized banks. However, this has become less profound since the transition from

Basel I to the Basel II regime. The mechanics of such manipulation can thus become apparent by examining the Basel Accord capital requirements. That is, under the new regime, the TRCR measures Tier 1 plus Tier 2 capital and should amount to at least 8%. Whereby, the Tier 1 Regulatory Capital Ratio, which includes shareholder funds plus perpetual non-cumulative preference shares as a percentage of risk weighted assets and off balance sheet risks are measured under the Basel rules, of at least 4% (Basel Committee on Banking Supervision, 2006). Indeed, the Bank of International Settlements (BIS) (2006) stresses the importance of equity capital, as "[….] the key element of capital on which the main emphasis should be placed is equity capital and disclosed reserves. This key element of capital is the only element common to all countries' banking systems; it is wholly visible in the published accounts and is the basis on which most market judgements of capital adequacy are made; and it has a crucial bearing on profit margins and a bank's ability to compete (page 14)" Furthermore, Tier 2 (Supplementary capital) comprises of undisclosed reserves, asset revaluation reserves, LLR, hybrid capital subordinated term debt and it is limited to 100% of Tier 1 capital (BIS).

To recap, concerning the recent Basel II regime, the purpose of regulatory capital is to cover unexpected losses only and any such losses should be covered by individual and general loan loss provisions[79]. That is, the expected losses are estimated within the time horizon of one year and are hence calculated as the product of the Probability of Default (PD) and Loss Given Default (LGD). This framework also makes a clear distinction that banks which comply with the Internal Ratings-Based (IRB) approach are required to cover expected credit losses via total LLP. In the case where the expected losses are greater than the eligible provisions, 50% of the excess amount is deducted from Tier 1 and 50% from Tier 2 capital. Furthermore, banks which use the standardised approach have an opportunity to include LLP into Tier 2 capital and under the standardised approach to credit risk (general provisions can be included in Tier 2 capital subject to the limit of 1.25% of risk weighted assets). Our hypothesis of capital management is therefore based on the notion that managers use LLP to avoid the cost of violating the minimum capital requirements. That is, instead of raising new capital

[79] Basel II was implemented in the EU in 2007 for banks applying the standardised approach and 2008 for those using the IRB approach.

(which may be an extremely costly process, especially during a recession), banks with low Tier 1 capital ratios will be inclined to increase their general provisions in order to maintain the minimum capital adequacy ratio (see Bikker and Metzemakers, 2005).

As discussed above, according to the Basel II Accord, Retained Earnings (representing accumulated net income minus payment of stockholder dividends) are part of Tier 1 capital. That is, an increase in LLP could lead to a reduction in Retained Earnings thus leading to a negative effect of Tier 1 via a reduction of Retained Earnings. Hence, low-capitalised banks could be less willing to make loan loss provisions. On the other hand, in the case where a bank has LLR levels below the 1.25% threshold of risk-weighted assets, the aforementioned increase in LLP could lead to an increase in LLR, thus raising Tier 2 capital by one unit implying a net positive impact of LLP on Tier 2. Therefore, an increase in general provisions could lead to an increase in the regulatory capital as long as the decrease of Tier 1 capital is offset by the corresponding increase in Tier 2 capital. Interestingly, Bouvatier and Lepetit (2008) note that "To the extent that such discretionary behaviour increases regulatory capital without a corresponding reduction in risk of insolvency, it constitutes a regulatory capital arbitrage (page 515)". Hence, the direction of the relationship between LLP and capital depends on which of the aforementioned effects prevail.

Interestingly, prior research has provided rather inconclusive findings with respect to the capital management hypothesis[80]. For example, Kim and Kross (1998) use data after the 1988 capital adequacy regulation became effective and find results consistent with capital management hypothesis. Moreover, after implementation of Basel I, low capitalised banks tended to decrease LLP in order to increase capital ratios; while banks with high capital ratios did not experience any relevant change in their loan-loss provisioning. Ahmed et al., (1999) find strong support in favour of capital management practises in 113 bank holding companies; indicating that loan loss provisions are driven by changes in the expected loan quality but also by managerial incentives to control capital adequacy ratios. Whereas, Bikker and Metzemakers (2005) use data form 29 OECD countries covering the period between 1991-2001 and find support of the capital

[80] Prior research examining the relationship between LLP and capital management extends back to 1990, for examples, see, Moyer (1990) and Beatty et al., (1995).

management hypothesis, that is, banks provision more when their capital ratio is low. Next, examining Australian commercial banks for 1991-2001, Anandarajan et al., (2007) also provide evidence of such LLP manipulation. That is, they find evidence that banks manage capital levels but find no evidence of a change behaviour after the implementation of the Basel Accord. In addition, examining an extended sample of 186 European banks, Bouvatier and Lepetit (2008) posit that poorly capitalized banks use LLP to manage their regulatory capital position. However, in contrast, investigating the capital management practises of 91 European commercial listed banks covering both the pre and post IFRS implementation period, Leventis et al., (2010), report that capital management behaviour by bank managers is insignificant in both pre and post IFRS regimes. Whereas, Pérez et al., (2008) utilize a sample of 142 commercial and saving Spanish banks for a period up to 17 years and in contrast to Bouvatier and Lepetit (2008) find no evidence to suggest that Spanish banks had practiced capital management[81]. Also examining EU banks, Curcio and Hasan (2015) use a sample of 195 institutions and examine provisioning policies during the recent financial crisis, during 2007-2010. They examine both European and non-European banking institutions and similar to Perez at al., (2008) find that banks located outside the EU do not use LLP to manage capital ratios.

Overall, the aforementioned studies which have examined LLP practises, with respect to the minimum capital requirements, yield contradictory findings. This is evident more so with respect to practises regarding Greek banks. To the best of our knowledge, there is no study examining the loan loss provisioning practises of Greek banks in isolation – hence offering a detailed account of the managerial practises of commercial banks operating in Greece.

5.3.3 Cost Efficiency

In this section we discuss and analyse the determinants of increases in NPL and LLP amongst macroeconomic variables which could produce misleading findings. That is, the distinctive features of the financial systems and various policy implications, as

[81] For an extended discussion of dynamic provisions in Spain, see Mann and Michael (2002) and Saurina (2009 and 2011).

discussed above, could lead to improvements in cost efficiency, and influence the evolution of NPLs. Indeed, several hypotheses have been proposed to explain the relationship between bank risk, capital and cost efficiency. For example, Berger and DeYoung (1997) in their seminal paper propose four theories based upon the intertemporal relationships between NPLs, efficiency and capital and posit four models of managerial behaviour with respect to the loan portfolio, capital and 'efficiency choice'. That is, the bad management hypothesis, the bad luck hypothesis, the skimping hypothesis and moral hazard hypothesis. It should be noted that each behavioural model is defined on the intertemporal relationship amongst key components and our aim is to incorporate these determinants in an estimation of Greek bank management behaviour.

To begin with, the bad management hypothesis suggests that low cost efficiency (CE) levels precede and are positively associated with increases in NPLs. That is, low bank cost efficiency can be seen as a signal of poor managerial quality and consequently the day-to-day operations of managing the loan bank portfolio. The theory offers a link between "bad" managers with poor skills in credit control, risk appraisal and the process of monitoring borrowers with a deterioration of the bank's asset quality. That is, they argue that poor managers are not adept at credit scoring and exhibit a tendency of selecting a relatively high proportion of investments with a low or negative net present values (see Williams, 2004). In addition, insufficient control over the risk exposure of sub-performing managers could fail to control and sufficiently monitor operating expenses – which could translate to reductions in efficiency levels. Thereby, reductions in efficiency levels, stemming from increased operating expenses, sub performance practices, with respect to the loan portfolio could materialize with a lag in the production process.

The bad luck hypothesis however, takes an opposing view on the relationship between the aforementioned variables (NPL and CE). That is, deteriorating macroeconomic conditions may explain the causality from NPLs to reduced efficiency levels - NPLs Granger-cause reductions in efficiency levels[82]. This relationship can be explained by

[82] A variable x is said to Granger-cause a variable y if, given the past values of y, past values of x are useful for predicting y. Typically, this relationship can be estimated by regressing y on its own lagged values and on lagged values of x and test the null hypothesis that the estimated coefficients on the lagged

the following thought experiment. After a loan becomes delinquent, because of an unforeseen event, a bank is expected to allocate resources and expend extra managerial effort in dealing with the increased NPLs. Managerial costs could include any extra precautions taken to preserve the high quality of loans that are currently performing and increased costs may stem from increases in allocating extra resources in monitoring the defaulted loans and their subsequent collateral revaluation. Of particular importance, costs that may incur in the process of negotiating possible restructuring agreements with borrowers. For example, Law 3869/2010, enacted September 2010, was the initial Greek legislation dealing with the issue of over-credited individuals, providing them with an option to achieve an official judicial settlement concerning debts they were not able to repay to the bank. However, this law was later on amended (Law 4161/2013), whereby debts of individuals who, (i) do not have the legal capacity to ascertain bankruptcy (according to the merchants bankruptcy law) and (ii) have, by no fraudulent intention, a permanent inability to pay back their debts. That is, prior to being amended by Law 4161/2013, this legal procedure in Greece proceeded in three distinct steps

- Out of Court Settlement
- In-Court Compromise, and
- Judicial settlement –debts discharge.

Finally, according to Law 4161/2013, an Out of Court Settlement is not any more a prerequisite to proceed with a petition for bankruptcy and was replaced by discretionary mediation procedures. Therefore, most of the costs discussed above, especially those associated with workout agreements and defaults, could materialize with a lag, after an increase in problem loans. Interestingly, under the bad luck hypothesis, we expect an increase in NPL to Granger-cause (i.e., temporally precede) decreases in efficiency levels of Greek banks. Whereas, with respect to the aforementioned bad luck hypothesis, we expect an opposite temporal order to the bad management hypothesis; both could predict a negative relationship between NPL and efficiency.

On the other hand and under the skimping hypothesis (in the short run) managers may choose to reduce the resources utilised in the monitoring, (underwriting process) in

values of x are jointly zero. Failure to reject the null hypothesis is equivalent to failing to reject the hypothesis that x does not Granger-cause y.

order to ensure long term profitability. As a result, a bank could face a potential loan quality deterioration because of the trade-off between reductions in operating costs in the short-term, and future loan quality in the long-run. That is, managers could choose to achieve long-term profitability targets by minimizing short-term operating costs, preferring to defer the issue of addressing problems occurring from deteriorations of asset quality. In this argument, we could posit that banks engaging in skimping behaviour give misleading impressions of increased levels of cost efficiency in the short run since fewer resources are allocated to support the same quantity of output. Therefore, reduced managerial effort to ensure the quality of the loans portfolio could lead to increases in future NPLs. Thus, in line with the bad management hypothesis, skimping assumes that cost efficiency levels are Granger-causing increases in NPLs (temporally preceding an upward NPL shift). However, contrary to the former, the latter's Granger-causality effect running from efficiency to NPL is a positive one. It is important to note that the cost of monitoring loans and NPL, which is the main cost behind the skimping hypothesis, may only reflect a small percentage of the overall costs and could be difficult to disaggregate (for example, disaggregating the percent of costs of NPL write downs to total costs may not be possible due to lack of available data). Therefore, one possible limitation when testing for cost skimping, is the use of operating expenses as a proxy, which is reflects the costs of a bank at a macro level and not at a micro level.

Our final hypothesis is to link risk exposure to managerial behaviour and this can be delineated as the moral hazard hypothesis. This theory suggests that managers of thinly capitalized banks are less risk averse than their counterparts, whereby, constituting an example of excessive risk taking when cost is carried by another party. That is, management of low capitalized banks respond to moral hazard incentives by increasing the riskiness of their loan portfolio which in turn translates to increased future NPLs on average. Therefore, under the moral hazard hypothesis, we expect that banks with weaker capital positions exhibit higher level of defaulted loans[83]. More specifically, low capital positions Granger-cause high NPLs. Even though the moral hazard hypothesis does represent a decisive part in the explanation of efficiency and NPLs, it

[83] According to the notion of moral hazard, banks could expand their risky lending activities and take on more risk, as they anticipate bank support policies, a practice that could end up rewarding capital insufficiency.

offers a possible alternative interpretation to their relationship. Indeed, Berger and DeYoung (1997) note the importance of controlling for moral hazard when examining bank specific determinants of NPLs, "[….] moral hazard gives an alternative explanation for nonperforming loans, so the effects of measured cost efficiency on nonperforming loans could be biased if the potential effects of capital were neglected. Second, moral hazard effects can magnify the effects of the other three hypotheses, and any of those hypotheses could be the primary cause of reduced capital and moral hazard incentives (page 6)".

It is with respect to prior research, the literature has provided inconclusive results. For example, Berger and De Young (1997), in a sample of U.S. commercial banks, show that the declines in cost efficiency temporally precede increases in problem loans, a concern becoming more apparent in thinly capitalised banks[84]. In addition, they also highlight that problem loans result in reductions in cost efficiency. For example, Kwan and Eisenbeis (1997) find that poorly performing banks are more prone to taking more risk and that highly capitalised banks are more efficient than less capitalised institutions. Furthermore, Williams (2004) who replicated Berger and DeYoung's (1997) study and expanded it to European saving banks, examined the inter-temporal relationship between LLP, efficiency and capital levels. He confirms the presence of the bad management hypothesis for European banks, a finding that is inconsistent with previous U.S. banks studies. Finally, Williams (2004) finds no support for the skimping hypothesis[85]. In line with Williams (2004), Podpiera and Weill (2008) also report strong evidence in favour of the bad management hypothesis for a panel data set of Czech banks, covering 1994-2005.

Subsequent research uses a static simultaneous equation model instead of Granger-causality frameworks, and investigates the relationship between LLP and cost efficiency for EU banks, covering 1992-2000. That is, Altunbas et al., (2007), do not find a positive relationship between inefficiency and bank risk-taking, that is more

[84] A thinly capitalised bank can be thought of as a bank that holds capital levels that are close to or below minimum capital requirements. In econometric testing this can be formally expressed as a bank that holds capital that is less than the industry median (see Berger and DeYoung, 1997).
[85] To recap, the cost skimping hypothesis implies that bank managers may choose to maximize long-run profits through having lower costs in the short-run by skimping on the resources devoted to underwriting and monitoring loans.

inefficient EU banks appear to hold more capital and therefore take on less risk. More recently, and building on the framework proposed by Berger and DeYoung (1997) and Kwan and Eisenbeis (1997), Fiordelisi et al., (2011) assess the inter-temporal relationship of several definitions of efficiency (risk and capital on a set of European commercial banks). Their results suggest that banks operating at a lower cost/profit efficiency level take on more risk, thereby confirming bad management. In addition, more efficient banks become better capitalized and that higher capital levels improve cost efficiency levels. It is worth noting that Fiordelisi et al., (2011) take into account issues surrounding potential endogeneity of regressors (otherwise neglected in the literature), via the use of the system Generalized Method of Moments (GMM) estimators developed for dynamic panel models by Arellano and Bover (1995) and Blundell and Bond (1998).

Unsurprisingly, prior empirical research in this important area concerning Greek banking has become even more scarce. Indeed, to the best of our knowledge, only two studies have examined the extent of NPLs in the Greek sector. For example, Louzis et al., (2012) examine the hypothesis that both macroeconomic and bank-specific variables have had an effect on loan quality and that these effects vary between different loan categories. This modelling strategy includes dynamic panel data methods in which data of the nine largest banks (2003-2009) consider NPLs with respect to consumer loans, business loans and mortgages. Their findings indicate that for all loan categories, NPLs can be explained by macroeconomic variables (GDP, unemployment, interest rates, and public debt) and management quality. That is, performance and inefficiency pose an additional explanatory power when added to their baseline specification lending support to bad management hypothesis. However, it is worth noting that their efficiency estimation procedure deviates from the original cost/profit SFA efficiency estimates found in U.S. and E.U. studies (for example, Louzis et al., (2012) utilise an inefficiency proxy estimated as the ratio of operating expenses to operating income). Furthermore, Louzis et al., (2012) and Monokroussos et al., (2016) also find that macroeconomic conditions play a different role in the evolution of different loan categories examined (consumer, corporate and mortgage loans). Their findings point towards the unprecedented contraction of economic activity in Greece as the primary

cause for a sharp increase in NPLs after the sovereign debt crisis[86]. Finally, Monokroussos et al., (2016) find no support for the argument that major Greek banks systemically boosted their earnings by extending credit to low credit quality clients, thus rejecting the presence of the bad management hypothesis – in contrast to the finding offered by Louzis et al., (2012).

In relation to the above discussion it is evident that the empirical literature, with respect to, the link between risk exposure, loan quality and efficiency is rather limited. That is, Louzis et al., (2012) and Monokroussos et al., (2016) offer a significant wealth of new findings regarding the evolution and determinants of bad loans. In retrospect though, their scope is limited in that without analysing risk managerial behaviour surrounding respective loan loss provisioning choices, enables us to add to the literature. That is, our current study aims to fill this gap presenting estimates of LLP behaviour concerning the Greek banking sector. Furthermore, building upon the standard LLP models, we extend the literature by incorporating estimates of cost efficiency into our econometric framework. That is, it is clear there is a well-established theoretical and empirical link between efficiency estimates and bad loans, and as such we propose a variation of the standard LLP models used widely in applied banking studies. That is, modelling LLP strategies without the inclusion of cost efficiency could lead to misleading results, given the almost deterministic relationship (however, part of the relationship is to an extent subject to managerial discretion) between NPLs and LLP. The confirmed temporal links of the former with cost efficiency, omitting an efficiency indicator from an LLP model, may reduce the strength of the model.

However, it should be noted that such an omission may indeed prove to be critical as cost efficiency estimates have played a key part in the explanation of the relationship between NPL and bank efficiency. That is, given the primary role of LLP in covering future credit risk exposures, we see efficiency as an integral component of provisioning behaviour. For example, cost efficiencies may indeed interpret part of the variation of LLP via the indirect manifestation of either bad management or skimping hypotheses.

[86] Following direct creditor-borrower negotiations, a significant amount of problem loans have been restructured in Greece. At the end of 2015, the outstanding amount of NPL in Greek banks was 43.5% of total outstanding loans and the respective level excluding the restructured loans was 35.6%.

That is, in the presence (or absence) of the above hypotheses, inclusion of efficiency estimates in an LLP regression model may prove to offer additional explanatory power as it could capture that part of the LLP variance that is otherwise not accounted for by discretionary components (NPL, or the capital management hypothesis). Furthermore, efficiency estimates may serve as an additional control variable as it can act as proxy of unobserved managerial behaviour and ability that does not affect the available technology[87]. Therefore, building on Berger and DeYoung's (1997) and Kwan and Eisenbeis' (1997) argument that the concept of bank cost efficiency needs to be recognised explicitly in empirical models, analysing the determinants of banks' risk, we proceed by introducing cost efficiency in a standard LLP model[88].

More specifically, cost efficiencies may have numerous effects with respect to loan loss provisioning through a number of channels. For example, a bank which operates at a low efficiency level may be inclined to make more provisions for two reasons. First, borrowing from the bad management hypothesis, we expect that on average, banks which are less efficient will eventually have to provision more than their respective counterparts. As the bad management theory suggests, poor senior management day-to-day practises could lead to inadequate credit monitoring and hence a lack of control over their loan portfolio (implying an increase in future levels of NPLs). These increased costs could also lead to increases in operating expenses, thus translating to immediate reductions in cost efficiency. Therefore, *ceteris paribus*, the temporal effect of efficiency on higher NPLs could pass through to an LLP model, suggesting that higher levels of provisioning via the increase in NPLs, imply a negative relationship between the two aforementioned variables (NPL and cost efficiency). Interestingly, it is important to highlight that a possible negative coefficient of cost efficiency in an LLP model should not be mistaken as evidence in favour of the presence of the bad management hypothesis for two reasons. First, the structure of the LLP model is fundamentally different than the standard Granger-causality tests employed in prior studies as the latter employ lagged terms of both NPL and cost efficiency. Secondly, since LLP may be subject to manipulation for the reasons discussed above, and hence

[87] Triebs and Kumbhakar (2012 and 2015) note that the productivity literature as expressed by Meeusenand van Den Broeck (1977), Aigner et al., (1977) and Charnes et al., (1978) describes the units of observation as "decision making units" which strongly hints at the implied link between inefficiency and management.

[88] The link between risk and efficiency has also been addressed by Pastor and Serrano (2005).

over or under-stated at any given year, interpreting such a model as evidence of either supporting or rejecting the presence of the aforementioned hypotheses may indeed be subject to criticism.

An innovative interpretation is that a bank with low cost efficiency and low financial capital may find it harder to raise the desired amount of new capital, especially in the unfavourable economic environment in Greece. That is, in a small banking market like Greece, banks that appear to under-perform with respect to cost efficiency levels, may find it more difficult to raise the required new capital needed to remain above the minimum capital requirements. Indeed, Hughes and Mester (1998) note that "even though the amount of labour and physical capital devoted to risk management cannot be directly observed by outsiders, it must be inferred from the level of financial capital the bank chooses (page 9)". Hence, due to the relatively small financial sector in Greece, investors may have an accurate overview of the riskiness and performance of each bank, thus making the process of obtaining additional capital even more cumbersome and expensive. In this scenario, a low efficient bank could be even more inclined to adjustment their regulatory capital via LLP changes in order to avoid any extra cost assigned to it by the market with respect to risk and hence to raising fresh capital.

In contrast, a potential positive relationship between cost efficiency and LLP could emanate from two theoretical rationales. Firstly, similar to the interpretation of the bad management hypothesis, the positive relationship could be indicative of the presence of cost skimping behaviour. That is, the quality of the loan portfolio of a bank in the long-run, could be a consequence of the choices of risk management, with respect to a short-run resource allocation concerning monitoring lending activities. In this case, banks could appear to be cost efficient in the short term as they devote fewer resources to credit screening and therefore the lack of monitoring could have an adverse effect in the future levels of NPL. Therefore, on average, an industry where banks engage in cost skimping behaviour, these effects could also be present when modelling LLP, thus implying positive cost efficiency relationships. In contrast, a positive relationship may also reflect increased management quality with respect to cost minimizing and/or optimal resource control over the production process. In that respect, our argument presents that better managerial abilities, which could be translated in optimal statistical

forecasting (with respect to the evolution of future NPLs), could mislead the interpretation of the positive link between cost efficiency and higher LLP. It is therefore challenging to distinguish the true cause as a positive finding could either indicate prudent/optimal provisioning or cost skimping. In all cases, this relationship between cost efficiency and LLP is one that needs to be established empirically in an LLP model and hence it is the aim of this Thesis to substantiate whether Greek banks follow the aforementioned theoretical construction. With respect to our discussion of the importance of determining Greek bank management behaviour, we next turn to present the basis of the estimation procedure and data utilised to determine the previous discussions.

5.4 Data and Methodology

5.4.1 Static Panel Data Models

The data we are utilizing follows from Chapter 4, which fully discusses the sample and rationale for the banks included in this Thesis. To recap the basis of our analysis, panel data has been widely applied in recent banking studies to better analyse their practises (see, for example, Bikker and Metzemakers, 2005; Fonseca and González, 2008; Bouvatier and Lepetit, 2008; Pérez et al., 2008; Kosmidou 2008; Bouvatier and Lepetit 2012 and Curcio and Hasan 2015). Indeed, as Sorge and Virolainen (2006) note, "both static and dynamic models have been proposed where the dependent variables are primarily loan loss provisions, non-performing loans and profitability measures (i.e., net interest margin), while bank-specific characteristics are added to the macro fundamentals among the explanatory variables (page 120)". Furthermore, Baltagi (2005) and Hsiao (2014) also note significant advantages utilizing panel data whereby observing that such data sets allow to control for individual heterogeneity, suggesting that the panel dimension of the data set can be treated as heterogeneous. In addition, panel data can be considered to be more informative and help mitigate issues of collinearity among explanatory covariates and at the same permit study of adjustment dynamics. Finally, the use of panel data helps reduce the magnitude due to the impact of omitted variable bias – an issue often arising in empirical studies – as both the static and the dynamic panels data estimation methods proceed take into account any unobserved effects present in the specifications.

We begin our discussion based on a representation of the static specifications, which serves as the basis of our analysis in this section. We then build upon this model and present limitations of traditional estimators when autoregressive components are introduced in the specifications. An alternative estimator that addresses issues of heterogeneity and endogeneity is additionally presented, together with the relevant estimation tests employed.

The initial primal model analysed in this Chapter is thus a static panel data regression model, equation (5.2),

$$y_{i,t} = \beta x'_{it} + \alpha z'_i + \varepsilon_{i,t} \tag{5.2}$$
$$y_{i,t} = \beta x'_{i,t} + c_i + \varepsilon_{i,t}, \qquad i = 1, \dots, N; t = 1, \dots, T.$$

Where subscript i and t denote the cross sectional and time dimensions of the panel data set and where x_{it} includes K regressors excluding the constant term. The term $\alpha z'_i$ contains a constant term and a set of individual or group specific variables, z_i, which may be observed (bank location) or unobserved, c_i, such as firm specific characteristics (managerial ability, skills and/or risk preferences). These individual effects represent the heterogeneity effect in the panel data set of Greek banks and they are assumed to be constant over time. In the case where z_i is observed for all individuals, the model expressed in equation (5.2) is treated as an ordinary least squares. However, as Greene (2007) notes, complications arise when c_i is unobserved, which will be the case in most applications Finally, the term ε_{it} represents the zero mean, $i.i.d.$ disturbance term.

In terms of analysis, the main objective is the estimation of the partial effects, equation (5.3), under the assumption of strict exogeneity, equation (5.4),

$$\beta = \frac{\partial E[y_{i,t}|x_{i,t}]}{\partial x_{i,t}}. \tag{5.3}$$

$$E\left[\varepsilon_{i,t}\middle|x_{i,1}, x_{i,2} \dots\right] = 0. \tag{5.4}$$

That is, with respect to the assumption of strict exogeneity, equation (5.4) implies that the explanatory variables are uncorrelated with the error term in the past, present and future. A crucial aspect of our model concerns the unobserved bank heterogeneity effect, c_i, expressed in equation (5.2). A convenient assumption is mean independence, equation (5.5)[89],

$$E\left[c_i\middle|x_{i,1}, x_{i,2} \dots\right] = \alpha. \tag{5.5}$$

[89] The conditional mean expresses the average of one variable as a function of some other variables. This can be formally expresses as the mean of y conditional on x is the mean of y for given values of x; in other words, $E[y|x]$.

If the unobserved effects are uncorrelated with the explanatory regressors, then they can be included into the error term, forming the underlying assumption of the Random Effects specification. However, this is a strong and restrictive assumption implying that the Greek banks' unobserved effects are uncorrelated with the explanatory variables. For example, in a traditional LLP and/or profitability model, this assumption implies that the bank specific regressors (for example, the level of equity) are uncorrelated with the unobserved effects such as managerial risk preferences. In other words, risk management behaviour does not have an active impact on the level of equity, a rather rigid and restrictive assumption in our view. An alternative can be further expressed, in equation (5.6),

$$E\left[c_i \middle| x_{i,1}, x_{i2}, \ldots\right] = h\left(x_{i,1}, x_{i,2} \ldots\right). \tag{5.6}$$

With respect to the above specifications, standard treatment in the econometrics literature considers the following structures (Greene, 2007):

- Pooled Ordinary Least Squares (POLS): In the case where the z_i' contain only a constant term, consistent and efficiency estimates of the constant α and β can be obtained via the use of the Ordinary Least Squares estimator. Whereas, in the POLS framework the assumption is that all panels are identical and there no observable/unobservable differences maintained. This latter assumption is rather unrealistic and restrictive given the nature of the sample selected for our study. That is, in the data set it would imply that the four core banks share the same risk management preferences and expertise in managing accumulated risks as the smaller banking institutions operating in Greece. Similarly, POLS treats all banks as having common characteristics, hence ignoring several of the observed/unobserved factors previously discussed.
- Fixed Effects (FE): If z_i contains unobserved effects that are correlated to the explanatory variables, x_{it}, then OLS will produce biased and inconsistent estimated parameters for β, due to omitted variable bias. In this case, the FE model can be expressed, equation (5.7),

$$y_{i,t} = \beta x_{i,t}' + \alpha_i + \varepsilon_{i,t}. \tag{5.7}$$

Where, $\alpha_i = \alpha z_i'$ captures the observable effects and specifies an estimable conditional mean and α_i is a group-specific constant term in the regression model. It is worth noting that the term fixed refers to the correlation of the unobserved bank specific effect, c_i, with the explanatory variables. This formulation implies that any differences across groups will be captured in differences in the constant term, suggesting that each α_i is treated as a parameter to be estimated. One shortcoming of the FE model is that any effect of possibly time invariant variables present in x_{it} will be absorbed in α_i.

- Random Effects (RE): Unobserved variation across panels is assumed to be random and uncorrelated with both the right and left-hand-side variables and in this case, the model can be formulated as a linear regression with a compound disturbance term that can be consistently but inefficiently estimated by least squares, equation (5.8),

$$y_{it} = \beta x_{i,t}' + E[\alpha z_i'] + \alpha + u_i + \varepsilon_{i,t}. \quad (5.8)$$

Where, $u_i = \alpha z_i' - E[\alpha z_i']$, represents the group-specific random element and α, consists of a fixed intercept representing the population average and individual differences that are not correlated with the X variables.

When typical assumptions surrounding the classical model are met, Ordinary Least Squares (OLS) is an efficient estimator providing valid inference opportunities, whereas, panel data estimation is complicated when the assumptions of a pooled model are not fully satisfied giving rise to the issue of heterogeneity[90,91]. Indeed, it is not uncommon for heterogeneity to be present in panel data, which preferences the fixed/random effect models and as such can be estimated via either the Least Squares Dummy Variable (LSDV) approach or by applying Within Transformation, whereas the RE model is estimated via the Generalised Least Squares (GLS) estimator.

[90] $E[\varepsilon_{i,t}|x_{i,1}, x_{i,2}, \dots x_{i,T_i}] = 0$,zero conditional mean; $var[\varepsilon_{i,t}|x_{i,1}, x_{i,2}, \dots x_{i,T_i}] = \sigma_\varepsilon^2$, homoscedasticity; $cov[\varepsilon_{i,t}, \varepsilon_{j,s}|x_{i,1}, x_{i,2}, \dots x_{i,T_i}] = 0$ if $i \neq j$ or $t \neq s$, independence across observations and $E[\varepsilon_{i,t}|x_{i,1}, x_{i,2} \dots]$

[91] This assumption can be easily tested via the Breusch and Pagan Lagrangian multiplier test for random effects.

More specifically we are interested in fitting a model of the general form to Greek banks, equation (5.9),

$$y_{i,t} = \alpha + \beta x_{i,t} + u_i + \varepsilon_{i,t}. \quad (5.9)$$

In this respect, the term $u_i + \varepsilon_{it}$ represents the error term that we have little interest in as the main focus is obtaining estimates of $\hat{\beta}$(the term u_i represents the unit-specific error term as discussed before and ε_{it} is the traditional error term). Estimating the general form of equation (5.9) via LSDV implies the inclusion of a set of $k - 1$ dummy variables to capture the individual differences across groups.

$$y_{i,t} = \alpha + \beta x_{i,t} + \boldsymbol{i}u_i + \varepsilon_{i,t}. \quad (5.10)$$

This formulation can be estimated as a classical regression via OLS, however, the LSDV may suffer from a loss of degrees of freedom as we are estimate $(N - 1)$ number of extra parameters and this may aggravate issues of multicollinearity among the regressors (Baltagi, 2005). This is mathematically equivalent to the Within Transformation, giving identical estimates of $\hat{\beta}$. By performing a simple transformation, irrespective of the properties of u_i and ε_{it}, then it must also be true that, equation (5.11) can be defined,

$$\bar{y}_i = \alpha + \beta \bar{x}_i + u_i + \bar{\varepsilon}_i, \quad (5.11)$$

Where $\bar{y}_i = \sum_t y_{i,t}/T_i$, $\bar{x}_i = \sum_t x_{i,t}/T_i$, $\bar{\varepsilon}_i = \sum_t \varepsilon_{i,t}/T_i$. Further, by subtracting equation (5.11) from (5.9) we obtain within estimator, or the FE model, equation (5.12),

$$(y_{i,t} - \bar{y}_i) = \beta(x_{i,t} - \bar{x}_i) + (\varepsilon_{i,t} - \bar{\varepsilon}_i) \quad (5.12)$$

Whereby, the within transformation can be easily estimated via OLS, providing an unbiased and consistent estimate of $\hat{\beta}$, and in the process eliminating the fixed effects u_i. However, one drawback of the aforementioned transformation is that any time-invariant variables are also eliminated. Due to these difficulties, we now turn our

attention to the RE model which contrary to the FE model assumes no correlation between these effects and the explanatory variables ($cov(x_{it}u_i) = 0$). The proposed estimator for the RE models is the Generalized Least Squares (GLS) estimator, which is equivalent to estimating the following transformed equation via OLS (equation (5.13)),

$$\left(y_{i,t} - \lambda\bar{y}_i\right) = (1-\lambda)\alpha + \beta\left(x_{i,t} - \lambda\bar{x}_{i,t}\right) + v_{i,t}. \tag{5.13}$$

Where $\lambda = 1 - \sqrt{\frac{\sigma_\varepsilon^2}{T\sigma_u^2 + \sigma_\varepsilon^2}}$ and $v_{i,t} = (1-\lambda)u_i + (\varepsilon_{i,t} - \lambda\bar{\varepsilon}_i)$.

We identify two distinct cases with respect to λ; if $\lambda = 1$, then the RE estimator is identical to the FE estimator and if $\lambda = 0$ the RE estimator is identical to the POLS.

5.4.1a Static Models - Empirical Results

We next present a model specification for analysing the LLP behaviour of Greek banks by presenting the static model and ignoring the possible dynamic nature of provisioning and to an extent the dynamic effect of risk appreciation within the chosen sample (we account for the dynamic nature in latter specifications presented in the subsequent section). Indeed, Bushman and Williams (2012) and also Curcio and Hasan (2015) share similar specifications. Our parsimonious Static Baseline Model (SBM) is defined as, equation (5.14)[92],

$$\frac{LLP_{it,}}{TA_{i,t}} = \alpha_0 + \alpha_1\frac{TCE_{i,t}}{TA_{i,t}} + \alpha_2\frac{NI_{i,t}}{TA_{i,t}} + \alpha_3\frac{NPL_{i,t}}{GL_{i,t}} + \alpha_4 GDP_t + \alpha_5 UNEMP_i + \varepsilon_{i,t}. \tag{5.14}$$

Where $LLP_{i,t}/TA_{i,s}$ represents $\text{LLP}_{i,t}$of bank i at time period t, scaled by total assets at period t (following Curcio and Hasan, 2015)[93]. Total Common Equity scaled by total assets, $TCE_{i,t}/TA_{i,s}$ and is included to test for the capital management hypothesis (where a negative coefficient is an indication towards the existence of the capital

[92] We refrain from including additional explanatory variables in our estimation as they would significantly reduce the efficiency of our subsequent econometric specification in the next section.

[93] The estimation of our results remained unchanged to different scaling methods. That is, we also scaled the dependent and explanatory variables by average total assets, gross loans and average gross loans. In all cases our results remained stable across specifications.

management hypothesis)[94]. The effects of the business cycle can be tested by considering the coefficient of two macroeconomic variables, Gross Domestic Growth (GDP) and the annual change in unemployment rate ($UNEMP$). Bikker and Metzemakers (2005) test the counter or pro-cyclicality business cycle hypothesis with the inclusion of the same variables. In the former a positive and latter a negative coefficient indicates respectively pro-cyclical managing of LLP. In addition, following Liu and Ryan (2006), Pérez et al., (2008), Curcio and Hasan (2015) and Skala (2015), we also include the ratio of Non-Performing Loans to gross loans, $NPL_{i,t}/GL_{i,t}$, as an indicator of bank risk credit and also as a proxy for the non-discretionary component of the LLP. We expect a positive sign for the coefficient of NPL as banks with low credit quality are expected to provision more. As Bolt et al., (2012) find evidence that bank profits behaves pro-cyclically and this co-movement is significant during severe recessions, finally, among the different profit components, loan-loss provisioning could be a driver of this asymmetry. Thus, we introduce, Net Income scaled by total assets, $NI_{i,t}/TA_{i,t}$ in order to capture the link between profitability and provisioning and treat this variable as an indicator suggesting that better managed banks may have lower provisions and on average better quality of assets.

In the second stage of our analysis we test the impact of cost efficiency and LLP introducing the cost efficiency scores into equation (5.14) and hence leading to three distinct model specifications; SM1, SM2 and SM3[95]. That is, we extend equation (5.16) to include the efficiency scores derived from our SF models (TVM1-4Z, TVM2-4Z and TVM31-4Z), equation (5.15)[96],

[94] We use the equity to total assets ratio instead of the regulatory capital ratio, as data availability would reduce our available sample.

[95] Individual bank specific cost efficiency scores ($CE_{i,t}$) estimated under the TVM models discussed in Chapter 4 are utilised.

[96] It is interesting to note that the estimation of different equations, including and then excluding variables is quite common in the loan loss provisioning GMM literature. For example, Laeven and Majnoni (2003) includes and omits negative earnings; Ghosh (2007), 2 different capital and profitability variables; Bouvatier and Lepetit (2008) 3 different discretionary and nondiscretionary components of LLP; Fonseca and González (2008), 5 different corporate governance interaction variables; Pérez et al (2008), Tier 1 capital, capital buffer, and cross products of earnings; Bouvatier et al., (2014), 3 different earnings ratio interaction variables with respect to clusters or corporate governance; whereas, Skala (2015) includes and omits NPL, LLR and loan growth across their models. This list excludes the common practice of whether to include or exclude (either/and/or), period, time and country specific dummies, see for example Bouvatier et al., (2014).

$$\frac{LLP_{i,t}}{TA_{i,t}} = \alpha_0 + \alpha_1 \frac{TCE_{i,t}}{TA_{i,t}} + \alpha_2 \frac{NI_{i,t}}{TA_{i,t}} + \alpha_3 \frac{NPL_{i,t}}{GL_{it}} + \alpha_4 GDP_t + \alpha_5 UNEMP_i + \alpha_6 CE_{i,t} + \varepsilon_{i,t}. \quad (5.15)$$

Where, CE_{it} represents TVM1-4Z, TVM2-4Z and TVM3-4Z for the SM1,SM2 and SM3 models respectively. It is worth noting that the use of the panel data estimation methods discussed above help reduce the magnitude of the impact of omitted variables as the within estimator the RE remove any unobserved heterogeneity and its associated omitted variable bias. Therefore, in a well-executed panel data framework, we should not expect to see significant changes in the right-hand side coefficients of the previously included variables when an additional bank specific variable is introduced to the model. If this is the case, potential underlying problems with either the model specifications or the data may be present. Of course, this interpretation leaves out any confounding effects between the explanatory effects that may be present - a problem mitigated in panel data, but still potentially important. It is with this caveat, we present two sets of model, a base and a secondary that includes costs efficiency estimates within the specifications. This will offer an insight, albeit tentatively, to whether previous specifications that omit bad luck or skimping hypotheses have present less than perfect results.

Table 5.1 reports the summary statistics for the estimated model. A brief examination of the data reveals that Piraeus Bank reports the maximum $LLP_{i,t}/TA_{i,t}$ for our sample in 2011 – and the respective maximum $NPL_{i,t}/TA_{i,t}$ for the same year. The minimum scaled LLP value is reported by Proton Bank S.A. for 2006. With respect to NPL, General Bank of Greece SA reports the highest $NPL_{i,t}/TA_{i,t}$ value in 2012, whereas Proton Bank S.A. records the minimum. Finally, Proton Bank S.A. is the most profitable bank in our sample ($NI_{i,t}/TA_{i,t}$) (a value reported in 2005) whereas Piraeus Bank SA reports the highest losses for 2011.

Table 5.1. Summary Statistics - Static Models

	Observations	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
$LLP_{it}/TA_{i,t}$	59	0.029	0.035	0.0009	0.157
$CE_{i,t}/TA_{i,t}$	59	0.052	0.050	-0.052	0.242
$NI_{i,t}/TA_{i,t}$	59	-0.018	0.034	-0.134	0.020
$NPL_{i,t}/TA_{i,t}$	59	0.152	0.123	0.001	0.594
$GDPgr$	59	-2.698	4.293	-7.105	5.507
Un	59	13.396	6.041	7.8	24.5
$TVM1-4Z$	59	0.897	0.110	0.445	0.978
$TVM2-4Z$	59	0.886	0.116	0.445	0.978
$TVM3-4Z$	59	0.895	0.113	0.419	0.978

Where LLP_{it}/TA_{is} represents the loan-loss provisions (LLP) of bank i at time period t scaled by total assets at period t; TCE_{it}/TA_{is} represents Total Common Equity of bank i at time period t scaled by total assets at period t; NI_{it}/TA_{it} represents Net Income of bank i at time period t scaled by total assets at period t; NPL_{it}/GL_{it} represents Non-Performing Loans of bank i at time period t to gross loans, at time t; $GDPgr$ represents the annual change of Gross Domestic Product (%); Un represents the unemployment rate. $TVM1-4Z$ Time Varying Model 1, without a risk metric; $TVM2-4Z$ Time Varying Model 2, with Equity as a risk metric; $TVM3-4Z$ Time Varying Model 1, with LLP as a risk metric.

4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio.

Sources for macroeconomic variables: World Bank, the European Central Bank and Eurostat database.
Source for bank specific variables: Bankscope by Bureau Van Dijk database.

To provide an overview of our model, we first estimate equations (5.14) and (5.15) using a pooled time series OLS using all banks in all years, and then via the within estimator and Random Effects. In all cases, we test for the presence of heteroskedastic residuals using the Breusch-Pagan/Cook-Weisberg test for heteroskedasticity and the White's original heteroskedasticity test. With respect to the Breusch-Pagan/Cook-Weisberg test we find evidence against the null hypothesis and the presence of homoscedastic residuals (Panel A, Table 5.2). Our results are also confirmed by the White test, indicating the validity of the pooled OLS is plagued by heteroskedastic disturbances. Similar findings are also reported for the within estimator via the Modified Wald test where we again find evidence against homoskedasticity (Panel B, Table 5.2). Finally, we control for groupwise heteroskedasticity using Levene's (1960) robust test statistic (W0) for the equality of variances between the groups (Panel C, Table 5.2). As such, the Random Effects residuals do not suffer from groupwise

heteroskedastic disturbances, however, we maintain a consistent modelling approach and proceed to estimate all models by using the Huber-White sandwich estimators[97].

To further determine the validity of our analysis, we conduct a series of post-estimation diagnostics which reveal that our estimated equations exhibit normally distributed error terms, Shapiro-Wilk and Shapiro-Francia W tests for normality (Table 5.3). As expected, correcting for heteroskedastic error terms also corrects for the possibility of non-normal error terms. That is, for models SM1, SM2 and SM3, we fail to reject the null of normally distributed residuals under all estimation methods. That is, the Pooled OLS, FE and RE models all exhibit normally distributed residuals. With respect to the SBM, only the Pooled OLS regression exhibits normally distributed disturbance terms as under the FE and RE estimation we strongly reject the null hypothesis. This raises concerns as to the validity of the estimated models which take into account unobserved heterogeneity (graphical representations of the Quantile–normal plots and Normal probability plots are presented in Appendix C, Table 10.5).

In addition to the above diagnostics, we control for collinearity by examining the Centred Variance Inflation Factors (VIFs) (Table 5.4). Using the rule of thumb that VIF values greater than 10 indicate worrisome results, it is evident that none of the variables included in our model merit further investigation. Thereby multicollinearity, is irrelevant in our estimations as all values are below the threshold ranging from a minimum of 2.51 (SBM) to a maximum of 3.37 (SM3).

[97] Such robust standard errors deal with minor concerns about normality of residuals (to be examined next), heteroskedasticity, or some observations that exhibit large residuals and leverage or influence. Therefore, in our results section we present the estimated results from our robust pooled OLS, FE and RE models.

Table 5.2. Heteroskedasticity tests

	SBM	*SM1*	*SM2*	*SM3*
Panel A (OLS)				
Breusch-Pagan / Cook-Weisberg	0.000	0.010	0.009	0.009
White	0.015	0.075	0.245	0.059
Panel B (FE)				
Modified Wald Test	0.000	0.000	0.000	0.000
Panel C (RE)				
Levene's (W0)	0.126	0.593	0.619	0.610

H_0: Homoscedastic residuals. This table report the p-values of the test. Where, SBM represents the Static Base Model in equation (5.16), SM1 represents the Static Model 1 in equation (5.17) including TVM1-4Z, SM2 represents the Static Model 2 in equation (5.17) including TVM2-4Z, SM3 represents the Static Model 3 in equation (5.15) including TVM3-4Z. TVM1 Time Varying Model 1, without a risk metric, 4Z; TVM2 Time Varying Model 2, with Total Equity as netput; TVM3 Time Varying Model 3, with Loan Loss Provisions as netput, 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio.

Table 5.3. Tests for normality of residual distributions

	SBM	*SM1*	*SM2*	*SM3*
		Panel A (OLS)		
Shapiro-Francia W	0.193	0.376	0.315	0.358
Shapiro-Wilk	0.361	0.407	0.342	0.399
		Panel B (FE)		
Shapiro-Francia W	0.002	0.177	0.464	0.123
Shapiro-Wilk	0.005	0.388	0.832	0.269
		Panel C (RE)		
Shapiro-Francia W	0.007	0.457	0.475	0.420
Shapiro-Wilk	0.015	0.738	0.775	0.691

H_0: Normally distributed residuals. This table report the p-values of the test. Where, SBM represents the Static Base Model in equation (5.16), SM1 represents the Static Model 1 in equation (5.17) including TVM1-4Z, SM2 represents the Static Model 2 in equation (5.17) including TVM2-4Z, SM3 represents the Static Model 3 in equation (5.15) including TVM3-4Z. TVM1 Time Varying Model 1, without a risk metric, 4Z; TVM2 Time Varying Model 2, with Total Equity as netput; TVM3 Time Varying Model 3, with Loan Loss Provisions as netput, 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio.

Table 5.4. Centred Variance Inflation Factors (VIFs)

	SBM	*SM1*	*SM2*	*SM3*
CE_{it}/TA_{it}	1.29	1.41	1.39	1.43
NI_{it}/TA_{it}	2.14	2.33	2.29	2.33
NPL_{it}/GL_{it}	2.65	2.65	2.65	2.65
$GDPgr$	2.89	6.64	6.42	6.68
Un	3.59	4.05	3.88	4.06
$TVM1-4Z$		3.03		
$TVM2-4Z$			3.10	
$TVM3-4Z$				3.07
Mean VIF	2.51	3.35	3.29	3.37

The reported VIF values are obtained from the respective Huber-White sandwich estimators. This table report the p-values of the test. Where, SBM represents the Static Base Model in equation (5.16), SM1 represents the Static Model 1 in equation (5.17) including TVM1-4Z, SM2 represents the Static Model 2 in equation (5.17) including TVM2-4Z, SM3 represents the Static Model 3 in equation (5.15) including TVM3-4Z. TVM1 Time Varying Model 1, without a risk metric, 4Z; TVM2 Time Varying Model 2, with Total Equity as netput; TVM3 Time Varying Model 3, with Loan Loss Provisions as netput, 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio.

Thus far in our discussion, we have focused on a set of post-estimation diagnostic tests confirming the validity of the estimated regressions. We now turn our focus on further examining the structure of the data at hand and account for the presence of unobserved heterogeneity (by estimating robust RE model and conduct the Breusch and Pagan (1980) Lagrange multiplier test for random effects). That is, the null hypothesis in the LM test is that variance of the random effect across banks is zero - no significant difference (i.e., no panel effect). In all but one case, we reject the null hypothesis at the maximum 10% level, indicating that unobserved heterogeneity is indeed present in our data (Table 5.5). Surprisingly, only in the case of the SBM we fail to reject the null hypothesis, thus preferring the Pooled OLS regression over the RE model (indicating no evidence of a significant difference across banks when cost efficiency is excluded in the estimation). This finding is consistent with the results reported above where FE and RE SBM indicate towards a potentially not accurately specified regression, as their respective residuals do not satisfy the normality of the residuals assumption.

Table 5.5. Breusch and Pagan Lagrangian multiplier test for random effects

Model	*LM Test p-value*
SBM	0.132
SM1	0.020
SM2	0.011
SM3	0.022

Where, SBM represents the Static Base Model in equation (5.16), SM1 represents the Static Model 1 in equation (5.17) including TVM1-4Z, SM2 represents the Static Model 2 in equation (5.17) including TVM2-4Z, SM3 represents the Static Model 3 in equation (5.15) including TVM3-4Z. TVM1 Time Varying Model 1, without a risk metric, 4Z; TVM2 Time Varying Model 2, with Total Equity as netput; TVM3 Time Varying Model 3, with Loan Loss Provisions as netput, 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio.

As a final post-estimation diagnostic and having identified unobserved heterogeneity in the data we implement the Robust Hausman test using the artificial regression approach described by Arellano (1993) and Wooldridge (2010). For this purpose, we re-estimate the augmented random effects equation with additional variables consisting of the original regressors transformed into deviations-from-mean form. The test of FE vs. RE models can be seen as a test of overidentifying restrictions. That is, the FE estimator uses the orthogonality conditions that the regressors are uncorrelated with the idiosyncratic error whereas the RE model uses the additional orthogonality conditions that the regressors are uncorrelated with the group-specific error (the random effect). These additional orthogonality conditions are overidentifying restrictions and as such the test statistic is a Wald test of the significance of these additional regressors. Furthermore, under homoscedastic errors, this statistic is equivalent to the Hausman fixed-vs-random effects test. Also, in the case of a balanced sample, both statistics would obtain numerically equal results. Our estimates show that in all cases, we strongly reject the null hypothesis that the individual bank specific effect is not correlated with the explanatory variables chosen, hence preferring the FE specification over the RE (Table 5.6)[98].

[98] It is important to note that we estimate the Robust Hausman test for the SBM only for consistency purposes as no bank specific effects were identified in the previous step of our analysis.

Table 5.6. Test of overidentifying restrictions: Fixed vs. Rrandom effects

Model	*Sargan-Hansen*	*P-value*
SBM (χ_5^2)	19.528	0.001
SM1 (χ_6^2)	124.499	0.000
SM2 (χ_6^2)	74.691	0.000
SM3 (χ_6^2)	118.409	0.000

Where, SBM represents the Static Base Model in equation (5.16), SM1 represents the Static Model 1 in equation (5.17) including TVM1-4Z, SM2 represents the Static Model 2 in equation (5.17) including TVM2-4Z, SM3 represents the Static Model 3 in equation (5.15) including TVM3-4Z. TVM1 Time Varying Model 1, without a risk metric, 4Z; TVM2 Time Varying Model 2, with Total Equity as netput; TVM3 Time Varying Model 3, with Loan Loss Provisions as netput, 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio.

To investigate the LLP behaviour of the Greek banking system with respect our static models, we focus on estimates from the Pooled OLS, SBM, and the estimated coefficients of the Fixed Effects estimator for the augmented regressions (SM1, SM2 and SM3)[99]. Overall, the models indicate a high R^2 value, ranging from 0.916 for the Pooled OLS to 0.969 and 0.971 for SM1/ SM3 and SM2 respectively (Table 5.7, Table 5.8, Table 5.9 and Table 5.10). With respect to the FE estimated models, the intraclass variation (a measure indicating the percent of the error variance due to difference across panels) is stable, ranging from 70.7% for SM3 to 70.8% and 71.6% for the SM1 and SM2 respectively.

Turning to the bank specific and macroeconomic variables, all models remain relatively consistent. Specifically, in the SBM (Table 5.7), by observing the signs of the macro indicator coefficients, there is an insignificant relationship with GDP – thus indicating no counter/pro-cyclical provisioning behaviour. With respect to the additional macro variables, the unemployment rate is found to be positively correlated to LLP – thus indicating procyclical behaviour. However, when we estimate the augmented regressions, including the three cost efficiency estimates using the FE estimator, the results change and produce conflicting findings (Tables 5.8 to 5.10). That is, both the

[99] Additional variables where tested and found to be insignificant. For example, time dummies covering the aftermath of both the Global financial crisis and the Greek crisis were in both cases insignificant. This is not surprising as Greek banks remained relatively insulated from those effects in the recent years after the crises. We would expect, though, significant coefficients in data covering also the years after 2012, when the recession deepened in Greece. Also, the natural log of total assets proved to be insignificant. As Kim and Kross (1998) note, this may be in line the too big to fail hypothesis, which argues that regulators are reluctant to intervene in the operations of large banks - thus implying an insignificant coefficient. Finally, two versions of the Z-score as proposed by Laeven and Levine (2009) and Tabak et al., (2013) were also found to be insignificant.

unemployment rate and GDP growth rate are negative and significant. Furthermore, with respect to the LLP, a negative GDP growth rate coefficient indicates procyclical provisioning behaviour, whereas, a negative unemployment coefficient indicates counter cyclical provisioning. It is thus difficult to disentangle whether or not Greek banks turned from an intermediation mechanism to a mechanism that amplifies the business cycle effect via their provisioning strategies.

With respect to the bank specific factors affecting LLP, surprisingly, and contrary to our theoretical prior expectations, NPLs prove to be negatively correlated with LLP under SBM (Table 5.7). This relationship between the two variables, aligns to our theoretical expectations when we estimate the augmented regressions SM1, SM2 and SM3, where in all cases we find a positive coefficient with values of 0.024, 0.019 and 0.025 for SM1, SM2 and SM3 respectively (Table 5.8, Table 5.9 and Table 5.10 respectively). We also find similar stability to the associated scaled Net Income variable, thus finding it has a negative and significant effect on LLP. Our estimations show that the relationship remains statistically significant at the 1% level, with short-run coefficients ranging from -0.967 to -1.07 (see Table 5.8, Table 5.9 and Table 5.10). Therefore, profitable banks exhibit lower provisions reflecting superior managerial abilities and skills in exercising control over the risk management loan portfolio.

Regarding the capital to assets ratio, we find support for the capital management hypothesis as all FE specifications report a negative coefficient. That is, we find evidence that on average, banks report higher provisions when the capital ratio is relatively low. The respective coefficients equal to -0.087, -0.081 and -0.089 for SM1, SM2 and SM3 (see Table 5.7 - Table 5.10). Surprisingly, under the Pooled OLS regression, even though we find a negative coefficient (-0.017), we find little evidence to support the capital management hypothesis as there is an insignificant effect (Table 5.7).

Finally, given our initial results, we focus only on the augmented regression including the cost efficiency estimates. TVM1-4Z, TVM2-4Z and TVM3-4Z respectively (Table 5.8, Table 5.9 and Table 5.10). In all the aforementioned models, LLP is negatively correlated with efficiency scores and TVM1-4Z, TVM2-4Z and TVM3-4Z have a negative and statistically significant impact on provisions with short-run coefficients

equal to -0.060, -0.063 and -0.057 respectively. Therefore, Greek banks who operate away from the optimal frontier, on average, report a higher level of provisioning. That is, our results could reflect greater difficulties in raising new capital and/or be caused via an indirect indication of the bad management. We return and further explore the aforementioned finding in the next section.

Table 5.7. Loan Loss Provisioning - SBM

Dependent variable: LLP_{it}/TA_{it}			
	Pooled OLS	Random Effects	Fixed Effects
$CE_{i,t}/TA_{i,t}$	-0.017	-0.018	-0.061
	(0.040)	(0.042)	(0.055)
$NI_{i,t}/TA_{i,t}$	-1.047***	-1.053***	-1.006***
	(0.077)	(0.065)	(0.055)
$NPL_{i,t}/TA_{i,t}$	-0.057**	-0.031	0.049**
	(0.024)	(0.024)	(0.023)
$GDPgr$	0.001	0.000	0.000
	(0.000)	(0.000)	(0.000)
Un	0.001**	0.000	-0.001**
	(0.000)	(0.001)	(0.001)
$constant$	0.010**	0.013**	0.024***
	(0.005)	(0.006)	(0.006)
R^2	0.916		0.959[a]
F(5, 53)	100.46		
Prob > F	0.000		
R^2*within*		*0.9448*	*0.9509*
R^2*between*		*0.7786*	*0.5652*
R^2*overall*		*0.9122*	*0.8610*
Wald chi2(5)		*1282.54*	
Prob > chi2		*0.000*	
F(5,14)			*169.79*
Prob > F			*0.000*
σ_u		*0.006*	*0.013*
σ_e		*0.008*	*0.008*
Intraclass Variation (ρ)[b]		*0.386*	*0.697*
Observations	59	59	59

Huber-White sandwich estimators/Robust Standard errors are reported in parentheses. For the within estimator we also report the R^2 *of the LSDM estimation as we do not assess significance in the* R^2 *of the within estimator as we suppressed the constant in the de-meaning process, equation (5.12). Where* $LLP_{i,t}/TA_{i,t}$ *represents the loan-loss provisions (LLP) of bank* i *at time period* t*, scaled by total assets at period* t*;* $TCE_{i,t}/TA_{i,t}$ *represents Total Common Equity of bank* i *at time period* t *scaled by total assets at period* t*;* $NI_{i,t}/TA_{i,t}$ *represents Net Income of bank* i *at time period* t *scaled by total assets at period* t*;* $NPL_{i,t}/GL_{i,t}$ *represents Non-Performing Loans of bank* i *at time period* t *to gross loans, at time* t*;* $GDPgr$ *represents the annual change of Gross Domestic Product (%);* Un *represents the unemployment rate.*

Sources for macroeconomic variables: World Bank, the European Central Bank and Eurostat database. Source for bank specific variables: from Bankscope by Bureau Van Dijk database.

[a] *LSDV* R^2.

[b] *% of the variance is due to differences across panels.*

λ: min: 0.334, 5%: 0.334, median: 0.467, 95%: 0.570, max: 0.570

** p < 0.10, ** p < 0.05, *** p < 0.01*

Table 5.8. Loan Loss Provisioning - SM1

Dependent variable: LLP_{it}/TA_{it}			
	Pooled OLS	Random Effects	Fixed Effects
$CE_{i,t}/TA_{i,t}$	-0.039	-0.051	-0.087**
	(0.039)	(0.041)	(0.039)
$NI_{i,t}/TA_{i,t}$	-1.007***	-1.002***	-0.967***
	(0.075)	(0.067)	(0.058)
$NPL_{i,t}/TA_{i,t}$	-0.055**	-0.033	0.024
	(0.022)	(0.027)	(0.036)
$GDPgr$	-0.001	-0.001*	-0.002**
	(0.001)	(0.001)	(0.001)
Un	0.000	-0.000	-0.001**
	(0.000)	(0.000)	(0.001)
$TVM1-4Z$	-0.051**	-0.061***	-0.060**
	(0.023)	(0.021)	(0.022)
$constant$	0.059**	0.072***	0.080***
	(0.025)	(0.022)	(0.021)
R^2	0.925		0.969[a]
F(6, 52)	98.13		
Prob > F	0.000		
R^2*within*		*0.9597*	*0.9629*
R^2*between*		*0.7564*	*0.611*
R^2*overall*		*0.9210*	*0.894*
Wald chi2(6)		*1729.13*	
Prob > chi2		*0.000*	
F(6,14)			*341.87*
Prob > F			*0.000*
σ_u		*0.006*	*0.011*
σ_e		*0.007*	*0.007*
Intraclass Variation (ρ)[b]		*0.459*	*0.708*
Observations	59	59	59

Huber-White sandwich estimators/Robust Standard errors are reported in parentheses. For the within estimator we also report the R^2 *of the LSDM estimation as we do not assess significance in the* R^2 *of the within estimator as we suppressed the constant in the de-meaning process, equation (5.12). Where* $LLP_{i,t}/TA_{i,t}$ *represents the loan-loss provisions (LLP) of bank* i *at time period* t*, scaled by total assets at period* t*;* $TCE_{i,t}/TA_{i,t}$ *represents Total Common Equity of bank* i *at time period* t *scaled by total assets at period* t*;* $NI_{i,t}/TA_{i,t}$ *represents Net Income of bank* i *at time period* t *scaled by total assets at period* t*;* $NPL_{i,t}/GL_{i,t}$ *represents Non-Performing Loans of bank* i *at time period* t *to gross loans, at time* t*;* $GDPgr$ *represents the annual change of Gross Domestic Product (%);* Un *represents the unemployment rate.* $TVM1-4Z$*: Time Varying Model 1, without a risk metric; 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio.*

Sources for macroeconomic variables: World Bank, the European Central Bank and Eurostat database. Source for bank specific variables: from Bankscope by Bureau Van Dijk database.

[a] *LSDV* R^2.

[b] *% of the variance is due to differences across panels.*

λ*: min: 0.391, 5%:0.391, median: 0.523, 95%:0.620, max: 0.620*

** p < 0.10, ** p < 0.05, *** p < 0.01*

Table 5.9. Loan Loss Provisioning - SM2

Dependent variable: LLP_{it}/TA_{it}			
	Pooled OLS	Random Effects	Fixed Effects
$CE_{i,t}/TA_{i,t}$	-0.038	-0.049	-0.081**
	(0.038)	(0.039)	(0.037)
$NI_{i,t}/TA_{i,t}$	-1.010***	-1.005***	-0.972***
	(0.073)	(0.063)	(0.053)
$NPL_{i,t}/TA_{i,t}$	-0.056**	-0.032	0.019
	(0.022)	(0.027)	(0.036)
$GDPgr$	-0.001	-0.001*	-0.002**
	(0.001)	(0.001)	(0.001)
Un	0.001	-0.000	-0.001**
	(0.000)	(0.000)	(0.001)
$TVM2-4Z$	-0.052**	-0.064***	-0.063**
	(0.022)	(0.022)	(0.023)
$constant$	0.058**	0.073***	0.081***
	(0.022)	(0.022)	(0.021)
R^2	0.925		0.971[a]
F(6, 52)	97.96		
Prob > F	0.000		
R^2*within*		*0.962*	*0.965*
R^2*between*		*0.746*	*0.616*
R^2*overall*		*0.921*	*0.893*
Wald chi2(6)		*1522.58*	
Prob > chi2		*0.000*	
F(6,14)			*315.07*
Prob > F			*0.000*
σ_u		*0.007*	*0.011*
σ_e		*0.007*	*0.007*
Intraclass Variation $(\rho)^b$		*0.500*	*0.716*
Observations	59	59	59

Huber-White sandwich estimators/Robust Standard errors are reported in parentheses. For the within estimator we also report the R^2 *of the LSDM estimation as we do not assess significance in the* R^2 *of the within estimator as we suppressed the constant in the de-meaning process, equation (5.12). Where* $LLP_{i,t}/TA_{i,t}$ *represents the loan-loss provisions (LLP) of bank* i *at time period* t*, scaled by total assets at period* t*;* $TCE_{i,t}/TA_{i,t}$ *represents Total Common Equity of bank* i *at time period* t *scaled by total assets at period* t*;* $NI_{i,t}/TA_{i,t}$ *represents Net Income of bank* i *at time period* t *scaled by total assets at period* t*;* $NPL_{i,t}/GL_{i,t}$ *represents Non-Performing Loans of bank* i *at time period* t *to gross loans, at time* t*;* $GDPgr$ *represents the annual change of Gross Domestic Product (%);* Un *represents the unemployment rate.* $TVM2-4Z$*: Time Varying Model 2, with Equity as a risk metric; 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio.*

Sources for macroeconomic variables: World Bank, the European Central Bank and Eurostat database. Source for bank specific variables: from Bankscope by Bureau Van Dijk database.

[a] *LSDV* R^2.

[b] *% of the variance is due to differences across panels.*

λ*: min: 0.423, 5%:0.423, median: 0.553, 95%:0.646 , max: 0.646*

** p < 0.10, ** p < 0.05, *** p < 0.01*

Table 5.10. Loan Loss Provisioning - SM3

Dependent variable: LLP_{it}/TA_{it}			
	Pooled OLS	Random Effects	Fixed Effects
$CE_{i,t}/TA_{i,t}$	-0.040	-0.051	-
	(0.040)	(0.042)	0.089**(0.040)
$NI_{i,t}/TA_{i,t}$	-1.008***	-1.004***	-0.967***
	(0.076)	(0.068)	(0.059)
$NPL_{i,t}/TA_{i,t}$	-0.055**	-0.033	0.025
	(0.023)	(0.027)	(0.036)
$GDPgr$	-0.001	-0.001	-0.002**
	(0.001)	(0.001)	(0.001)
Un	0.000	-0.000	-0.001**
	(0.000)	(0.000)	(0.001)
$TVM3-4Z$	-0.048**	-0.058***	-0.057**
	(0.024)	(0.021)	(0.021)
$constant$	0.056**	0.069***	0.078***
	(0.025)	(0.022)	(0.021)
R^2	0.924		0.969[a]
F(6, 52)	98.29		
Prob > F	0.000		
R^2*within*		*0.958*	*0.962*
R^2*between*		*0.756*	*0.606*
R^2*overall*		*0.923*	*0.888*
Wald chi2(6)		*1792.43*	
Prob > chi2		*0.000*	
F(6,14)			*312.70*
Prob > F			*0.000*
σ_u		*0.006*	*0.011*
σ_e		*0.007*	*0.007*
Intraclass Variation (ρ)[b]		*0.451*	*0.707*
N	59	59	59

Huber-White sandwich estimators/Robust Standard errors are reported in parentheses. For the within estimator we also report the R^2 of the LSDM estimation as we do not assess significance in the R^2 of the within estimator as we suppressed the constant in the de-meaning process, equation (5.12). Where $LLP_{i,t}/TA_{i,t}$ represents the loan-loss provisions (LLP) of bank i at time period t, scaled by total assets at period t; $TCE_{i,t}/TA_{i,t}$ represents Total Common Equity of bank i at time period t scaled by total assets at period t; $NI_{i,t}/TA_{i,t}$ represents Net Income of bank i at time period t scaled by total assets at period t; $NPL_{i,t}/GL_{i,t}$ represents Non-Performing Loans of bank i at time period t to gross loans, at time t; $GDPgr$ represents the annual change of Gross Domestic Product (%); Un represents the unemployment rate. $TVM3-4Z$ Time Varying Model 1, with LLP as a risk metric; 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio.

Sources for macroeconomic variables: World Bank, the European Central Bank and Eurostat database. Source for bank specific variables: from Bankscope by Bureau Van Dijk database.

[a] LSDV R^2.

[b] % of the variance is due to differences across panels.

λ: min: 0.385, 5%:0.385, median: 0.517, 95%:0.615, max: 0.615

** p < 0.10, ** p < 0.05, *** p < 0.01*

5.4.2 Dynamic Panel Data Models

The static models discussed in the previous sections assume that the probability of moving (or staying) in or out of a state is independent of the occurrence or past non-occurrence. Furthermore, the previously specified models make some rather rigid and restrictive assumptions regarding the behaviour of the explanatory variables. That is, it assumes strict exogeneity between the error term and the vector of right-hand side variables, $x_{i,t}$, whereas, endogeneity is a common occurrence in LLP models and it may occur due to simultaneous bias and/or reverse causality. For example, Bouvatier and Lepetit (2008) and Louzis et al., (2012) discuss the issue of potential reverse causality and simultaneity bias in their models. In addition, Skala (2015) also acknowledge the problem of endogeneity and estimate a "dynamic OLS" model where they scale the variables under consideration by lagged values of assets.

That is, the dependant variable reversely causing the microeconomic factors allows for feedback effects from LLP to the bank specific regressors. Despite the additional estimation complexity introduced, we relax both assumptions as we believe that a dynamic model is a more appealing specification than the static models presented above as it allows to us to capture; time persistence and the gradual adjustment of provisions, and in addition to take into account the effect of any residual lagged information. Such dynamic credit risk relationships can be identified from the presence of the lagged dependent variable as one of the independent variables (Bikker and Metzemakers, 2005). That is, if banks adjust their provisions slowly to recognize potential losses against loans following a default event then provisions could be systematically related to each period. Therefore, we believe that it is wise to allow the data to indicate whether dynamics in changes in LLP should play a role in our model. Thus, we adopt a dynamic approach to further disentangle the LLP behaviour of Greek banks (examples of studies using a dynamic model include Bouvatier and Lepetit, 2008; Pérez et al., 2008; Matousek and Sarantis, 2009; Louzis et al., 2012; and Akinci et al., 2013).

We begin by presenting the general form of our estimated regression, equation (5.16)[100],

[100] For consistency we follow the same i, t notations as the ones used in the previous sections and we follow the presentation of Baltagi (2005) and Greene (2007).

$$y_{i,t} = \alpha y_{i,t-1} + \beta x_{i,t} + \varepsilon_{i,t}, \qquad |\alpha| < 1, i = 1, \ldots., N, t, \ldots., T. \tag{5.16}$$
$$\varepsilon_{i,t} = u_i + v_{i,t}.$$

Where, $y_{i,t-1}$ represents the autotregressive component of equation (5.16), $x_{i,t}$, represents the vector of explanatory variables other than the $y_{i,t-1}$ term, u_i represents unobserved bank specific effects and $v_{i,t}$ represents the error term.

In a dynamic model, the presence of the lagged dependent regressor introduces additional complications into the estimation process. That is, contrary to the static model where discussion is mainly focused on whether fixed effects are correlated or not with the included variables, in the dynamic framework, these effects are always correlated with the lagged dependent variable, see equation (5.17),

$$y_{i,t-1} = \alpha y_{i,t-2} + \beta x_{i,t-1} + \varepsilon_{i,t-1}. \tag{5.17}$$
$$\varepsilon_{i,t-1} = u_i + v_{i,t-1}.$$

Indeed, the first source of bias is the correlation of one of the right-hand-side variables, $y_{i,t-1}$with the error term, thus violating the assumption of strict exogeneity – rendering the OLS estimator biased and inconsistent even in the absence of serial correlation. One way of attempting to correct the bias is via the use of the within estimator that will eliminate the fixed effect, u_i, hence addressing the problem of not having strict exogeneity in the estimated regression.

That is, using the within estimator yields the following model, equation (5.18),

$$(y_{i,t} - \bar{y}_i) = \alpha(y_{i,t-1} - \bar{y}_{i.-1}) + \beta(x_{i,t} - \bar{x}_i) + (v_{i,t} - \bar{v}_i) \tag{5.18}$$

Where, $\bar{y}_i = \sum_t y_{i,t}/T_i$, $\bar{y}_{i.-1} = \sum_{t=2}^{T} y_{i,t-1}/T - 1$, $\bar{x}_i = \sum_t x_{i,t}/T_i$ and $\bar{v}_i = \sum_t v_{i,t}/T_i$.

Although the transformation of the within estimator helps to eliminate the fixed effect, the demeaning process brings into the foreground an additional source of bias –

commonly known as the Nickell bias. That is, $y_{i,t-1}$ is still correlated with $\bar{v}_i$ as the latter average contains the term $v_{i,t-1}$, a term correlated with $y_{i,t-1}$. The resulting correlation creates a bias that cannot be mitigated by further increasing the number of banks N as the demeaning process is generating a regressor that is not independently distributed from the error term. As Nickel (1981) shows, the inconsistency of $\hat{\alpha}$ is of order $(1/T)$ as $N \to \infty$, and the within estimator's consistency will depend upon T being large. The extent of the bias as $N \to \infty$ is equal to $-(1+\alpha)/(T-1)$, which in the case of the sample employed in the current study implies a bias of -0.214 when $\alpha = 0.5$. Thereby, inclusion of additional regressors not only does not remove the bias, but in the case where the extra covariates are correlated with the autoregressive components, their coefficients may be seriously biased as well. In a similar manner, the quasi-demeaning performed in the RE estimator and the GLS estimator is also subject to the same bias in the dynamic specification as $\left(y_{i,t-1} - \lambda \bar{y}_{i.,-1}\right)$ and will be correlated with $(v_{it} - \lambda \bar{v}_{i.,-1})$.

Anderson and Hsiao (1981) discuss transformation where the remainder error will be easier to handle, by taking the first difference of equation (5.16). One main advantage of this transformation is that it removes any heterogeneity present in data, irrespective of the nature (i.e., fixed or random effects). However, the subsequent transformed model, equation (5.19) is also free from any time-invariant variables from the mode, equation (5.19),

$$\Delta y_{it}, = \alpha \Delta y_{i,t-1} + \beta \Delta x_{i,t} + \Delta \varepsilon_{it}. \qquad (5.19)$$

Where, Δ is the first difference operator. Anderson and Hsiao (1981) propose to construct instruments for the lagged dependent term from the second and third lags of $y_{i,t}$ either in the form of differences or lagged levels. That is, $\Delta y_{i,t-2} = \left(y_{i,t-2} - y_{i,t-3}\right)$ or $y_{i,t-2}$ can be used as instruments for $\Delta y_{i,t-1} = \left(y_{i,t-1} - y_{i,t-2}\right)$. However, Arrelano and Bond (1991) argue that even though the Anderson and Hsiao (1981) estimator is consistent; it does not take advantage of all the potential orthogonality conditions. Subsequently they propose a Generalized Method of Moments (GMM) procedure that is more efficient as it utilizes the orthogonality

conditions between the lagged values of y_{it} and the error term ε_{it}. In a simple dynamic model as in equation (5.16), for $t = 3$, after first differencing , equation (5.20),

$$y_{i,3} - y_{i,2} = \alpha(y_{i,2} - y_{i,1}) + \beta(x_{i,3} - x_{i,2}) + (\varepsilon_{i,3} - \varepsilon_{i,2}). \quad (5.20)$$

In this case, $y_{i,1}$ becomes a valid instrument as it satisfies the aforementioned necessary conditions, is predetermined with respect to $(\varepsilon_{i,3} - \varepsilon_{i,2})$, and correlated with $(y_{i,2} - y_{i,1})$. Therefore, the instrumental variables, $Z_{i,3}$, for $(y_{i,2} - y_{i,1})$ would be equal to $Z_{i,3} = (y_{1,1}, y_{2,1}, \ldots, y_{n,1})$, for n number of observations. In addition, and for the next time period $t = 4$, we obtain , equation (5.21),

$$y_{i,4} - y_{i,3} = \alpha(y_{i,3} - y_{i,2}) + \beta(x_{i,4} - x_{i,3}) + (\varepsilon_{i,4} - \varepsilon_{i,3}). \quad (5.21)$$

In this case, $y_{i,2}$ and $(y_{i,2} - y_{i,1})$ become available instruments for $(y_{i,3} - y_{i,2})$ as they are uncorrelated with $(\varepsilon_{i,4} - \varepsilon_{i,3})$. In fact, proceeding in a similar manner, and for $t = T$, the set of valid intruments becomes, $Z_{i,T} = (y_{i,1}, y_{i,2}, \ldots, y_{i,T-2})$. Indeed, Arellano and Bover (1995) and Blundell and Bond (1998) suggest to use lagged levels as well as lagged differences, covering any potential weakness arising from the Arellano and Bond (1991) estimator in the case where lagged levels are poor instruments (especially if the variables are close to a random walk). Thus, the Arellano and Bover (1995) and Blundell and Bond (1998) estimator augments Arellano and Bond (1991) by making an additional assumption that first differences of instrumental variables are not correlated to the fixed effect. That way, the introduction of additional instruments becomes a valid option, thus dramatically improving efficiency – building a system of two equations (the original equation and the transformed one) - known as system GMM (SGMM). Extending our discussion and taking into account the exogenous regressors, not only the lagged values of $y_{i,t}$ are appropriate instruments, but also all values of $x_{i,t}$ become available. For example, in the previous case, for $t = 4$, the available instruments are, $y_{i,1}$, $y_{i,2}$ and $(x'_{i,1}, x'_{i,2}, \ldots, x'_{i,T})$ for all T periods. It is therefore evident that even in a moderate sized sample, this process could lead to a substantial number of instruments which may compromise efficiency of the estimation process – a subject which we return to and take into account in the subsequent section of our modelling strategy.

To recap, the aforementioned estimating process has some appealing characteristics as the difference and SGMM estimator is designed for panel data analysis and also embodies the following assumptions about the data (see for example Roodman, 2009):

- The process may be dynamic, with current realizations of the dependent variable influenced by past ones.
- There may be arbitrarily distributed fixed individual effects
- Some regressors may be endogenous, while others predetermined (i.e., correlated by past disturbances) but not strictly exogenous (i.e., independent of the current error term). A prime example of a predetermined regressor is the lagged dependent variable.
- The idiosyncratic disturbances (those apart from the fixed effects) may have individual-specific patterns of heteroskedasticity and serial correlation.
- The idiosyncratic disturbances are uncorrelated across individuals.
- The number of time periods of available data, *T*, may be small.
- Finally, the estimators are designed for general use and they do not assume that good instrumental variables (IV) are available in the form of excluded instruments. Therefore, by design they allow for the inclusion of internally based instrumental variables; that is the lags of the instrumented variables.

Given the above discussion of dynamic models, we therefore progress our econometric analysis to a more determinate and inclusive specification.

5.4.2b Dynamic Models - Empirical Results

We now present the estimated dynamic specifications employed and our modelling strategy in which we adopt a similar estimation approach to Fonseca and González (2008), Louzis et al., (2012), Bouvatier and Lepetit (2012) and Skala (2015). That is, building on the static specification presented in Section 5.4.1, and introduce an autoregressive component, thus estimating the following dynamic baseline model (DBM) regression via System GMM, equation (5.22)[101],

[101] Skala (2015) notes the lack of a uniform approach when estimating variation of LLP models, "[….] Laeven and Majnoni (2003) and Fonseca and González (2008) apply the Arellano and Bond (1991) estimator, while Bornemann et al. (2012) and Bouvatier et al. (2014) use the Blundell and Bond (1998) system GMM. Similarly, the number of lags to the dependent variable varies across these papers, as does as the treatment of independent variables as endogenous or exogenous (page 30)".

$$\frac{LLP_{i,t}}{TA_{i,t}} = \alpha_0 + \alpha_1 \frac{LLP_{i,t-1}}{TA_{i,t-1}} + \alpha_2 \frac{TCE_{i,t}}{TA_{i,t}} + \alpha_3 \frac{NI_{i,t}}{TA_{i,t}} + \alpha_4 \frac{NPL_{i,t}}{GL_{i,t}} + \alpha_5 GDP_t + \alpha_6 UNEMP_t + v_{i,t}. \quad (5.22)$$

Building on equation (5.15), we estimate an additional dynamic regression including bank specific cost efficiency scores, equation (5.23),

$$\frac{LLP_{it}}{TA_{it}} = \alpha_0 + \alpha_1 \frac{LLP_{i,t-1}}{TA_{i,t-1}} + \alpha_2 \frac{TCE_{i,t}}{TA_{i,t}} + \alpha_3 \frac{NI_{i,t}}{TA_{i,t}} + \alpha_4 \frac{NPL_{i,t}}{GL_{i,t}} + \alpha_5 GDP_t + \alpha_6 UNEMP_t + \alpha_7 CE_{i.t} + v_{it}. \quad (5.23)$$

As previously mentioned, the SGMM estimator is designed to address the issue of potentially endogenous regressors via the use of instrumental variables. In the context of the classical linear regression, and in the case where the error distribution cannot be considered independent of the regressors', the use of Instrumental Variables (IVs) is called for (Baum et al., 2003). The IV regression is designed to correct the estimates in the main equation by finding appropriately exogenous variables for the potentially endogenous covariates; that is, movements in the IVs are not related to movements in the error term, but are related to movements to the endogenous explanatory variables. Therefore, the excluded IVs are used to help control for potential endogeneity issues with respect to the main equation (the main challenge is to find variables correlated with the endogenous variable but uncorrelated with the part of the error term that is due to the unobserved heterogeneity). In the estimation of equations (5.22) and (5.23) we assume the right-hand side variables to be potentially endogenous, with the exception of the macroeconomic indicators (GDP growth and unemployment rate) and the autoregressive term, where the standard in the literature treatment is followed and it is treated as such predetermined, instrumentalizing it with its own first lag (Roodman, 2009).

In addition, we further assume that TVM3-4Z may be treated as a predetermined regressor (i.e., $\varepsilon_{i,t}$ may affect $x_{i,s}$, for $s > t$), as by construction the effect of LLP on efficiency has been taken into account during the SFA estimation process. That is, any unpredictable LLP shocks are already reflected in past and present cost efficiency

scores have been taken into consideration during the estimation of the cost efficiency estimates. However, in the case of a negative shock in LLP via an increase in NPL for example - a likely scenario given the unfavourable economic conditions in Greece - this shock could be reflected in future realizations of cost efficiency in an indirect manner as banks may be forced to adjust their input choices in order to offset a potential increase in cost by closer monitoring of their existing loan portfolio and current NPLs. However, we adopt a cautious modelling approach and control for any potential endogeneity effect in all cases. In that way, we control for any reverse causality and feedback effects coming through the dependent variable to the bank specific regressors with the use of appropriate excluded regressors. That is, we examine potential instruments relying on two assumptions, that the excluded instruments are independently distributed of the error term and that they are sufficiently correlated with the included regressors.

The instrumentalisation process is integral to the GMM technique; however, such estimation could potentially suffer from two shortcomings. The first one is relates to the number of instruments used and their lag lengths. In general, instrument proliferation tends to cause a downward bias in the GMM estimates, and this bias outweighs any gains in efficiency (Ziliak, 1997). In addition, Roodman (2009a) also argues that using too many instruments tends to bias the GMM estimates towards the direction of OLS, also leading to implausibly high Hansen J-statistic p-values. Unfortunately, Roodman (2009a) recognizes that there is no precise guidance with respect to the number of instruments used and instead recommends that the ratio of j/N should not be to high, where j represents the number of instruments excluding dummies for fixed effect and N is the number of cross sections in the panel data (pages 140-142). It is evident therefore, that the number of cross sectional units (15 in our sample) poses limitations on the number of instruments that can be used in the estimation and hence subsequently the number of exogenous variables that can be added to equations (5.22) and (5.23). In addressing the aforementioned limitation we follow Louzis et al., (2012) and implement a "restricted GMM" procedure, including only the subset of instruments that performed well in the selection process described in the subsequent section[102].

[102] Judson and Owen (1999) show that such a selection process does not worsen the efficiency of the GMM estimation.

As part of a parsimonious modelling strategy, we determine the number of instruments so that their total number remains close to the number of groups present in our data. In order to achieve that goal and to avoid overfitting the endogenous variables, we use the instruments as "collapse", thus avoiding instrument proliferation and restricting the number of the generated IVs. This standard approach implies that the instrument count depends on both the time period count and the lag available count. The "collapse" style GMM instruments generate only one for each variable and lag distance. In large sample, this option may reduce statistical efficiency but in small sample like the one employed, it helps avoid the bias that arises as the instrument count increases towards the number of groups[103]. Thus, accounting for the potential instrument count problem, in only in two cases we exceed the number of groups by one instrument (DM1 and DM2), thus obtaining 16 instruments, whereas, in the remaining two specifications, we restrict the number of instruments to 14 (DBM) and 15 (DM3).

The second potential limitation is with respect to the correlation between the instrumental variable and the potentially endogenous variables. In the presence of weak correlation, the weak-instrument problem arises as the parameters are only weakly identified and the estimator is likely to be biased (Stock and Yogo 2002). The proposed instruments were therefore assessed for relevance and "strength" by estimating the individual significance of the excluded regressors in the first- stage regressions[104]. That is, we initially instrumentalise the suspect variables using both excluded instruments (not included as explanatory variables) all their available lags as potential instruments and control for redundancy of the said instruments[105]. Once we identify redundant instruments, as part of our parsimonious modelling approach, we then remove them from the estimation process and examine the first stage regression p-values and the

[103] For a more extended review of the "collapsed" instruments, see Roodman (2009a).
[104] The first-stage regression in the instrumental variable context, including that of dynamic panel data models as the one estimated here, is a mechanical construct separating the endogenous variable into that part which is a linear combination of the first-stage regression regressors and that left unexplained. In that sense the coefficients reflect the partial correlations between endogenous and each exogenous factor and therefore no economic meaning is assigned to the examined instruments and their coefficients.
[105] Excluded instruments are redundant if the asymptotic efficiency of the estimation is not improved by using them. Breusch et al., (1999) show that instrument redundancy can be stated in several equivalent ways. For example, in the reduced form regressions of the endogenous regressors on the full set of instruments, the redundant instruments have statistically insignificant coefficients, or the partial correlations between the endogenous regressors and the instruments in question are equal to zero.

Sanderson-Windmeijer (SW) first-stage chi-squared and F statistics for weak and underidentified instruments, for individual regressors (Tables 5.11 to 5.14).

Hence, we control for whether the potentially endogenous variable is uncorrelated with the chosen instruments, or that is it only weakly correlated. In all cases we reject the null that the instruments are underidentified (i.e., uncorrelated with the potentially endogenous variable) and weak identification (i.e., that the IVs are only weakly identified). Tests for all but two variables ($TVM2-4Z$ amd $TVM3-4Z$) produce statistics either close to 10 (expect in one case where we did not obtain the desired level), or in most cases higher than rule of thumb threshold (Baum, 2007). Once appropriate instruments were identified, an endogeneity test was performed to identify possible endogenous regressors. This test is defined as the difference of two Hansen statistics: one for the equation with the smaller set of instruments (where the suspect regressor was treated as endogenous) and one for the equation with the larger set of instruments (where the suspect regressor was treated as exogenous). In all but one case we reject the null hypothesis that the specified regressor can actually be treated as an exogenous.

Therefore, the examined regressors are identified as endogenous and hence are instrumentalised using GMM-style instruments lags 3 and 4 on all equations, plus as an IV-style instrument Pre-tax Profit, the square term of Pre-tax Profit, and the loans to deposits ratio (LODEP) (these were identified as appropriate instrumental variables in our selection process (Table 5.12 to Table 5.14). As expected, we identify TVM3-4Z as an exogenous regressor and is treated as such[106].

Finally, the over identification test, also popular in the literature as Hansen J-statistic, was conducted to evaluate the validity of the instrumental variables employed; evaluating the entire set of over identifying restrictions. This test confirmed the validity of our instruments and the absence of correlation between the instruments used and the error term in the models, since we failed to reject the null hypotheses in all of the model specifications, with p-values that fall within the credible range higher than 0.25 and not

[106] In context to our cautious modelling approach, we also treat TVM3-4Z as predetermined. The results remain qualitatively the same and the respective SGMM estimation satisfies all the relevant post-estimation diagnostics.

close to 1.00, as proposed by (Roodman, 2009b)[107]. In fact, (Roodman, 2009b), states "do not take comfort in a Hansen test p-value below 0.1. View higher values, such as 0.25, as potential signs of trouble (page, 129)." Our estimated Hansen values are equal to 0.39, 0.45, 0.38 and 0.35 for the DBM, DM1, DM2 and DM3 respectively (Table 5.17). We are therefore satisfied, that these results show the above specification are not subject to weak instrument bias, correctly specified and hence giving a basis for system GMM analysis[108]. Furthermore, we assess the fundamental assumption of non-serially correlated error terms by testing that the differenced error terms, $\Delta\varepsilon_{it}$, are not second order serially correlated, AR(2). In all cases we fail to reject the null hypothesis of no serial correlation. Finally, addressing the possibility of obtaining severely downward biased estimated, we apply the finite sample correction to the standard errors, as proposed by Windmeijer (2005) (Table 5.17).

[107] Rejection of the joint null hypothesis that the instruments are valid instruments and that the excluded instruments are correctly excluded from the estimated equation casts doubt on the validity of the IVs chosen.

[108] It should be noted at this point the importance of the Hansen J-statistic and how researchers have misinterpreted the estimate and Roodman's 0.25 lower bound (Roodman, 2009a). Indeed, Roodman (2009b) notes that "simply by being numerous, instruments can overfit instrumented variables, failing to expunge their endogenous components and biasing coefficient estimates towards those from non-instrumenting estimators" (page 139, our emphasis). For example, Skala's (2015) system GMM models (7) and (8) present p-values equal to 0.17 and 0.03; whereas, Olszak et al., (2016) Table 3 gives actual values ("*** denotes significant at the 1% level") equal to 1343.45*** (model 3), 1310.45*** (model 4) and 284.4*** (model 8), Table 4, models 2, 3, 5, 6, 7 and 10 all have 'significant at the 1% level', in Table 5, all 13 different models all have 'significant at the 1% level' and even in their 'robustness check, Table 9 has 9 of the 12 models all rejecting at the 1% critical level Hansen statistics!

Table 5.11. Sanderson-Windmeijer multivariate F test of excluded instruments and test of endogeneity - DBM

Covariate tested	*Underidentification*	*Weak-identification*	*Endogeneity*
$CE_{it}(CE_{it-3}, LODEP, PTP, PTP^2)$	0.000	17.74	0.036
$NPL_{it}(NPL_{it-3}, NPL_{it-4})$	0.000	38.31	0.067
$NI_{it}(PTP, PTP^2)$	0.000	16.19	0.024

In the parenthesis we report the identified IVs. The diagnostics refer to the obtained values after we control for redundant IVs as described above. Where, DMB is the Dynamic base model as in equation (5.22). Underidentification, the endogenous regressor is underidentified, Weak-identification, the endogenous regressor is weakly identified and Endogeneity, the endogenous regressor can be treated as exogenous.

Table 5.12. Sanderson-Windmeijer multivariate F test of excluded instruments and test of endogeneity - DM1

Covariate tested	*Underidentification*	*Weak-identification*	*Endogeneity*
$CE_{it}(CE_{it-3}, PTP, PTP^2)$	0.000	27.48	0.080
$NPL_{it}(NPL_{it-3}, NPL_{it-4})$	0.000	25.000	0.058
$NI_{it}(PTP, PTP^2)$	0.000	17.29	0.056
$TVM1\text{-}4Z(TVM1 - 4Z_{it-4}, LODEP)$	0.000	9.20	0.049

In the parenthesis we report the identified IVs. The diagnostics refer to the obtained values after we control for redundant IVs as described above. Where, DM1 is the Dynamic base model as in equation (5.23), including TVM1-4Z. Underidentification, the endogenous regressor is underidentified, Weak-identification, the endogenous regressor is weakly identified and Endogeneity, the endogenous regressor can be treated as exogenous.

Table 5.13. Sanderson-Windmeijer multivariate F test of excluded instruments and test of endogeneity - DM2

Covariate tested	*Underidentification*	*Weak-identification*	*Endogeneity*
$CE_{it}(CE_{it-3}, PTP, PTP^2)$	0.000	30.58	0.085
$NPL_{it}(NPL_{it-3}, NPL_{it-4})$	0.000	23.79	0.063
$NI_{it}(PTP, PTP^2)$	0.000	34.22	0.097
TVM2-4Z$TVM2-4Z_{it-4}, LODEP)$	0.001	4.97	0.028

In the parenthesis we report the identified IVs. The diagnostics refer to the obtained values after we control for redundant IVs as described above. Where, DM1 is the Dynamic base model as in equation (5.23), including TVM2-4Z. Underidentification, the endogenous regressor is underidentified, Weak-identification, the endogenous regressor is weakly identified and Endogeneity, the endogenous regressor can be treated as exogenous.

Table 5.14. Sanderson-Windmeijer multivariate F test of excluded instruments and test of endogeneity - DM3

Covariate tested	*Underidentification*	*Weak-identification*	*Endogeneity*
$CE_{it}(CE_{it-3}, PTP, PTP^2)$	0.000	22.19	0.081
$NPL_{it}(NPL_{it-3}, NPL_{it-4})$	0.000	29.68	0.050
$NI_{it}(PTP, PTP^2)$	0.000	30.13	0.089
TVM3-4Z($TVM3-4Z_{it-4}, LODEP)$*)*	0.001	7.30	0.112

In the parenthesis we report the identified IVs. The diagnostics refer to the obtained values after we control for redundant IVs as described above. Where, DM1 is the Dynamic base model as in equation (5.23), including TVM3-4Z. Underidentification, the endogenous regressor is underidentified, Weak-identification, the endogenous regressor is weakly identified and Endogeneity, the endogenous regressor can be treated as exogenous.

We now turn to discussing the empirical findings estimated via the SGMM[109]. In all the estimated models, the lagged dependent coefficient is less than one, thus indicating dynamic stability[110]. The coefficient of the autoregressive components captures the persistence of the process and reflects the portion of short-run adjustment that is translated to the next year - thus the closer to 1 the higher the persistence in the dependent variable. The data suggest that, under all models LLP exhibit mild autocorrelation. That is, the coefficient of the lagged LLP is statistically significant at the maximum 10% level for all but the DM2, with coefficients ranging from 0.141, 0.181, 0.133 and 0.191, for DBM, DM1, DM2 and DM3 respectively (Table **5.17**). The reported positive lagged coefficient indicates that a dynamic specification to model bank provisioning is recommended (Fonseca and González, 2008). Indeed, the aforementioned values suggest that a shock to LLP is un likely to have a prolonged effect on the Greek banking system.

[109] We also included the same additional variables as discussed Note 78, Section 5.4.1.1 in the estimation of the dynamic model. The results did not differ than the ones reported under the static models. That is, time dummies covering the aftermath of both the Global financial crisis and the Greek crisis where in both cases are insignificant. Furthermore, the natural log of total assets also proved to be insignificant. Finally, two versions of the Z-score as proposed by Laeven and Levine (2009) and Tabak et al., (2013) were also found to be insignificant.

[110] Roodman (2009) suggests using the OLS and FE coefficient of the lagged dependant variable as a guide (upper and lower limit) in order to evaluate the performance of the GMM estimator. Table 10.1 to Table 10.4 in Appendix C presents the estimated results. It is evident that the lagged dependant coefficient does not lie within the expected limits. However, we do not believe that this finding is suspect as we further examined the performance of the OLS regression. Initially, we estimated additional regressions using the standardized covariates (we standardized all the right and left hand side regressors as $x^* = (x - m)/sd$, where m is the mean of x, and sd is the standard deviation of x). Those sets of regressions did not reveal any insight regarding the behaviour of the OLS estimator and produced similar results to the ones estimated when the non-standardized covariates where used. In addition, similar results were also obtained when we included the natural log of the real GDP ((in €B) into the equations. Furthermore, we estimated additional regressions using at first only the bank specific variables and then introducing the macro-economic covariates. Introduction of the aforementioned macro-variables cause the coefficient of the lagged dependent variable to become lower than the respective FE one. Finally, we converted the GDP growth into an index using the following transformation, $index_{gdp} = (GDP \times 100)/ref_{gdp}$, where $index_{gdp}$ represents the index metric with a reference year in 2005, GDP, represents the Real GDP (in €B) for the year of transformation and ref_{gdp} represents the Real GDP (in €B) for the reference year 2005 and we perform the same two-step approach. As presented in Table 10.5, Appendix C it appears that indexing Gross Domestic Product growth helps mitigate the aforementioned discrepancy with respect to the lower and upper bound. The OLS estimator, even incrementally, produced higher coefficient estimates, hence leading us to believe that it is the introduction of the GDP growth rate in the OLS regression at the presence of autoregressive component leads to a surprisingly low coefficient (Table 10.5, Appendix C). Subsequently, this leads us to maintain our confidence in the dynamic GMM estimates presented in Table 5.17 as they meet all the post-estimation conditions discussed in the literature. That is, they show higher coefficients than the expected FE lower limit, however, it is the OLS upper limit that is not as consistent as one would expect.

As expected, the speed of adjustment of LLP towards its mean value, $(1-\alpha)$ (where α represents the coefficient of the autoregressive component), remains relatively stable across all estimated models. The results indicate some stability across all estimated models, ranging from 0.80 to 0.86 (DM3 and DM2 respectively) and are higher than the ones reported by Bikker and Metzemakers (2005). To further assess the speed of the long-run adjustments we also estimate the median lag of the process as $-\ln(2)/\ln(a)$, where α represents the coefficient of the autoregressive component), thus obtaining an estimate of years required for completing 50% of the long-run adjustment. DBM and DM2 show slightly less persistence, with median lags equal to 0.353 and 0.344, against 0.415 and 0.427 for DM1 and DM3 respectively. All coefficients are statistically significant at the 1% level. Table 5.17 reports the short-run effects of the explanatory bank specific and macroeconomic variables, measuring the immediate (within one year) effect response of LLP to a temporary shock coming from the right-hand side variables. To capture the long-run effect of the explanatory regressors, we also estimate the respective long-run coefficients for each variable as the sum of the current coefficient, γ, divided by 1 minus the lagged coefficient of the dependent variable, α, $\gamma/(1-\alpha)$. The estimated effects measure the total cumulative adjustment of LLP following sustained shocks in the right-hand side variables and in all cases, except for the macroeconomic variables, which do not exhibit deviation from the short-run, these effects are consistent with prior expectations, exhibiting higher values (Table 5.16).

Table 5.15. Long-Run Effects

Dependent variable, LLP_{it}/TA_{it}		
Model	$(1-\alpha)$	$-ln(2)/ln(a)$
BDM	0.858***	0.353***
	(0.075)	(0.096)
DM1	0.811***	0.415***
	(0.059)	(0.079)
DM2	0.866***	0.344***
	(0.083)	(0.106)
DM3	0.802***	0.427***
	(0 .086)	(0.115)

Where, DMB is the Dynamic base model as in equation (5.22) and DM1, DM2, DM3 are the augmented dynamic models as in equation (5.23), including $TVM1-4Z$, $TVM2-4Z$ *and* $TVM3-4Z$ *respectively.*
* p < 0.10, ** p < 0.05, *** p < 0.01
.

Table 5.16. Long-Run Effects

Coefficient	*DBM*	*DM1*	*DM2*	*DM3*
CE_{it}/TA_{it}	-0.150**	-0.188**	-0.178*	-0.222**
	(0.069)	(0.095)	(0.092)	(0.089)
NI_{it}/TA_{it}	-1.287***	-1.278***	-1.169***	-1.362***
	(0.206)	(0.1825)	(0.188)	(0.244)
NPL_{it}/TA_{it}	-0.044	-0.039	-0.017	-0.064**
	(0.048)	(0.0301)	(0.043)	(0.031)
$GDPgr$	0.000	-0.002	-0.002*	-0.002
	(0.000)	(0.001)	(0.001)	(0.001)
Un	-0.001	-0.002***	-0.002***	-0.002**
	(0.000)	(0.000)	(0.000)	(0.001)
TVM1-4Z		-0.107*		
		(0.059)		
TVM2-4Z			-0.105***	
			(0.039)	
TVM3-4Z				-0.100***
				(0.035)

Where, DMB is the Dynamic base model as in equation (5.22) and DM1, aDM2, DM3 are the augmented dynamic models as in equation (5.23), including $TVM1-4Z$, $TVM2-4Z$ *and* $TVM3-4Z$ *respectively.*
Where TCE_{it}/TA_{is} *represents Total Common Equity scaled by total assets at period* t; NI_{it}/TA_{it} *represents Net Income scaled by total assets at period* t; NPL_{it}/GL_{it} *represents Non-Performing Loans to gross loans, at time* t; $GDPgr$ *represents the annual change of Gross Domestic Product (%); Un represents the unemployment rate;* $TVM1-4Z$*: Time Varying Model 1, without a risk metric;* $TVM2-4Z$*: Time Varying Model 2, with Equity as a risk metric;* $TVM3-4Z$ *Time Varying Model 1, with LLP as a risk metric.*
4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), and top five Concentration Ratio.
Sources for macroeconomic variables: World Bank, the European Central Bank and Eurostat database.
Source for bank specific variables: Bankscope by Bureau Van Dijk database.
** p < 0.10, ** p < 0.05, *** p < 0.01*

Closer examination of the short-run coefficients in Table 5.17 reveal that in all the estimated models, the bank specific variables have significant negative effects on LLP, whereas the macroeconomic indicators included to capture the counter/pro-cyclical behaviour are for the most part either insignificant or show a negative and statistically significant effect. When estimating the DBM, both macroeconomic variables do not have a significant impact on LLP. However, when we re-estimate the extended models via inclusion of the cost efficiency estimates, unemployment turns significant, whereas GDP growth still remains insignificant, except under DM2. That is, in all the estimated models excluding BDM, the short-run coefficient of the unemployment rate is significant at the 1% level, however, the magnitude of the effect is very close to zero. Therefore, unemployment, a measure reflecting structural unbalances, surprisingly not only does it not increase loan loss risk significantly but it leads to minor reductions! Hence, even though the Greek banking system shows indications of counter-cyclical behaviour, structural economic imbalances do not seem to exert significant impacts on LLP. Indeed, the data suggest similar findings with respect to the short-run effect of GDP growth on LLP. Under all specifications, the GDP growth coefficient is negative but insignificant, thus pointing away from a pro-cyclical behaviour, with the exception of DM2 when it is significant. Thereby, our findings indicate that the macroeconomic environment, for the most part, does not have a strong impact on the provisioning behaviour of Greek banks,. However, we do find stronger evidence towards a counter-cyclical behaviour.

With respect to the bank specific factors effecting LLP, Surprisingly, and contrary to expectations, NPLs are insignificant (under DM3 they even have a negative effect). Apparently, in our data there is no clear link between the recorded impaired loans and provisioning practises - a finding also reported by Kim and Kross (1998) and Bikker and Metzemakers (2005).

Concerning the scaled Net Income variable, under all estimated models it suggests a negative and significant effect on LLP. The estimations show that the relationship remains statistically significant at the 1% level, with short-run coefficients ranging from -1.013 to -1.106. The implication arising is that higher profitability contributes to lower provisions, suggesting higher asset quality and potentially better managerial abilities in exercising control over the loan portfolio.

Furthermore, regarding the capital management hypothesis, all specifications report that the capital to asset ratio is negatively correlated with provisions, supporting the capital management hypotheses. The short-run coefficients reported are equal to -0.129, -0.153, 0.155, -0.1656 for the BDM, DM1, DM2 and DM3 respectively. An alternative explanation for the negative coefficient may be due to the risk preferences of Greek banks. Indeed, Bikker and Metzemakers (2005) note that, "[….] an alternative phenomenon contributing to these results might be that some banks are more risky in the sense that they (i) hold a greater share of risky loans (and hence incur more losses and provision more) and (ii) have a lower capital ratio. This also engenders a negative relationship between provisioning and capital (page 150)". This excessive risk taking may be an indication of the moral hazard hypothesis as bank managers respond to moral hazard incentives by increasing the riskiness of the loan portfolio, resulting in increases in NPL and hence LLP.

In order to further disentangle the hypothesised relationship, we conduct a parsimonious standard Granger-causality test as proposed by Berger and DeYoung (1997) and further tested by Casu and Girardone (2009) and Fiordelisi et al., (2011). Indeed, Casu and Girardone (2009) note with respect to the Granger causality test that "[….] even though Granger causality tests may constitute an improvement on the methodology commonly used in the literature, they only indicate that changes in one variable precede changes in another variable of interest (with a positive or negative sign) rather than establishing causation in the traditional sense of the word (page 136)". Furthermore, it worth noting that conceptually it is not clear how to think about the test in a panel context, as one variable may Granger cause another in one panel but not in another. Furthermore, as discussed in Section 5.3.3, we do not treat the negative coefficient of equity in our LLP models as a direct interpretation of evidence in favour if the moral hazard hypothesis. That is, the structure of the LLP model is fundamentally different than the standard Granger-causality tests employed in prior studies. Secondly, since LLP may be subject to adjustments and hence over or under-stated in any given year. Interpreting such a model as evidence of either supporting or rejecting the presence moral hazard could be misleading.

Therefore, we estimate the following equation following the method described in Section 5.4.2 (that is a system GMM). The general Granger-causality model is expressed as in equation (5.24)[111].

$$y_{i,t} = \alpha_0 + \alpha_1 y_{i,t-1} + \alpha_2 y_{i,t-2} + \beta_1 x_{1,i,t-1} + \beta_2 x_{2,i,t-2} + \gamma_1 x_{2,i,t-1} + \gamma_2 x_{2,i,t-2} + u_{i,t}. \quad (5.24)$$

Where $y_{i,t}$ represents the individual bank specific NPL scaled by gross loans and $x_{i,t-1}$ and , x_{it-2} represent the capital to total assets ratios and cost efficiency scores respectively. Following Casu and Girardone (2009), we test the following joint null hypotheses of $\beta_1 = \beta_2 = 0$ and $\gamma_1 = \gamma_2 = 0$, which we interpret as panel data Granger causality test, distributed as χ^2 with two degrees of freedom. For consistency we also estimate the following null hypothesis in the same manner, $\alpha_1 = \alpha_2 = 0$. A rejection of the above null hypotheses is interpreted as a sign that the explanatory variables are Granger-causing the dependent variable, with the direction of the effect being determined by the sum of the lagged coefficients of the variable examined. A positive (negative) sum implies that the causal relationship is positive (negative), that is, an increase (decrease) in the right-hand side variable in the past increased (decreased) the dependent in the present. Finally, the estimated models are checked for the stability over time (or 'long-run effect') of the explanatory variable y_{it} by testing the following three restrictions, $\beta_1 + \beta_2 = 0$, $\gamma_1 + \gamma_2 = 0$ and $\alpha_1 + \alpha_2 = 0$. A rejection of the null hypothesis implies evidence of a long run effect of the examined explanatory variable on y_{it}.

Our results find no support of the moral hazard hypothesis as the estimated sum of the coefficients (the Granger coefficient of the lagged capital) is insignificant (Table 5.18). These finding is therefore in line with the results reported in Louzis et al., (2012) and Monokroussos et al., (2016). A possible explanation may be the nature of the Greek banking sector. That is, the market is small and this could create disincentives for

[111] The choice of including two lags in the Granger-causality test is dictated by the sum of the lagged dependent coefficients and the post-estimation tests. That is, when we included only 1 lag, the estimated regressions showed evidence of mild serial correlation and hence where deemed as not robust. We then re-estimated the models including 3 and 4 lags respectively. In all cases we either obtained a Hansen *J* statistic that where relatively close to 1 or the sum of the lagged dependent coefficients was higher than that theoretical threshold of one.

excessive risk taking and short-termism since such behaviour may indeed hide high reputational costs for the managers. Furthermore, due to the small number of banks operating, the Greek regulatory authorities can have a more accurate overview of the risk exposure of individual banks and proceed to timely interventions when necessary. Such supervisory practises may indeed minimize moral hazard incentives. In fact, Monokroussos et al., (2016) note that, "[….] the oversight of the domestic banking system has tightened significantly in recent years not only due to the fact that domestic financial stability has been a key pillar in the country's three consecutive bailout programmes since May 2010, but also because of the phasing in of the SSM mechanism since early 2014 (page 13)". Finally, with respect to the capital management hypothesis, contrary to the results reported in Pérez et al., (2008), Leventis et al., (2010) and Skala (2015), our results are in line with findings reported by Anandarajan et al., (2007), Bikker and Metzemakers (2005) and Bouvatier and Lepetit (2008).

We now focus on the final bank specific variable included in the LLP models, that is the different cost efficiency estimates, TVM1-4Z, TVM2-4Z and TVM3-4Z respectively. As discussed above, all the estimated models remain relatively stable despite the inclusion of the different efficiency estimates. That is, all bank specific and macroeconomic variables maintain the same sign in their respective coefficients, thus without changing the interpretation with respect to the examined hypotheses. In all the augmented regression the effect of cost efficiency on LLP is the same. Indeed, TVM1-4Z, TVM2-4Z and TVM3-4Z have a negative and statistically significant impact on provisions with short-run coefficients of -0.087, -0.091 and -0.062 respectively. Therefore, banks operating with low efficiency levels, on average report higher provisions. An explanation for this finding is the bad management hypothesis, where the least cost efficient banks pay the price of not exercising rigorous credit control practices and poor day-to-day risk management operations. As a result, such subpar banks register immediate reductions in cost efficiency which leads to reporting higher NPLs in the future, as poor quality borrowers default on their loans obligations. This behaviour may also translate into higher LLPs. However, in our data, we do not find evidence of the bad management hypothesis, as presented in Table 5.18. Instead, in all cases the sum of the respective lagged cost efficiencies are significantly different than zero, with a positive Granger coefficient, thus indicating towards the presence of cost

skimping behaviour. That is, Greek banks exhibit high short-run cost efficiency levels due to reduced operating costs that affect the loan quality in the long-term. Banks engaging in cost skimping practices allocate fewer resources in credit monitoring in the short-term, thus maximizing short-term cost efficiency levels but have to bear the consequences of greater loan performance problems and the possible costs of dealing with these problems, in the future. Our findings come in contrast to Louzis et al., (2012) where they report results indicating bad management. This discrepancy between our results and their findings could be due to the different efficient indicators chosen. That is, in our current study we employ SFA cost efficiency estimates that take into account of the impact of the economic environment in Greece in an one step estimation, as originally proposed by Berger and DeYoung (1997), whereas Louzis et al., (2012) estimate the ratio of operating expenses to operating income. Furthermore, in their sample only the nine largest banks are included, covering the 2003-2009 period, whereas we provide more extensive coverage for the 2005-2012 period.

The negative coefficient of equity comes in agreement with the presence of the capital management hypothesis. That is, during recessionary periods, capital is tight and it is difficult for undercapitalized banks to face the squeeze in their equity base, which may not be easily restored by raising external funding (El Sood, 2012). Such an effect may be even more profound for banks operating away from the optimal cost frontier, therefore increasing their cost of raising new capital in order to maintain the minimum regulatory requirements. That is, for such banking institutions, engaging in capital adjustments via LLP changes may indeed become an appealing practise. Finally, this result may reflect differences in LLP levels which are due to differences in the skills and abilities of management with respect to an optimized credit risk appreciation and bad loan minimization. That is, cost efficiency estimates reflect the maximum possible radial contraction of input prices, keeping the output vector constant – possibly indicating a very specific set of skills. Scores close to the theoretical maximum of one, reflect the management's ability to optimize their production and resource allocation with respect to cost minimization. This set of "skills" could also be reflected in the choice of the provisioning strategy, hence indicating that banks that are operating close to the cost minimizing optimal behaviour are also outperforming their counter parts with respect to the choices surrounding their provisions. Hence, they choose their

lending and provisioning strategies in such a way as to minimize the amount of required provisions needed to cover future loan losses.

Table 5.17. Two-Step System GMM

Dependent variable: LLP_{it}/TA_{it}				
	DBM	*DM1*	*DM2*	*DM 3*
LLP_{it-1}/TA_{it-1}	0.141*	0.189***	0.133	0.191**
	(0.075)	(0.060)	(0.083)	(0.080)
CE_{it}/TA_{it}	-0.129**	-0.153**	-0.155**	-0.165**
	(0.059)	(0.076)	(0.075)	(0.072)
NI_{it}/TA_{it}	-1.106***	-1.037***	-1.013***	-1.106***
	(0.123)	(0.095)	(0.086)	(0.097)
NPL_{it}/TA_{it}	-0.038	-0.032	-0.015	-0.044*
	(0.040)	(0.023)	(0.037)	(0.024)
$GDPgr$	0.001	-0.002	-0.002*	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)
Un	-0.001	-0.002***	-0.002***	-0.002***
	(0.001)	(0.000)	(0.001)	(0.001)
TVM1-4Z		-0.087*		
		(0.048)		
TVM2-4Z			-0.091***	
			(0.035)	
TVM3-4Z				-0.062**
				(0.031)
constant	0.031***	0.116***	0.117***	0.094***
	(0.008)	(0.039)	(0.029)	(0.032)
Wald chi2(6)	*628.74*			
Wald chi2(7)		*2143.35*	*2007.00*	*2394.48*
Prob > chi2	*0.000*	*0.000*	*0.000*	*0.000*
No of IVs (groups)[a]	*14(15)*	*16 (15)*	*16 (15)*	*15 (15)*
AR(1)	*0.151*	*0.098*	*0.095*	*0.106*
AR(2)	*0.203*	*0.615*	*0.337*	*0.492*
Hansen p-value	*0.394*	*0.455*	*0.388*	*0.359*
Observations	48	48	48	48

This table reports the Windmeijer (2005) robust standard errors in parentheses. Where, DMB is the Dynamic Base Model as in equation (5.22) and DM1, DM2, DM3 are the augmented Dynamic Models as in equation (5.23), including $TVM1-4Z$, $TVM2-4Z$ and $TVM3-4Z$ respectively. LLP_{it-1}/TA_{it-1} represents the autoregressive term; TCE_{it}/TA_{is} represents Total Common Equity of bank i scaled by total assets at period t; NI_{it}/TA_{it} represents Net Income of bank i scaled by total assets at period t; NPL_{it}/GL_{it} represents Non-Performing Loans of bank i scaled by gross loans at period t;; $GDPgr$ represents the annual change of Gross Domestic Product (%); Un represents the unemployment rate. $TVM1-4Z$ Time Varying Model 1, without a risk metric; $TVM2-4Z$ Time Varying Model 2, with Equity as a risk metric; $TVM3-4Z$ Time Varying Model 3, with LLP as a risk metric. 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), and top five Concentration Ratio.

Sources for macroeconomic variables: World Bank, the European Central Bank and Eurostat database. Source for bank specific variables: Bankscope by Bureau Van Dijk database.

[a] *Number of groups included in parenthesis*

** p < 0.10, ** p < 0.05, *** p < 0.01*

Table 5.18. Estimates of Granger Causality Tests in Non-Performing Loans

Dependent variable: NPL_{it}/GL_{it}			
	DM1	*DM2*	*DM3*
NPL_{it-1}/GL_{it-1}	0.649** (0.312)	0.597*(0.332)	0.592**(0.268)
NPL_{it-2}/GL_{it-2}	0.242**(0.119)	0.235**(0.119)	0.283***(0.100)
$\alpha_1 + \alpha_2 = 0$	0.890***(0.277)	0.831***(0.295)	0.875***(0.242)
$\alpha_1 = \alpha_2 = 0$ (p-value)	0.000	0.001	0.000
CE_{it-1}/TA_{it-1}	-1.267(0.828)	-1.349**(0.682)	-1.259*(0.676)
CE_{it-2}/TA_{it-2}	1.692(1.304)	1.942(1.421)	1.720(1.131)
$\beta_1 + \beta_2 = 0$	0.424(0.519)	0.593(0.853)	0.461(0.507)
$\beta_1 = \beta_2 = 0$ (p-value)	0.189	0.084	0.098
$TVM1 - 4Z_{\ it-1}$	-0.373(0.279)		
$TVM1 - 4Z_{\ it-2}$	0.475**(0.206)		
$\gamma_1 + \gamma_2 = 0$	0.101(0.092)		
$\gamma_1 = \gamma_2 = 0$ (p-value)	0.000		
$TVM2 - 4Z_{\ it-1}$		-0.100(0.205)	
$TVM2 - 4Z_{\ it-2}$		0.376*(0.205)	
$\gamma_1 + \gamma_2 = 0$		0.275***(0.089)	
$\gamma_1 = \gamma_2 = 0$ (p-value)		0.004	
$TVM3 - 4Z_{\ it-1}$			-0.432*(0.260)
$TVM3 - 4Z_{\ it-2}$			0.518***(0.179)
$\gamma_1 + \gamma_2 = 0$			0.086(0.098)
$\gamma_1 = \gamma_2 = 0$ (p-value)			0.000
Constant	-0.027(0.095)	-0.190**(0.084)	-0.011(0.098)
Wald chi2(6)	924.48	2640.42	1321.90
Wald chi2(7)			
Prob > chi2	0.000	0.000	0.000
No of IVs (groups)[a]	16(14)	16(14)	16(14)
AR(1)	0.063	0.030	0.068
AR(2)	0.275	0.292	0.306
Hansen p-value	0.500	0.656	0.568
N	53	53	53

This table reports the Windmeijer (2005) robust standard errors in parentheses. Where, DMB is the Dynamic base model as in equation (5.22) and DM1, aDM2, DM3 are the augmented dynamic models as in equation (5.23), including $TVM1 - 4Z$, $TVM2 - 4Z$ *and* $TVM3 - 4Z$ *respectively;* $TCE_{it-1,2}/TA_{it-1,2}$ *represent lags 1 and 2 of Total Common Equity scaled by total assets;* $NPL_{it-1,2}/GL_{it-1,2}$ *represent lags 1 and 2 of Non-Performing Loans to gross loans;* $TVM1 - 4Z_{\ it-1,2}$, $TVM2 - 4Z_{\ it-1,2}$, $TVM3 - 4Z_{\ it-1,2}$ *represent lags 1 and 2 of cost efficiency; 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio.*

Sources for macroeconomic variables: World Bank, the European Central Bank and Eurostat database. Source for bank specific variables: from Bankscope by Bureau Van Dijk database.

[a] *Number of groups included in parenthesis*

** p < 0.10, ** p < 0.05, *** p < 0.01*

5.5 Recent regulatory efforts - Basel III

This Chapter has focused on Greek banking for 2005-2012, but recently there have been changes to regulatory rules. That is, the recent financial crisis and the common global crisis arising thereafter, brought to the forefront the issue of inherent procyclicality of the financial system. In December 2010 and with a revised version in June 2011, the Basel Committee on Banking Supervision (BCBS) announced its final decisions, known as Basel III, on a series of amendments to the Basel II framework. The Committee introduced a series of measures to address procyclicality and raise the resilience of the banking sector in good times. These measures have the following key objectives (Basel III, 2011)[112]:

- Dampen any excess cyclicality of the minimum capital requirement;
- Promote more forward looking provisions;
- Conserve capital to build buffers at individual banks and the banking sector that can be used in stress; and
- Achieve the broader macro prudential goal of protecting the banking sector from periods of excess credit growth.

The proposals of the new framework will be implemented gradually from 2013 until 2019. For completeness, we present a brief discussion of changes in risk management behaviour which could alter our results in a future analysis with an increased sample size. That is undertaken to show that changes in regulations could have a substantial effect on Greek management.

Firstly, the BCBS agreed to impose an increase in the CAD ratio from 8% to 10.5%, raise the minimum capital requirements from 2% to 7% and restrict the definition of equity capital. They allow individual countries to raise the CAD to a higher minimum of 13% if deemed necessary due to country-specific cyclical fluctuations and to impose penalties in the earnings distributions in the case of governmental rescues in an attempt to mitigate the moral hazard problem. Finally, a long-term implementation horizon was set that helps ensure lending to the economy could continue to be supported by the

[112] Law 4261/2014 incorporates Directive 2013/36/EU which in conjunction with Regulation (EE) 575/2013 constitute the new enhanced framework for credit institutions (Basel III). Among other provisions, the new law "introduces capital buffers held in addition to the existing capital requirements in order to create a sufficient capital base to offset losses during periods of financial distress" (Bank of Greece, 2014c).

banks, while the banking sector complies with the new, stricter regulatory framework. More specifically, the Committee proposed the following key elements, amongst others:

Higher and better quality capital requirements

Regarding the capital requirements, the Commission raised core Tier 1 Ratio, the highest form of loss absorbing capital, from the existing level of 2% to 4.5%. The phasing in process will take place starting January 2015. In addition, the minimum Tier 1 capital requirements will also increase from 4% to a new level of 6% over the same period. Tier 1 capital includes common equity and other financial instruments which will be based on stricter criteria. Moreover, the Committee also decided the introduction of additional buffering mechanisms mitigating capital volatility. The first one is the capital conservation buffer and the second one is a countercyclical buffer, aiming to ensure that banking sector capital requirements take account of the macro-financial environment in which banks operate.

Regarding the capital conservation buffer, this has been decided to amount to an extra 2.5% above the minimum requirement, bringing the total common equity requirements to 7%. The goal of this buffer is to ensure that banking institutions have enough financial resources to endure potential losses during an economic downturn. When macroeconomic conditions dictate, banks will be able to draw on the buffer. However, this comes at the price of constraints on earning distributions, the more regulatory capital approaches the minimum required level. Capital distribution constraints will be imposed on a bank when capital levels fall within this range. Banks will be able to conduct business as normal when their capital levels fall into the conservation range as they experience losses. The constraints imposed only relate to distributions, not the operation of the bank.

The countercyclical nature of the conservation buffer lies in the fact that it allows for excess capital to be built up during the upward phase of the cycle, bolstering in that way the capital position of the bank. During stress periods, the banks will be able to cover any financial shortcomings through the use of these additional resources. Another interesting characteristic is that it allows for boosting capital in downturns or

stress periods that may not have been chosen by individual banks. The regulation addresses the collective action problem that has prevented some banks from curtailing distributions such as discretionary bonuses and high dividends, even in the case of deteriorating capital positions (Hardouvelis, 2010). Again, a phasing period between January 1, 2016 and year-end 2018 will be implemented. The buffer will become fully effective on January 1, 2019. National authorities have discretionary control over the phasing in timeframe.

The second addition is the countercyclical buffer. It serves as an extension to the capital conservation buffer. This buffer will be determined by the country's regulatory authorities and calibrated within the 0%-2.5% range irrespective of the conservation buffer. The objective of this particular buffer is to ensure stability in the banking system and to allow it to operate unhindered during economic recession. This will promote that broader macro prudential goal of protecting the banking sector from periods of excess aggregate credit growth that have often been associated with the build-up of system-wide risk (BIS, 2010). This measure will not only secure the solvency of individual banks, but combined with the capital conservation buffer, will ensure that the banking industry on aggregate has sufficient resources in order to maintain lines of credit to the real economy. Thus, the fear that capital regulatory requirements undermine the performance of the economy should be mitigated.

Implementation of this buffer requires a series of indicators that would point to significant risk accumulation, the state of the business cycle and the timing of the changes. Even though regulators give local authorities considerable discretion in the use of the buffer, the decision will be based on the deviation of bank loans to the real GDP (BIS, 2011). The credit-to-GDP ratio provides a normalisation of the credit variable to take into account the fact that credit demand and supply grow in line with the size of the economy, also taking into consideration that strong historical link between faster than average credit-to-GDP growth and banking crises (Drehmann et al., 2010). Additional factors should also be taken into consideration by local authorities, such as asset prices, yield spreads, credit default swaps, survey studies, the phase of the economic cycle, and the possibility of misleading (BIS, 2010 and 2011 and Behn et al., 2013).

Even though the built up of additional capital in the upward phase of the cycle is a proposal that has been advocated by regulatory authorities (De Larosiére Report, 2009; The Warwick Report, 2009; IMF, 2009) and was finally implemented by the Basel Committee, research indicates that the relationship between GDP growth and the countercyclical ratio may be negative. Repullo and Saurina (2011) argue that a mechanical application of the buffer would tend to reduce capital requirements when GDP growth is high and increase them when GDP growth is low, so it may end up exacerbating the inherent pro-cyclicality of risk-sensitive bank capital regulation. In order to correct this feature, the authors suggest a business cycle multiplier of the type proposed by Repullo et al., (2010), i.e., smoothing the input of the Basel II formula by using through-the-cycle PDs or to smooth output with a multiplier based on GDP growth.

A more restrictive definition of capital

The Basel III framework raised the quality, transparency and consistency of the capital base. The recent crisis brought forward disparities in the definition of capital across jurisdictions and the lack of disclosure that would have enabled the market to fully assess and compare the quality of capital between institutions (BIS, 2011). Thus, the main focus is now on the core elements of the capital base, namely retained earnings and common equity. Attention is also given towards the treatment of minority interest, investments in other financial institutions and various deductions. In particular, all deductions from capital will now occur at the level of common equity, instead of Tier 1 capital, as has been the case until now (Hardouvelis, 2010).

Strengthening the risk coverage

In addition to raising the quality and level of the capital base, the Committee acknowledges the need to ensure that all material risks are captured in the capital framework. Failure to capture major on and off-balance sheet risks, as well as derivative related exposures, was a key factor that amplified the crisis (BIS, 2011). Thus, improvements were made with respect to risk coverage and especially counter-party credit exposures. The recent crises uncovered weaknesses in the global financial system. More specifically, issues of coverage of structured, complex and illiquid credit

products, which were held in banks' books without an increase in capital to support the associated risks, were brought into the spotlight. Therefore, Basel's III proposals concerning trading book exposures; securitizations and off-balance sheet vehicles are now strengthened and institutions are required to hold much more capital to offset those risks.

Controlling leverage

The members of the G-20, in July 2010, restated the need for a new regime regarding the leverage ratio in the Basel III framework. The BCBS acknowledged the fact that the build-up of excessive on- and off-balance sheet leverage played an important role prior to the crisis. During the most severe part of the crisis, the banking sector was forced by the market to reduce its leverage in a manner that amplified downward pressure on asset prices, further exacerbating the positive feedback loop between losses, declines in bank capital, and contraction in credit availability (BIS III, 2011). Thus, under Basel III, in order to control for excessive leverage, a simple, transparent and non-risk based measure has been introduced. This measure is calibrated to act as a credible supplementary measure to the risk based capital requirements. The BCBS clearly defines the main goals of the ratio as to:

- Constrain the build-up of leverage in the banking sector, helping avoid destabilising, deleveraging processes which can damage the broader financial system and the economy; and
- Reinforce the risk based requirements with a simple, non-risk based "backstop" measure.

The Committee agreed on the design of a leverage ratio and an indicative calibration of a minimum Tier 1 leverage ratio of 3%. Implementation of the leverage ratio requirements has begun with bank-level reporting to national supervisors of the leverage ratio and its components from 1 January 2013, and will proceed with public disclosure starting 1 January 2015. The Committee will continue monitoring the impact of these disclosure requirements. The final calibration, and any further adjustments to the definition, will be completed by 2017, with a view to migrating to a Pillar 1 (minimum capital requirement) treatment on 1 January 2018 (BIS, 2014).

Introduction of a new global liquidity framework

Acknowledging the fact that a strong capital requirements framework on its own it is not sufficient to guarantee the safety and stability of a banking system, the Basel Committee introduced an internationally harmonised global liquidity framework. Thus, to further strengthen its liquidity framework the Committee introduced two minimum standards for funding liquidity. These measures aim to promote both short-term and long-term resilience of banking institutions. The Liquidity Coverage Ratio's (LCR) objective is to promote short-term resilience of a bank's liquidity risk profile by ensuring that it has sufficient high quality liquid resources to survive an acute stress scenario lasting for one month (30 days). The purpose is for banks to have enough liquid assets to withstand a stress testing scenario as specified by the regulatory authorities. The Net Stable Funding Ratio (NSFR) is a long-term structural measure and has a time horizon of one year. Its aim is to promote resilience in the long run by creating additional incentives for a bank to fund its activities with more stable sources of funding on an on-going structural basis; it is designed to address liquidity mismatches. After an observation period beginning in 2011, a minimum standard for the LCR will be introduced on January 1, 2015. The minimum standard for the NSFR will be introduced by January 1, 2018, after an observation period beginning in 2012.

Systemic risk, interconnectedness and too-big-to-fail

Excessive interconnectedness among financial institutions, and more importantly among systemically important institutions transmitted shocks across the system and the economy as a whole. Adopting a global perspective, Basel III developed a methodology comprising of both qualitative and quantitative indicators in order to assess the systemic importance of institutions at the world wide context. The framework put forward is supporting the fact that "too-big-to-fail" institutions should exhibit an increased loss absorbing capacity than their counterparts. As part of this approach the Committee and the Financial Stability Board are developing an integrated approach aiming to systemically important institutions which includes combinations of capital surcharges, contingent capital and bail-in debt (BIS, 2011). Additional measures that will help to mitigate the risks arising from firm-level exposures among global financial institutions will also help to address systemic risk and interconnectedness. These include:

- Capital incentives for banks to use central counterparties for over-the-counter derivatives;
- Higher capital requirements for trading and derivative activities, as well as complex securitisations and off-balance sheet exposures (e.g. structured investment vehicles);
- Higher capital requirements for inter-financial sector exposures; and
- The introduction of liquidity requirements that penalise excessive reliance on short-term, interbank funding to support longer dated assets (BIS, 2011).

5.5.1 Regulatory developments in the EU

Addressing procyclicality in the financial sector is not a national issue but rather a global concern. In the past, various tools had been used to mitigate the consequences of the problem, i.e., the dynamic provisioning system in Spain (see for example Mann and Michael, 2002 and Saurina, 2009, 2011). However, in the case of the Spanish regulatory efforts, the instrument used protected the banking industry from the risk of under-provisioning in the upward phase of the cycle, but it proved a less effective tool in moderating the financial cycle itself. Indeed, in the US, the Dodd-Frank Wall Street Reform and Consumer Act in 2010 introduced a series of leverage restrictions, implemented countercyclical buffers and granted the Fed the authority to adopt capital rules for all bank holding companies (BHC) and savings and loan holding companies (SLHC) (Hardouvelis, 2010). Finally, the Fed is responsible for making all capital requirements countercyclical.

In the European Union, the financial services reform is seen a key pillar for growth and future economic development. The current reforms are based on the proposals of the De Larosiére Report (2009) which recognises the effect of procyclicality in the Basel framework and proposed several measures. The most important being the following: (i) adoption of Through The Cycle Approach in banking books; (ii) dynamic provisions following the case of Spain and/or countercyclical capital requirements; (iii) modification of the existing Deposit Guarantee Schemes (DGS), giving preference to a pre-funded by the financial sector framework; and (v) The European Central Bank could assume responsibility of the regulatory efforts against procyclicality.

It is therefore of interest that our findings should be revaluated when the new regulations have 'bedded-down' However, it is obvious, from our current results, that the risk management behaviour in Greek banks will substantially have to change given these new regulatory requirements. At both BIS and EBA levels, how this will affect Greek risk management behaviour will, of course have to be re-examined.

5.6 Conclusion

This Chapter presented recent findings regarding the LLP behaviour for a panel of Greek banks via the estimation of various econometric model specifications. Using a sample covering both the 2008 global financial crisis and the beginning of the recent national debt crisis 2010, two sets of panel data models were estimated. Following prior research in the area we presented models examining the counter/pro-cyclicality of the banking system in Greece and investigated the behaviour of banks with respect to the adjustments of their minimum capital requirements. In addition, we extended 'traditional' LLP econometric specifications by including cost efficiency scores (CE_{it}) into our regression models. These models were examined using a comprehensive set of econometric modelling tools that allow us to draw inferences with respect to the structure of the data used. More specifically, we adopted techniques to take into account unobserved bank specific effects and the dynamic nature in the provisioning tactics of banks. That is, we estimated both static models using the Pooled OLS, Fixed Effects and Random Effects estimators as a preliminary starting point for our analysis, and then introduce an auto-regressive term to capture any latent information present in the data.

As discussed in Section 5.5, the procyclicality of the financial system has been worrisome to regulators as a macro level as financial stresses occur in periods of business cycle contractions. Addressing the above issue, the Basel Committee on Banking Supervision (BCBS) has agreed on proposals that will: promote macro prudential goals; protect the banking system from periods of excess credit growth; and secure the solvency of banks. That is, the countercyclical buffer of 0% to 2/5%, which serves as an extension of the capital conservation buffer, will allow for capital to be built up during a business cycle expansion. The aim is to ensure that the banking sector has the necessary capital reserves to maintain existing credit lines to the economy thereby decreasing any procyclicality effects on lending. With respect to the counter/pro cyclical behaviour of Greek banks, our results suggest that distinguishing whether our sampled banks work as an amplifying mechanism that could exacerbate the business cycle is ambiguous. Furthermore, empirical results are subject to model selection sensitivity and the underlying assumptions of each estimator, for example, endogeneity and ignoring dynamic persistence. That is, under the static models, we

find tentative evidence towards a pro-cyclical behaviour. In addition, ignoring the dynamic effect proves to be a restrictive assumption based on the significance of the lagged dependent variable, and as such evidence indicates towards counter-cyclical behaviour. Thus, during 2005-2012, banks did not amplify the business cycle in Greece via their LLP strategies. It is therefore interesting to note that in future analyses research must take into account the addition of the countercyclical buffer introduced under Basel III. That is we could find two results. The first is that we expect no relationship and hence meaning the countercyclical buffer is working as banks do not need to top up capital. Contrariwise, if there is a significant result this implies that banks are countercyclical buffering additional to the imposed countercyclical buffer (the one under Basel III) such that they believe the actual imposed countercyclical buffer (which is in the 0 to 2.5% range) is an inadequate percentage necessary in their risk models. For example, if the imposed buffer is set at 1% and banks believe that it should be 2%, from their internal risk models, then they would add 100% to the buffer (simply, a positive and significant GDP growth coefficient)!

In addition to the countercyclical buffer, the BCBS, in the interest of further enhancing and promoting stability, is introducing the capital conservation buffer, raising the minimum capital requirements to 10.5%. The aim is to ensure that banks have enough resources in order to overcome potential losses during an economic downturn. The countercyclical characteristic of the capital conservation buffer lies in the fact that is ensures the built up of additional capital resources, again helping to maintain the intermediation process during business cycle contractions. With respect to our results concerning capital management, we find that on average, Greek banks engage in capital adjustments via their LLP practices under all the estimated models – static and dynamic specifications. Due to the present ongoing economic crisis in Greece and the already financially stressed banks, it is unclear of the effect on the full implementation of the capital conservation buffer. Under the assumption that past empirical research results could reflect future findings, the implication of the new conservation buffer will not have an effect on the capital management hypothesis. That is, under Basel III, increases in capital originates on the income statement through retained earnings and through increases in loan loss reserves (built up form LLPs) as the latter is not included in the computation of capital under the new regulations.

Furthermore, we find evidence that banks operating away from the optimal cost minimizing behaviour, as proxied by the cost efficiency scores, report higher provisions. This result corresponds to the capital management hypothesis as low performing banks, a proxy of managerial ability and skills, may face greater costs at raising capital, thus making them more inclined towards maintaining the capital requirements via LLP increases instead. In addition, with respect to bank specific factors determining NPL we do not find support for the moral hazard hypothesis. This result implies that Greek banking, with high market concentration, has a disincentivising effect on excessive risk taking and short-termism due to high reputational costs.

Finally, our results indicate that Greek risk bank management engages in cost skimping practises. That is, banks reduce short-term monitoring costs for loans and, in favour of long-term profits, recording in the process increased levels of cost efficiency. This risk management behaviour and lack of scrutiny with respect to new loan applications, defer the issue of addressing problems occurring from deteriorations of asset quality in the future. The problem of sharp increases in NPL over the recent years highlights the importance of prudential lending strategies for the stability of the Greek financial system.

Chapter 6

Conclusion, Policy Recommendations and Further Research Directions

6.1 Conclusion

The focus of this Thesis was threefold. Firstly we focused on financial institution efficiency, looking at Greek banks. Utilising Stochastic Frontier Analysis methods, we constructed cost efficiency frontiers and examined the evolution of cost ionization in Greek banks, considering a pre and post 2008 and 2010 sample period. Secondly, we investigated the dominant Loan Loss Provisioning (LLP) practises in the domestic banking sector. Finally, we provided recent evidence with respect to the LLP practises in the Greek market, while determining the evolution of Non-Performing Loans (NPL) in Greece with respect to management quality.

It should be noted that this research study only covers 2005-2012. The rationale for the beginning in 2005 is due to data availability on Bankscope and data availability with respect to the necessary conditions that allows to disaggregate the data, missing values, and finally due to the implementation of the IFRS accounting standards in Greek banks. With respect to our end data, 2012, this is due to 2 factors, the first is quite simply that data was collected during the PhD and 2012 constituted the latest period available from Bankscope when I started modelling in years 2 and 3 and therefore writing up the Thesis in year 4. Recollecting additional year data was not an option as model specification and results might have changed therefore delaying further the completion of this research. In fact, 2012 is probably the most appropriate year to end when analysing the risk management LLP behaviour of Greek banks as after 2012 we saw (as discussed in Chapter 2) the recapitalization of the banks. Therefore, by extending past 2012 will, of course, muddy the waters and create problems disentangling the cause and effects relating to our estimated hypotheses, for example, bad management/skimping.

The Thesis begun with a review of the Greek banking system, covering the sampled period and extending the discussion to incorporate recent developments beyond the end of the our econometric sample period, 2012. We outline the key events that shaped the Greek financial system from what it was in the 1980's to what it has become in 2015. Over this time the banking sector in Greece has changed significantly with respect to the participants in the market, the activities which they undertook and the regulatory structure in which they operated. Greek banks experienced major changes resulting from a period of deregulation during the 1980's to the establishment of the common market and the introduction of the Euro currency. Responding to these changes, Greek banks modernized their technology and risk management measures, expanded their activities abroad and modernized their networks. After the introduction of the common currency, Greek banks achieved higher level of profitability following an upward economic trend, before the global financial crisis. However, deep structural economic shortcomings in Greece brought about a sovereign debt crisis in 2010. Even though limited exposure in toxic bonds meant that Greek banks managed to survive the 2008 financial turmoil, their exposure to Greek government bonds meant that they had to suffer a significant hit via the Private Sector Involvement in 2010-2012, which eventually led to the first round of recapitalizations in 2012. More recently, and subject to the deepening of the crisis and the dramatic increase in NPL, two more rounds of recapitalization were required in order to maintain a capital base that addressed regulatory standards

The analysis comprised a range of research questions. Firstly we considered various methodologies that are utilised in banking studies to evaluate the performance of financial institutions. Next, examination of the main efficiency concepts estimated in applied research and the various econometric techniques was discussed. We then presented both distribution free and parametric approaches and we gave preference to SFA as our main estimation methodology to analyse Greek banks. Finally, we addressed the main decisions that researchers should adhere when using SFA in an empirical study (that is distributional assumptions, pre/post estimation tests, the choice of the functional form and the choice of the input/output mix).

With respect to the empirical application, we present cost efficiency estimates for a panel of Greek banks from various econometric model specifications. Using a sample

that covers the recent crises that hit Greece, in 2008 and mainly in 2010, two sets of cost frontiers were estimated. Following the popular intermediation approach under both the Battese and Coelli (1995) Time Varying Model (TVM) and the Greene (2005a, 2005b) True Fixed Effects (TFE) model specifications, bank specific cost efficiency scores were estimated, taking into account various country specific macroeconomic factors that have in impact on the cost minimization behaviour of Greek banks. Following a set of consistency conditions proposed by Bauer et al., (1998), we address the lack of consensus as to which econometric approach is optimal when estimating a cost frontier. Therefore, we ensure a coherent and consistent econometric modelling strategy that presents estimated scores which are not an artificial artefact of the estimation process. The findings suggest that for the most part, all estimated SFA models generate cost efficiencies that meet the conditions, however, under specific conditions we observe that the TFE models exhibit instability (for example, under condition 4). The latter finding implies that these estimates are not suitable candidates for our second stage LLP/NPL modelling. Finally, through goodness of fit post-estimation tests we choose our preferred model specification, identifying at the same time the appropriate number of macroeconomic variables that can affect cost efficiency and which are supported by our data. That is, a Likelihood Ratio test and a set of information criteria indicate that the preferred models for the selected sample and model specification are those that incorporate only four macroeconomic indicators (Gross Domestic Product (% change), unemployment rate (% change), inflation rate (% change) and top five concentration ratio).

The final section with respect cost efficiency estimation concerns the differences in performance between systemically important banks operating in Greece the respective non-core institutions. We note that core banks record strong performances, outperforming their respective non-core counterparts. Even though the Greek economy suffered a substantial hit in 2010, Greek banks still operated close to the optimal frontier, indicating a sound financial system that was able to overcome the strain of the first two years of the Greek debt crisis. Furthermore, we notice the even though core institutions report higher efficiency scores with respect to non-core banks, after 2008, this performance gap between the two groups of banks was reduced, indicating that larger institutions adversely suffered consequences due to financial instability. In addition, and in line with the latter finding, we note that non-core institutions out-

performed the four systemically important banks after the outbreak of the sovereign debt crisis, hence indicating that the performance of the latter suffered significantly due to participation in the PSI, potentially contributing to a deepening of the recession in the Greece.

We note that, to the best of our knowledge, this study is the first to present findings with respect to Greek banks, empirically testing whether banks have the ability to manage their LLP levels to pursue LLP risk management objectives. The Thesis presented results regarding LLP behaviour for a panel of Greek banks via the estimation of various econometric model specifications, taking into account unobserved bank specific effects and the dynamic nature of ex-post risk exposure on LLP. Furthermore, following Bryce et al., (2015), we extended the traditional econometric specifications by including cost efficiency scores, gaining insights in the effect of the presence of bad management and/or cost skimping.

Our dynamic LLP models results suggest Greek banks as an amplifying mechanism of the business cycle and are sensitive to model selection and the underlying assumptions related to the econometric methods estimated. That is, when ignoring the persistence of LLP over time, we find evidence of pro-cyclical behaviour. However, re-estimating the regressions and taking into account the persistence of the series, a choice which is supported by our data, Greek banks do not exacerbate the economic cycle, thus showing a counter-cyclical behaviour. We confirm, that by not taking into account the dynamic component of credit risk provisioning may lead to biased and inconsistent findings. With respect to the capital management hypothesis, we find strong evidence to support that Greek banks engage in capital adjustments via their LLP resources. In addition, we present evidence that support banks operating at low efficiency levels, on average report higher LLP, a finding that could be linked with the difficulty of those institutions to raise capital in financial markets, thus increasing their motive for capital management. With respect to the development of NPL in Greece and in contrast with prior research (see, for example, Louzis et al., 2012) we find that Greek banks engage in cost skimping behaviour, thereby sacrificing long-term asset quality for reduced short-term operating costs which reflected in higher cost efficiency estimates. These differences in our results can be attributed to the choice of efficiency indicator and sample selection. Finally, we do not find evidence of the moral hazard hypothesis, a

result potentially compounded by our small sample and the disincentives for excessive risk taking and short-termism created as a result of high reputational costs for Greek bank management.

6.2 Policy Recommendations

Bauer et al., (1998) observe that in order to confirm that the efficiency scores are not an artificial construct of the various assumptions required during the estimation process, the aforementioned scores should exhibit positive relationships with standard "non-frontier" based measures of performance (ROAA, ROEE and Cost to Income). As discussed in Condition 6 of the Bauer et al., (19989) conditions, (see Section 4.5.6), such comparisons may be misleading at best. That is, the efficiency literature has focused and examined the limited nature of accounting based financial ratios on more than one occasion (for a more detailed discussion, see Section 4.5.6). Indeed, closer examination with respect to Condition 6, reveals that in the case of Greece, any policy recommendations based on financial ratios may indeed prove to be inaccurate as the SFA derived performance indicators show little to no correlation with the accounting based ratios. It is therefore critical in our view, that any regulatory body takes into account more than one estimation technique as public policy conclusions will yield different conclusions depending on the approach presented.

However, given this limitation, we advance that useful policy implications can be formed from this exercise regarding the ongoing Greek debt crisis. That is, examination of the Bauer et al., (1998) conditions reveal that modelling heterogeneity in empirical SFA models could lead to misleading policy recommendations, at least with respect to the target implementation period. Analysing the aforementioned conditions proves that the TVM models show good stability over time (Condition 4), with the exception of the Four-Year-Apart correlations, which were mostly insignificant – an unsurprising finding given the volatility in the economic environment in the country. The main finding of this exercise is the behaviour of the TFE models. All three estimated specifications collapse and with the exception of one positive and significant Spearman ρ value, all the correlations are either insignificant or negatively correlated, indicating high intertemporal volatility. Under the assumption that the estimated frontiers are

expected to show relative stability over time as efficient/inefficient firms are likely to exhibit only marginal changes in their performance between years, allowing firm specific effects into the estimation produces relatively unstable results over time. To the best of my knowledge, including or excluding firm effects (whether fixed or random) as part of inefficiency depends primarily on the interpretation of these effects. However, the literature is limited as to whether these effects are part of the inefficiency component or not and hence complicates any potential policy recommendations (see, a discussion of these problems in Kumbhakar et al., 2014).

Hence, the implication is that when modelling heterogeneity as part of the inefficiency component, results obtained are fairly stable over time and as thus regulatory policies targeted at either very efficient or inefficient banks could change management behaviour and costs only after a lag. That is, with respect to the TVM models, we find that high efficiency/inefficiency effects tend to persist over the sample period as many of the worst and best practice banks tend to remain consistently inefficient or efficient. Therefore, it is the correlations based on average efficiency scores presented in Section 4.5.6 that could be useful for regulatory analysis which forecast the effects of regulation on banks in the future. That is, if a policy recommendation is expected to be fully implemented with a lag of n years, then the n year apart correlation may give the best indication of whether this policy will change management practices at the intended institutions (i.e., cost reductions and increases in efficiency). Finally, our results suggest that short and medium term policies with an implementation period of 3 years could potentially prove to be more accurate given the significance of the Three-Year-Apart Spearman ρ value.

With respect to individual financial institutions, the four systemically important banks (Eurobank Ergasias SA, Piraeus Bank SA, Alpha Bank AE and National Bank of Greece SA,) entered the Single Supervisory Mechanism (SSM) on November 4, 2014. The implication of joining the SSM is that the European central Bank is now directly involved in the supervision process - overseeing prudential monitoring. More specifically, under SSM the ECB (in cooperation with the Bank of Greece) ensures that the institutions' robust governance arrangements and internal risk control mechanisms follow European norms of risk management practices. This includes (but not limited to): notifications concerning acquisition and disposal of qualifying holdings in credit

institutions; imposition of prudential requirements on credit institutions in the areas of own funds, liquidity, leverage risk; and Basel compliant remuneration policies. Examination of our results indicate that the systemically important banks outperform the non-core institutions, even though the performance gap was reduced after the debt crisis. Therefore, the core banks were able to maintain high efficiency levels despite the hit that they suffered to capital (due to non-performing loans) when the debt crisis started. Given that the future prospects of the Greek economy are not promising (at the time of writing), and that the big four core banks only marginally passed the recent EBA stress tests, any further regulation could prove to have long lasting effects and impede the recovery of Greek banks.

The efficiency increase exhibited prior to 2008 was supported by the good business environment at that time (for example, GDP growth shows the highest values in our sample, equal to 5.5%) - a pattern also observed by Humphrey and Pulley (1997) for US banks. One possible implication is that changes in regulation promoted under Basel III, even though they are considered as forward steps towards bolstering the Greek banking system, may not necessarily lead to higher efficiency in the short run as they may impose additional burden in an already strained system via increases in capital requirements. It is our view that the announcement and imposition of additional controls should be gradual and timely, so that banks can adjust their operations accordingly.

The latter discussion can be related to the implementation of Basel III and especially the counter-cyclical buffer. That is, under Law 4261/2014 (Article 127), the Bank of Greece is responsible for setting the countercyclical buffer rate for Greece (on a quarterly basis) from the first quarter of 2016. The decisions made by the Bank of Greece in setting the aforementioned capital buffer rate are made in agreement with the Hellenic Capital Market Commission. As discussed, the aim of the counter-cyclical buffer is to mitigate the pro-cyclical amplification of financial shocks to the real economy. These effects have been one of the most destabilising elements of the global financial crisis, as an economic downturn following a period of excess credit growth can lead to large losses in the banking sector and spark a vicious circle. The aim of the countercyclical capital buffer is to address the procyclicality of credit growth and leverage. That is, to ensure an appropriate level of credit growth and leverage in both

the upward and the downward phase of the business cycle. Our empirical findings suggest that the Greek banking sector did not exacerbate the economic cycle but exhibited counter-cyclical behaviour! The lack of pro-cyclical LLP practises in Greece together with the adverse economic environment lends support to a gradual implementation of the counter-cyclical buffer in order to allow banks to smoothly adjust their operations and capital positions to meet the new requirements[113] This gradual and conservative implementation strategy should be maintained eve in periods of economic expansion. In that way, the Bank of Greece could be in a position to promote macro prudential goals of protecting the banking sector from periods of excess aggregate credit growth. Furthermore, the lack of pro-cyclicality could be viewed as an indication that there is no immediate need to reform the existing rules regarding provisioning practices towards a dynamic provisioning regime. At this stage we do not advocate that regulators should ignore potential reforms in the provision system, however, reforms that change the current status, combined with new capital measures could prove to be too demanding for a banking system that is still under recovery.

Finally, as discussed in Section 5.4.2b, banks operating away from the optimal efficiency frontier, on average exhibit higher levels of LLPs – a finding in line with the presence of capital management. That is, in this case, a highly inefficient bank could be even more inclined to proceed to capital adjustments via LLP changes in order to avoid the extra cost of raising new capital in financial markets. Therefore, implementing policies that promote cost efficiency improvements in the Greek banking system may indeed help mitigate issues of capital management. It is worth noting that such policies may prove to be unsuccessful as long as the business environment is "hostile". The findings presented thus indicate that the Greek banking system, and the core-banks in particular, are more inclined to register increases in their efficiencies under a favourable economic cycle. However, it is important that these efficiency improvements are combined with rigorous control over the existing and future loan allocation – as suggested by the presence of the cost skimping hypothesis. That is, when banks reduce short-term monitoring costs for loans and in the process record

[113] Indeed, since 1 January 2016, the countercyclical buffer rate for Greece has been set at 0%, i.e. at the lowest possible level, and therefore does not affect the capital requirements for credit institutions and investment firms. Furthermore, the 0% has been held fixed until Q1 2017. To the best of our knowledge, no revision has been made public by the BoG.

higher levels of cost efficiency. However, this risk management behaviour and lack of scrutiny with respect to new loan applications, defers the issue of addressing problems occurring from deteriorations of potential asset quality in the future.

Indeed, NPL reduction is a key precondition for gradually restoring an adequate and efficient supply of credit to the Greek economy, and for achieving sustained growth. Therefore, improving the quality of loans and promoting improved loan screening practices could prove to be of a particular importance. The factors which contributed to lax screen standards in the years prior to the crisis include: the degree of competition in the banking system; external financial imbalances; the level of private sector debt; corporate governance in the banking sector; the relative tightness of monetary policy and; the intensity of banking supervision (see for example a discussion in Carbó-Valverde et al., 2011).

Furthermore, given the highly concentrated nature of the Greek banking system, bank competition will potentially be a decisive factor with respect to loan quality. However, the existing literature examining the relation between banking competition and the quality of bank loan portfolios present counter intuitive conclusions. More specifically, Allen and Gale (2000), Hellmann et al. (2000), Keeley (1990), Matutes and Vives (2000), and Repullo (2004) argue that increasing competition reduces the quality of loans (more competition erodes the monopolistic rents of banks, which in turn induces managers to take on more risks). Similarly, Broecker (1990), Freixas et al. (2007), and Shaffer (1998) show that by increasing the number of banks in the market increases the likelihood that low quality loans will be issued, so that the average quality of loan portfolios decreases. On the other hand, Boyd and De Nicolo (2005) argue that increases in the competition leads to increases in the amount of loanable funds and therefore decreases in loan interest rates – giving incentives to borrowers to repay their loans. Hence, there is a positive relationship between competition and the quality of loans. More recently, Gomez and Ponce (2014) study the link between bank competition and the quality of loans that considers both types of asymmetric information problems – moral hazard and adverse selection. The authors offer findings that there is an inverted U-shaped relationship between average loan quality and competition. One direct implication of the study is that competition should be promoted when its current level is below the optimal threshold and it should be

prevented when becoming excessive (i.e. above the threshold). It shall therefore be interesting to follow the future competitiveness and concentration in Greek banking to determine which side of the coin loan quality falls – negative or positive.

Finally, cost skimping practises could be potentially mitigated by identifying the optimal asset size threshold, which in turn could improve in an indirect way the average quality of the loanable funds in the economy. Furthermore, the practice of collecting and disclosing information about potential borrowers - something that could be facilitated via a closer collaboration between credit bureaus and public registers should be maintained. We note that it is important that the legal framework concerning the management of distressed loans is finalised and fully implemented. It is our view that three main topics should be managed within a reasonable timeframe: solutions for borrowers with exposures to multiple banks; development of a secondary market for NPLs; the establishment of banks' internal workout on managing distressed SMEs. Hence, establishing a legal framework that will allow for out of court settlements will contribute towards the swift resolution of non-performing exposures and in the process, unlock loanable funds to the real economy, bolstering investment and employment. In fact, the need to address bad loans has also been acknowledged at an EU level by the European Banking Authority, as a matter that has become "urgent and actionable". According to recent news report in the financial press, senior officials raised the prospect of an EU "bad bank" who would buy up toxic loans from national institutions. The EBA estimates that lenders hold more than €1tn of toxic loans[114,115].

6.3 Further Research Directions

This Thesis presents findings with respect to cost efficiency, LLP management practises and NPL management quality determinant in the context of Greek banks. The research presents a discussion on the extent of the application of panel data frontier model estimation. Since the introduction of SFA by Meeusen and van Den Broeck (1977) and Aigner et al., (1977), frontier estimation has been widely used in applied economic research. However, efficiency estimation is subject to a number of choices.

[114] https://www.ft.com/content/c8a91485-a773-3c10-bcb3-05e0522e1443
[115] https://www.ft.com/content/3b18e5ec-d047-36b2-a35a-10ae8e6a76ed

For example, the estimates of efficiency depend on the distributional assumptions concerning the one-sided error component and the temporal behaviour of efficiency. The models selected for the purpose of the Thesis, the TMV model by Batesse and Coelli (1995) and the TFE model proposed by Greene (2005a, 2005b), allow inefficiency to be a function of some exogenous variables. However, much like any empirical application estimating efficiency, our econometric procedures estimation makes assumptions regarding the nature of the inefficiency component and time invariant bank specific effects. Indeed, in the TFE model, the firm effects are not regarded as a component of inefficiency, in contrast to the TVM model, where all bank specific effects are regarded as part of the one-sided error term. Kumbhakar et al., (2014) note the lack of *a priori* economic reasoning either in favour or against treating these 'banks specific time invariant effects' as inefficiency. Whether these effects are treated as inefficiency or not is subject to the interpretation of the results. Further stressing the subjective model selection criteria, Kumbhakar et al., (2014) note that "the variability of the results from the different models clearly demonstrates the difficulty in 'correctly' measuring efficiencies. No model can be held to be 'correct', and the efficiencies will always be a kind of unobserved or modelled effect (page 335)".

Therefore, we note the importance to further explore the performance of Greek banks, by taking into account different error structures in an SFA model, allowing in that way to further decompose the inefficiency component from bank specific effects. That is, although some of the models utilised in the Thesis accommodate firm affects, these models do not take into account the presence of any factors that could have a permanent effect on inefficiency. However, again it should be noted that we were restricted by sample size and data availability. Hopefully, in a future research these problems could be overcome such that with longer panels we can re-examine the interesting results found in this Thesis concerning Greek banking. If there are any Greek banks left in the future!

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Appendix A

Table 8.1. Total Number of Braches for the sample period

Year	*Total Number of branches*
2005	2974
2006	3198
2007	3351
2008	3589
2009	3704
2010	3471
2011	2483
2012	2819

Source: Hellenic Bank Association

Table 8.2. Shephard's Duality

Technology	*Value Function*
Input Distance Function	Cost Function
Output Distance Function	Revenue Function
Indirect Input Distance Function	Revenue Indirect Cost Function
Indirect Output Distance Function	Cost Indirect Revenue Function

Source: Färe and Primont, 1995

Appendix B

Table 9.1. Selective Studies on bank X-efficiencies

	Period under study	*Methodology*	*Main findings (averages for Greece)*		*Type of Study*
			Overall operating efficiency (%)	*Overall profit efficiency (%)*	
Noulas (1997)	1991-1992	DEA	85	NA	Greece
Christopoulos et al.,(2002)	1993-1998	SFA	83	NA	Greece
Noulas (2001)	1993-1998	DEA	65	NA	Greece
Tsionas et al., (2003)	1993-1998	DEA	98	NA	Greece
Kamberoglou et al., (2004)	1993-1999	DFA	67	NA	Greece
Schure et al, (2004)	1993-1997	RTFA	28	NA	EU
Rezitis (2006)	1982-1997	DEA	91	NA	Greece
Staikouras et al., (2006)	1993-2005	SFA	84	45	Greece
Weill (2007)	1996 and 2000	SFA	62	NA	EU
Noulas et al., (2008)	2000-2001	DEA	70	NA	Greece branches
Pasiouras (2008)	2000-2004	DEA	95	NA	Greece
Pasiouras et al., (2008)	2000-2005	DEA	95	NA	Greece
Chortareas et al., (2009)	1998-2003	DEA	85	75	Greece

DEA: Data envelopment Analysis; SFA: Stochastic Frontier Analysis; DFA: Distribution Free Approach; RTFA: Recursive Thick Frontier Approach. The TFA is a variation of the TFA methodology that relies on an iterative procedure (for more details see Wagenvoort and Schure (2006). Type of Study defines whether the study is country specific or cross country.

Table 9.2. Choice of Input/Output Mix

	Inputs	*Outputs*
Model 1	*Price of Funding: Total Interest Expenses/Total customer deposits* *Price of labour: Labour/Fixed Assets* *Price of fixed assets: Other Operating expenses/Fixed Assets*	*Gross Loans* *Other Earning Assets* *Loans and advances to banks* *Non-interest income (net fee and commission and other operating income)*
Model 2	*Price of Funding: Total Interest Expenses/Total customer deposits* *Price of labour: Labour/Fixed Assets* *Price of fixed assets: Other Operating expenses/Fixed Assets* *Common Equity*	*Gross Loans* *Other Earning Assets* *Loans and advances to banks* *Non-interest income (net fee and commission and other operating income)*
Model 3	*Price of Funding: Total Interest Expenses/Total customer deposits* *Price of labour: Labour/Fixed Assets* *Price of fixed assets: Other Operating expenses/Fixed Assets* *Loan Loss Provisions*	*Gross Loans* *Other Earning Assets* *Loans and advances to banks* *Non-interest income (net fee and commission and other operating income)*
Model 4	*Price of Funding: Total Interest Expenses/Total customer deposits* *Price of labour: Labour/Fixed Assets* *Price of fixed assets: Other Operating expenses/Fixed Assets*	*Gross Loans* *Other Earning Assets* *Off Balance Sheet Items*
Model 5	*Price of Funding: Total Interest Expenses/Total customer deposits* *Price of labour: Labour/Fixed Assets* *Price of fixed assets: Other Operating expenses/Fixed Assets* *Common Equity*	*Gross Loans* *Other Earning Assets* *Off Balance Sheet Items*
Model 6	*Price of Funding: Total Interest Expenses/Total customer deposits* *Price of labour: Labour/Fixed Assets* *Price of fixed assets: Other Operating expenses/Fixed Assets* *Loan Loss Provisions*	*Gross Loans* *Other Earning Assets* *Off Balance Sheet Items*

Models 2 and 3 include common equity and loan loss provisions as risk variable. Modesl4, 5, 6 were not estimated via SFA as they failed to pass the OLS residuals test and the M3T statistic.

Table 9.3. Auxiliary Equations

$$m_{it} = \delta_0 + \delta_1 GDPGr + \delta_2 UN + \delta_3 \text{Inf} + W_{it} \quad (9.1)$$

$$m_{it} = \delta_0 + \delta_1 GDPGr + \delta_2 UN + \delta_3 \text{Inf} + \delta_4 CR5 + W_{it} \quad (9.2)$$

$$m_{it} = \delta_0 + \delta_1 GDPGr + \delta_2 UN + \delta_3 \text{Inf} + \delta_4 Credit + \delta_5 CR5 + W_{it} \quad (9.3)$$

$$m_{it} = \delta_0 + \delta_1 GDPGr + \delta_2 UN + \delta_3 \text{Inf} + \delta_4 CapGr + \delta_5 Credit + \delta_6 CR5 + W_{it} \quad (9.4)$$

Table 9.4. Descriptive Statistics for the Cost Function Terms

	Observations	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
lnTC	116	6.273	1.949	0.899	9.270
lnp1	116	-2.963	0.699	-4.449	-1.389
lnp2	116	0.153	0.358	-0.609	1.378
lnp1lnp1	116	4.634	1.993	.965	9.899
lnp2lnp2	116	0.0755	.1272	0.000	0.949
lnp1lnp2	116	-0.426	1.104	-4.208	2.713
lny1	116	8.742	1.540	3.933	11.163
lny2	116	8.549	0.490	4.605	9.333
lny3	116	6.433	1.424	3.312	8.704
lny4	116	5.436	0.573	4.605	6.907
lny1lny1	116	39.395	13.290	7.737	62.309
lny2lny2	116	36.669	3.605	10.603	43.555
lny3lny3	116	21.701	8.923	5.486	37.886
lny4lny4	116	14.942	3.259	10.603	23.859
lny1lny2	116	74.744	14.060	33.500	98.197
lny1lny3	116	58.046	21.211	15.763	93.157
lny1lny4	116	48.284	13.251	19.422	75.164
lny2lny3	116	55.210	13.526	26.597	78.897
lny2lny4	116	46.538	6.135	26.219	61.915
lny3lny4	116	35.605	11.065	16.467	56.994
lny1lnp1	116	-25.236	4.828	-33.727	-8.948
lny1lnp2	116	1.580	3.151	-2.911	10.086
lny2lnp1	116	-25.348	6.135	-37.892	-9.093
lny2lnp2	116	1.314	3.061	-5.192	11.733
lny3lnp1	116	-18.634	4.702	-27.763	-7.042
lny3lnp2	116	1.140	2.330	-2.477	7.167
lny4lnp1	116	-15.830	2.896	-21.969	-7.714
lny4lnp2	116	0.891	1.941	-3.010	6.742
lneq	116	8.100	0.585	4.605	9.444

lneqlneq	116	32.981	4.328	10.603	44.601
lnllp	116	4.501	1.939	0.381	9.470
lnllplnllp	116	11.995	9.332	0.072	44.842

Where; $lnTC$: total costs defined as operating costs, interest paid on deposits and labour expenses; lnp_1: Price of Total Customer Deposits (estimated as Total Interest Expenses/Total customer deposits); lnp_2: Price of Labour (estimated as Personnel Expenses/Fixed Assets); lnP_3: Price of Capital (estimated as Other Operating Expenses/Fixed Assets); lny_1: Gross Loans, lny_2: Other Earning Assets; lny_3: Loans and Advances to banks; lny_4: Non-interest income (net fee and commission and other operating income); $lneq$: Equity; $lnllp$: Loan Loss Provision. All values are expressed in natural logarithms.

Table 9.5. Parameter Estimates, Time Varying Model, TVM1

	Coefficient	*Standard Error*	*t-ratio*
lnp1	-5.202	1.087	-4.785
lnp2	-3.65	1.040	-3.514
lnp1lnp1	-0.814	0.174	-4.683
lnp2lnp2	0.291	0.356	0.817
lnp1lnp2	-0.587	0.252	-2.325
lny1	-0.656	0.806	-0.814
lny2	-3.862	1.020	-3.783
lny3	3.288	1.136	2.892
lny4	-0.595	1.004	-0.592
lny1lny1	0.110	0.100	1.100
lny2lny2	0.783	0.203	3.846
lny3lny3	-0.068	0.101	-0.676
lny4lny4	1.865	0.788	2.364
lny1lny2	0.481	0.160	3.002
lny1lny3	0.053	0.086	0.617
lny1lny4	-0.492	0.274	-1.792
lny2lny3	-0.397	0.130	-3.034
lny2lny4	-0.632	0.415	-1.522
lny3lny4	-0.074	0.189	-0.391
lny1lnp1	0.289	0.107	2.681
lny1lnp2	-0.041	0.179	-0.232
lny2lnp1	0.204	0.225	0.905
lny2lnp2	-0.353	0.261	-1.354
lny3lnp1	-0.123	0.090	-1.354
lny3lnp2	-0.057	0.113	-0.5025
lny4lnp1	0.069	0.289	0.239
lny4lnp2	1.077	0.495	2.175
Constant	5.68	1.02	5.54
CR5	-0.254	0.041	-6.163
GDP Growth	0.057	0.040	1.437
Inflation	0.031	0.152	0.204
Unemployment	0.106	0.064	1.639
Constant	16.05	2.92	5.51
σ^2	0.08	0.02	4.72
γ	0.66	0.07	9.89
N	*116*	*116*	*116*

Where TVM1: Time Varying Model 1, without a risk metric and 4 macroeconomic indicators (z); $lnTC$: total costs defined as operating costs, interest paid on deposits and labour expenses; lnp_1: Price of Total Customer Deposits (estimated as Total Interest Expenses/Total customer deposits); lnp_2: Price of Labour (estimated as Personnel Expenses/Fixed Assets); lnP_3: Price of Capital (estimated as Other Operating Expenses/Fixed Assets); lny_1: Gross Loans, lny_2: Other Earning Assets; lny_3: Loans and Advances to banks; lny_4: Non-interest income (net fee and commission and other operating income); $lneq$: Equity; $lnllp$: Loan Loss Provision. All values are expressed in natural logarithms. Where z's include: GDP Growth: Annual change of Gross Domestic Product (%); Unemployment: Unemployment rate (%); Inflation: Annual inflation rate (%); CR5: Concentration Ratio of assets for the top five banking institutions.

Table 9.6. Parameter Estimates, Time Varying Model, TVM2

	Coefficient	*Standard Error*	*t-ratio*
lnp1	-0.734	1.056	-0.695
lnp2	-0.512	1.205	-0.425
lnp1lnp1	-0.570	0.183	-3.118
lnp2lnp2	0.427	0.348	1.226
lnp1lnp2	-0.662	0.248	-2.664
lny1	0.701	0.807	0.869
lny2	-4.617	1.044	-4.422
lny3	3.887	1.158	3.358
lny4	-4.019	1.105	-3.639
lny1lny1	0.074	0.095	0.777
lny2lny2	0.855	0.224	3.821
lny3lny3	-0.059	0.099	-0.595
lny4lny4	2.365	0.770	3.072
lny1lny2	0.533	0.160	3.327
lny1lny3	0.050	0.081	0.615
lny1lny4	-0.698	0.276	-2.525
lny2lny3	-0.559	0.142	-3.948
lny2lny4	-0.638	0.397	-1.607
lny3lny4	0.086	0.194	0.446
lny1lnp1	0.411	0.119	3.450
lny1lnp2	-0.115	0.196	-0.587
lny2lnp1	-0.085	0.218	-0.388
lny2lnp2	-0.814	0.266	-3.064
lny3lnp1	-0.099	0.085	-1.160
lny3lnp2	0.021	0.104	0.201
lny4lnp1	-0.371	0.305	-1.220
lny4lnp2	1.204	0.515	2.339
lneq	-0.563	0.845	-0.666
lneqlneq	0.103	0.114	0.901
Constant	18.46	1.01	18.23
CR5	-0.261	0.043	-6.040
GDP Growth	0.033	0.026	1.268
Inflation	-0.076	0.096	-0.795
Unemployment	0.084	0.051	1.658
Constant	17.16	2.84	6.03
σ^2	0.760	0.02	3.97
γ	0.68	0.08	8.74
N	*116*	*116*	*116*

Where TVM2: Time Varying Model 2, with Total Equity as netput and 4 macroeconomic indicators (z); $lnTC$: total costs defined as operating costs, interest paid on deposits and labour expenses; lnp_1: Price of Total Customer Deposits (estimated as Total Interest Expenses/Total customer deposits); lnp_2: Price of Labour (estimated as Personnel Expenses/Fixed Assets); lnP_3: Price of Capital (estimated as Other Operating Expenses/Fixed Assets); lny_1: Gross Loans, lny_2: Other Earning Assets; lny_3: Loans and Advances to banks; lny_4: Non-interest income (net fee and commission and other operating income); $lneq$: Equity; $lnllp$: Loan Loss Provision. All values are expressed in natural logarithms. Where z's include: GDP Growth: Annual change of Gross Domestic Product (%); Unemployment: Unemployment rate (%); Inflation: Annual inflation rate (%); CR5: Concentration Ratio of assets for the top five banking institutions.

Table 9.7 Parameter Estimates, Time Varying Model, TVM3

	Coefficient	*Standard Error*	*t-ratio*
lnp1	-4.822	1.396	-3.456
lnp2	-3.940	1.172	-3.361
lnp1lnp1	-0.832	0.192	-4.335
lnp2lnp2	0.234	0.372	0.629
lnp1lnp2	-0.590	0.245	-2.405
lny1	-0.462	0.942	-0.490
lny2	-3.704	0.870	-4.256
lny3	2.927	0.960	3.050
lny4	-0.755	1.093	-0.691
lny1lny1	0.107	0.101	1.056
lny2lny2	0.721	0.209	3.450
lny3lny3	-0.080	0.104	-0.768
lny4lny4	1.823	0.803	2.271
lny1lny2	0.447	0.164	2.732
lny1lny3	0.062	0.091	0.685
lny1lny4	-0.483	0.264	-1.828
lny2lny3	-0.351	0.112	-3.144
lny2lny4	-0.592	0.389	-1.520
lny3lny4	-0.077	0.187	-0.412
lny1lnp1	0.289	0.111	2.607
lny1lnp2	-0.034	0.195	-0.175
lny2lnp1	0.144	0.241	0.596
lny2lnp2	-0.334	0.257	-1.301
lny3lnp1	-0.117	0.087	-1.355
lny3lnp2	-0.071	0.122	-0.583
lny4lnp1	0.081	0.303	0.268
lny4lnp2	1.105	0.495	2.232
lnllp	0.038	0.089	0.433
lnllplnllp	-0.005	0.019	-0.286
Constant	6.251	1.005	6.223
CR5	-0.240	0.040	-5.964
GDP Growth	0.062	0.064	0.962
Inflation	0.080	0.244	0.326
Unemployment	0.102	0.089	1.150
Constant	14.952	3.667	4.077
σ^2	0.08	0.019	4.225
γ	0.667	0.068	9.844
N	*116*	*116*	*116*

Where TVM3: Time Varying Model 3, with Loan Loss Provisions as netput and 4 macroeconomic indicators (z); Where; $lnTC$: total costs defined as operating costs, interest paid on deposits and labour expenses; lnp_1: Price of Total Customer Deposits (estimated as Total Interest Expenses/Total customer deposits); lnp_2: Price of Labour (estimated as Personnel Expenses/Fixed Assets); lnP_3: Price of Capital (estimated as Other Operating Expenses/Fixed Assets); lny_1: Gross Loans, lny_2: Other Earning Assets; lny_3: Loans and Advances to banks; lny_4: Non-interest income (net fee and commission and other operating income); $lneq$: Equity; $lnllp$: Loan Loss Provision. All values are expressed in natural logarithms. Where z's include: GDP Growth: Annual change of Gross Domestic Product (%); Unemployment: Unemployment rate (%); Inflation: Annual inflation rate (%); CR5: Concentration Ratio of assets for the top five banking institutions.

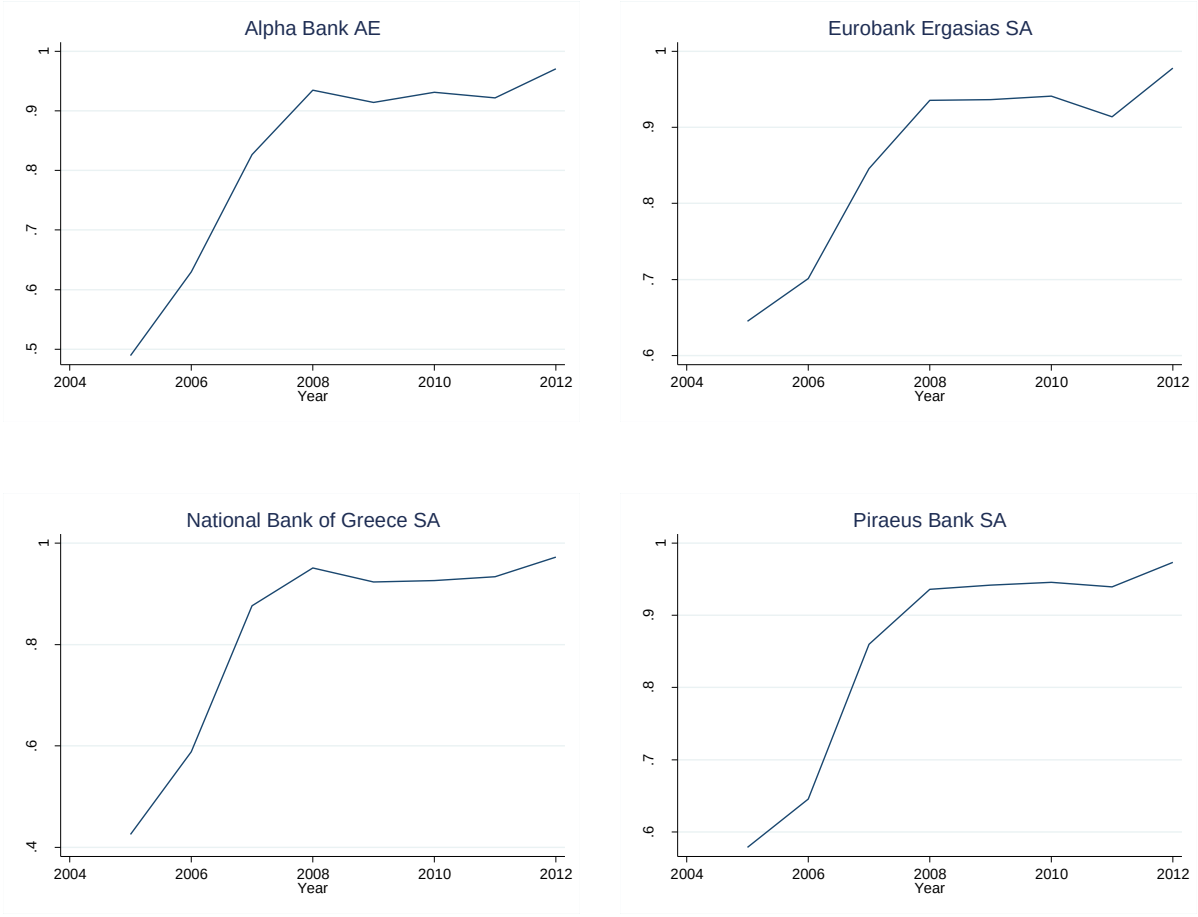
Table 9.8. Parameter Estimates, True Fixed Effects Models

	TFE1	*TFE2*	*TFE3*
lnp1	-0.017	1.272	1.905
	(1.529)	(1.671)	(1.852)
lnp2	-1.686	-0.315	-2.023
	(1.657)	(1.839)	(2.148)
lnp1lnp1	-0.076	-0.021	0.028
	(.074)	(.0771)	(.078)
lnp2lnp2	0.097	0.094	0.237
	(.171)	(.171)	(.217)
lnp1lnp2	-0.271**	-0.304**	-0.337**
	(.096)	(.098)	(.110)
lny1	2.378	3.288*	5.641***
	(1.274)	(1.640)	(1.647)
lny2	1.002	1.256	3.214
	(2.120)	(2.487)	(2.684)
lny3	1.047	1.091	0.648
	(1.034)	(1.157)	(1.252)
lny4	-6.645**	-8.238***	-11.86***
	(2.258)	(2.225)	(2.169)
lny1lny1	-0.106	-0.112	-0.236***
	(.059)	(.063)	(.063)
lny2lny2	0.066	0.121	-0.107
	(.124)	(.132)	(.144)
lny3lny3	-0.040	-0.081	-0.112*
	(.040)	(.058)	(.053)
lny4lny4	-0.656	-0.464	-1.054***
	(.340)	(.393)	(.317)
lny1lny2	-0.394*	-0.480*	-0.873***
	(.168)	(.205)	(.211)
lny1lny3	0.040	0.054	0.128**
	(.036)	(.043)	(.045)
lny1lny4	0.538***	0.510**	0.799***
	(.142)	(.164)	(.132)
lny2lny3	-0.064	-0.072	0.004
	(.106)	(.123)	(.124)
lny2lny4	0.591**	0.615**	1.187***
	(.209)	(.223)	(.251)
lny3lny4	-0.096	-0.069	-0.179*
	(.059)	(.068)	(.0797)
lny1lnp1	0.084*	0.105*	0.111*
	(.041)	(.045)	(.051)
lny1lnp2	-0.014	-0.044	-0.078
	(.093)	(.102)	(.093)
lny2lnp1	0.111	0.034	0.007
	(.148)	(.169)	(.210)
lny2lnp2	0.093	-0.063	0.073
	(.174)	(.219)	(.212)
lny3lnp1	0.041	0.047	0.076

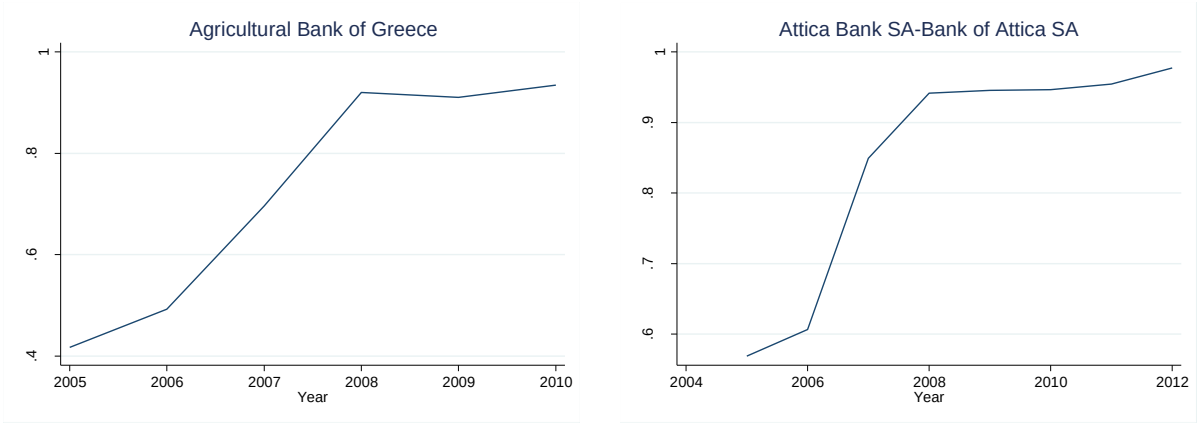
	(.034)	(.034)	(.049)
lny3lnp2	-0.060	-0.047	-0.051
	(.045)	(.047)	(.056)
lny4lnp1	-0.261	-0.389*	-0.470***
	(.145)	(.160)	(.139)
lny4lnp2	0.146	0.156	0.270
	(.310)	(.343)	(.297)
lneq		0.344	
		(.331)	
lneqlneq		-0.042	
		(.044)	
lnllp			-0.020
			(.034)
lnllplnllp			0.001
			(.008)
CR5	0.033	-.039	-.068***
	(2.585)	(.295)	(.013)
GDP Growth	1.506	1.869	-.132***
	(3.808)	(2.498)	(.041)
CapGr	-1.064	-1.297	.103***
	(2.633)	(1.753)	(.032)
Inflation	-0.858	-1.162	.010
	(1.101)	(1.754)	(.009)
Unemployment	0.051	.284	.045***
	(.372)	(.395)	(.007)
Credit	0.000	.0395	-.010***
	(.269)	(.117)	(.002)
Constant	-2.19	-2.374	5.44
	(155.771)	(10.826)	(198.086)
σ_u	.134***	.131***	.009
	(.025)	(.026)	(3.114)
σ_v	.0416***	.0390***	.067
	(.004)	(.007)	(.439)
λ	3.238***	3.380***	.141
	(.027)	(.030)	(3.554)
N	*116*	*116*	*116*

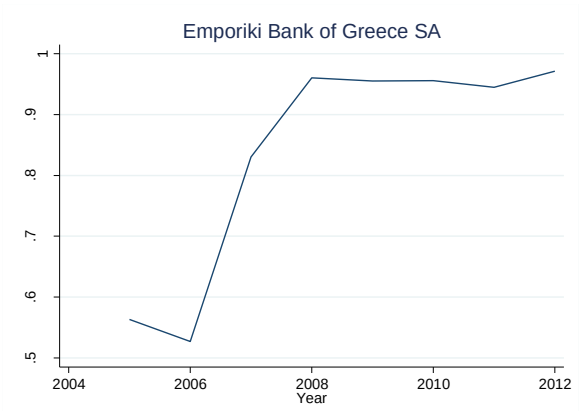
TFE1: True Fixed Effects Model 1, without a risk metric, TFE2: True Fixed Effects Model 2, with Total Equity as netput, TFE3: True Fixed Effects Model 3, with Loan Loss Provisions as netput. Where; lnTC: total costs defined as operating costs, interest paid on deposits and labour expenses; lnp_1: Price of Total Customer Deposits (estimated as Total Interest Expenses/Total customer deposits); lnp_2: Price of Labour (estimated as Personnel Expenses/Fixed Assets); lnP_3: Price of Capital (estimated as Other Operating Expenses/Fixed Assets); lny_1: Gross Loans, lny_2: Other Earning Assets; lny_3: Loans and Advances to banks; lny_4: Non-interest income (net fee and commission and other operating income); lneq: Equity; lnllp: Loan Loss Provision. All values are expressed in natural logarithms. Where z's include: GDP Growth: Annual change of Gross Domestic Product (%), Unemployment: Unemployment rate (and), Inflation: Annual inflation rate (%), CapGr: GDP per capita growth (%), Credit: Domestic credit to private sector, CR5: Concentration Ratio of assets for the top five banking institutions.
Standard errors in parentheses
** $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

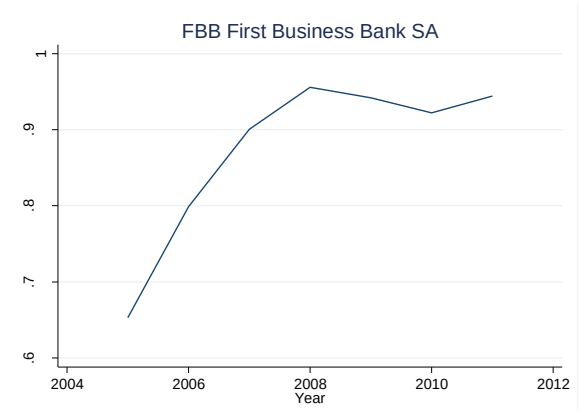
Figure 9.1. Evolution of Cost Efficiency, Time Varying Model 1
Panel A – Core Banks

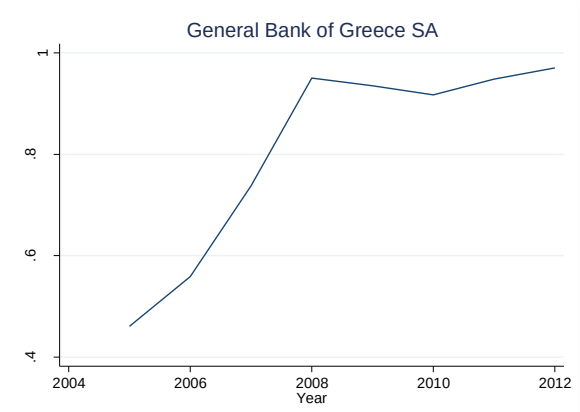


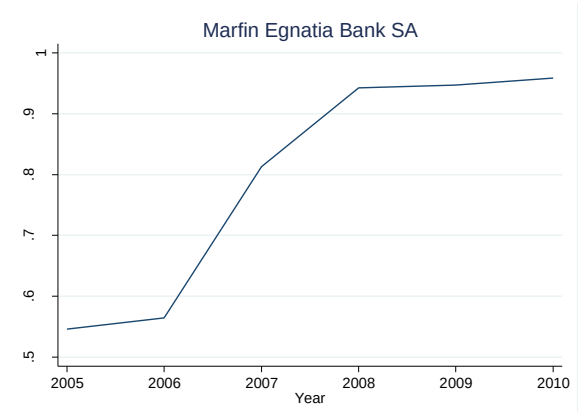
Evolution of Cost Efficiency, Time Varying Model 1
Panel B – Non Core Banks

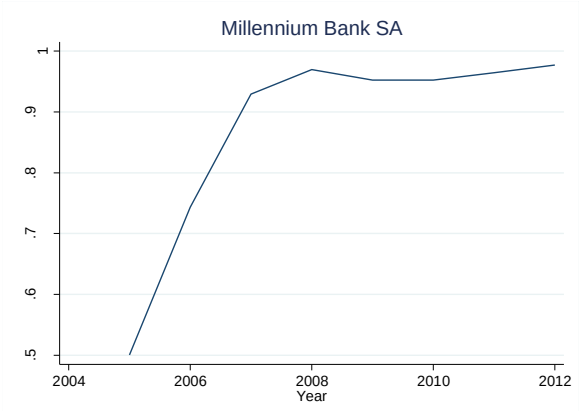


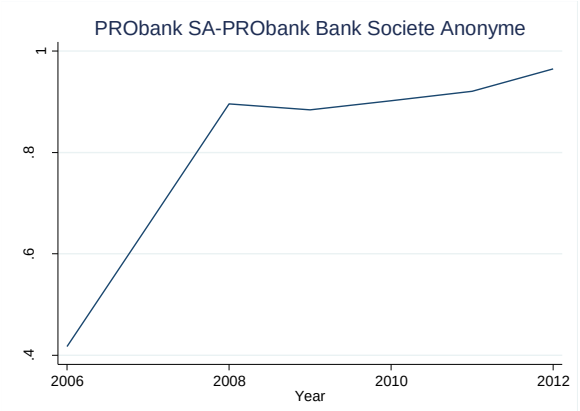

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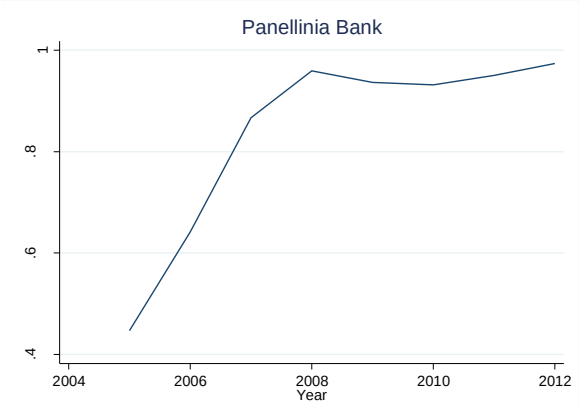

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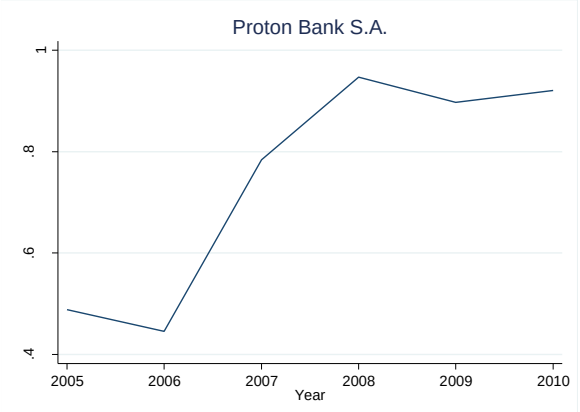

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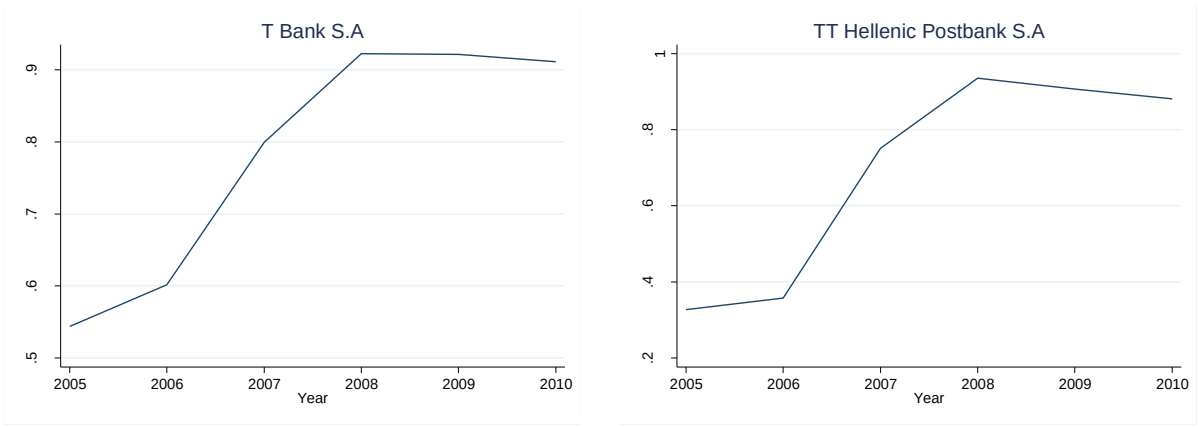
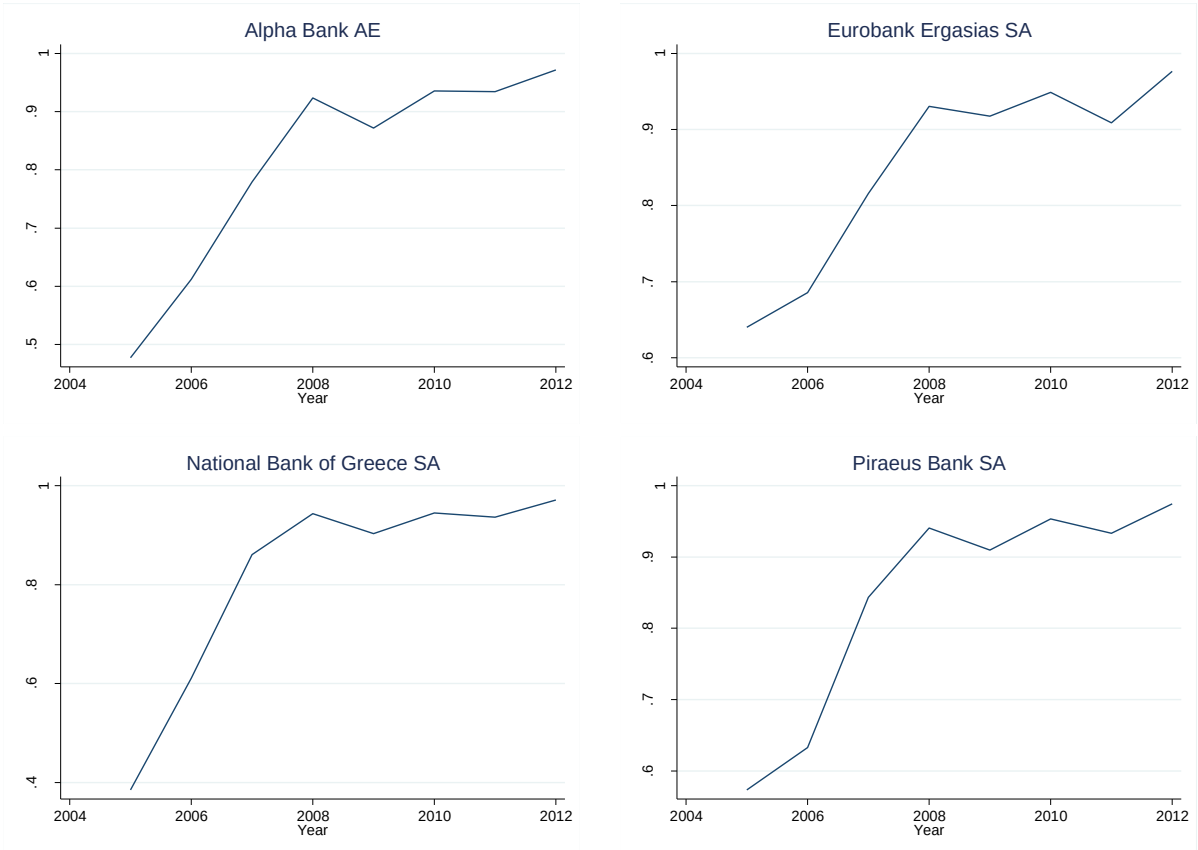
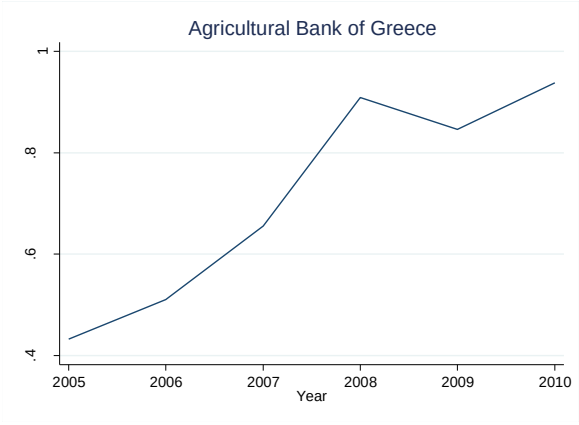
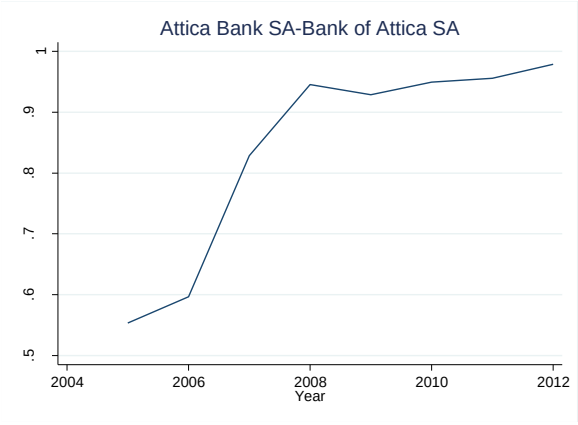


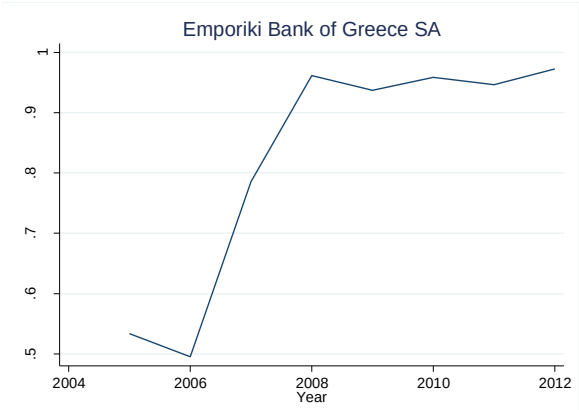
Figure 9.2. Evolution of Cost Efficiency, Time Varying Model 2
Panel A – Core Banks

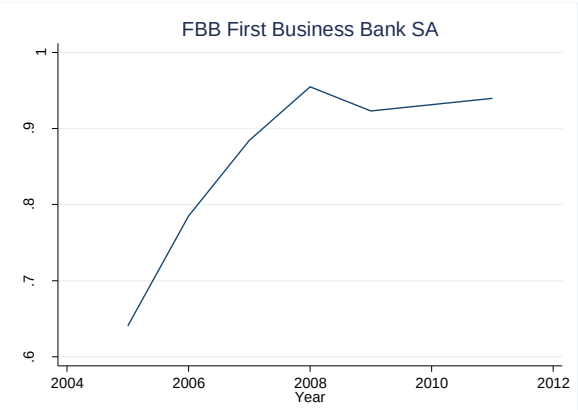


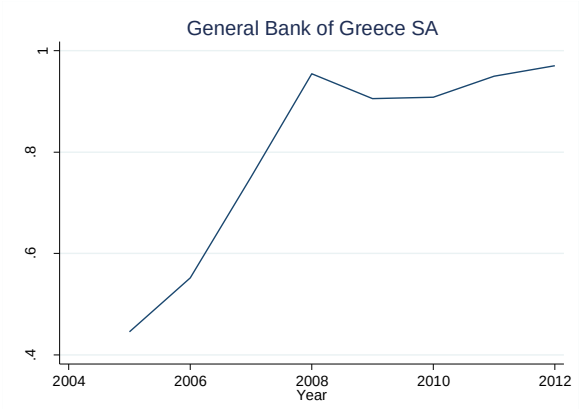
Evolution of Cost Efficiency, Time Varying Model 2
Panel B – Non Core Banks

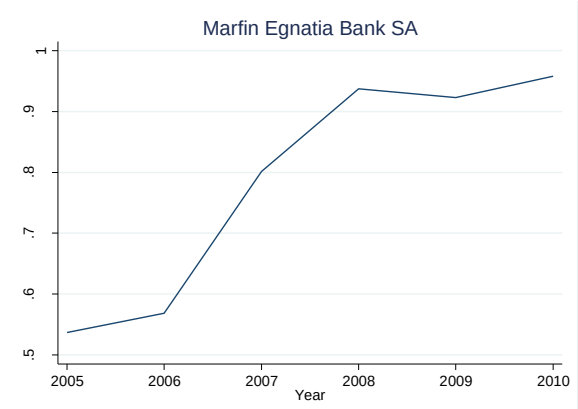


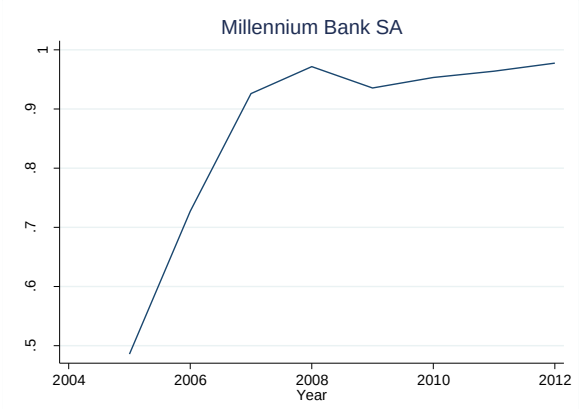


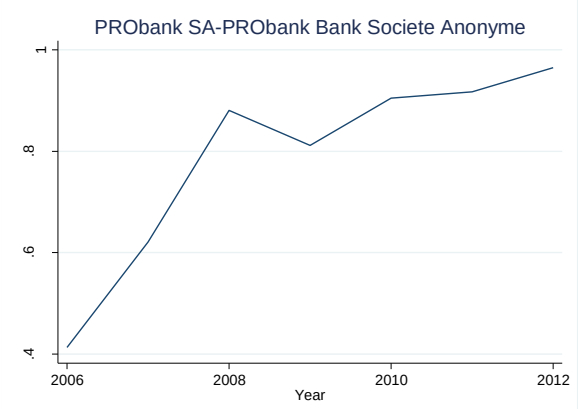


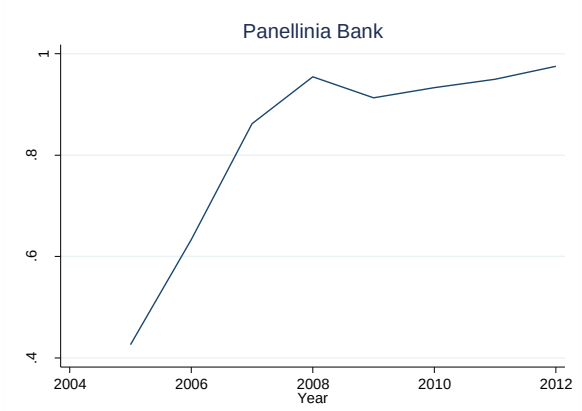


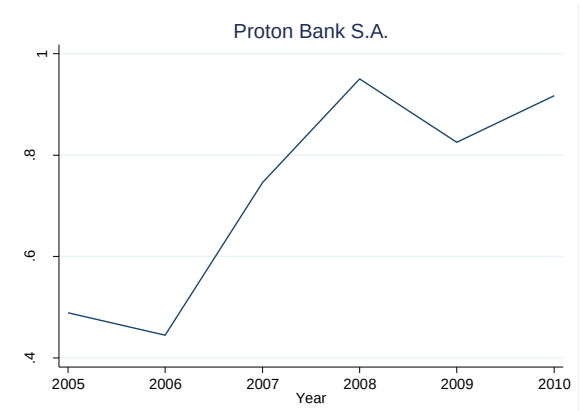


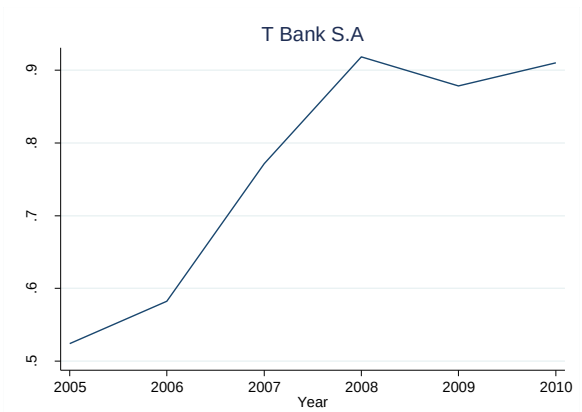







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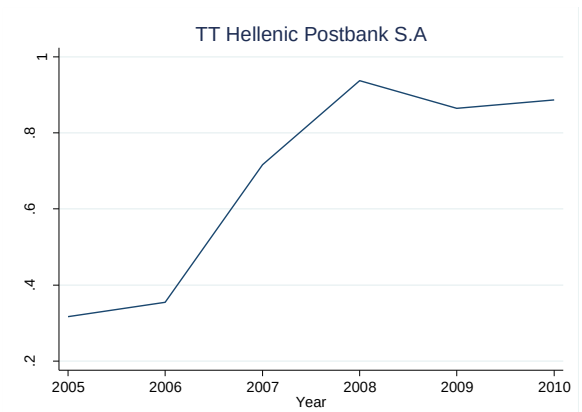
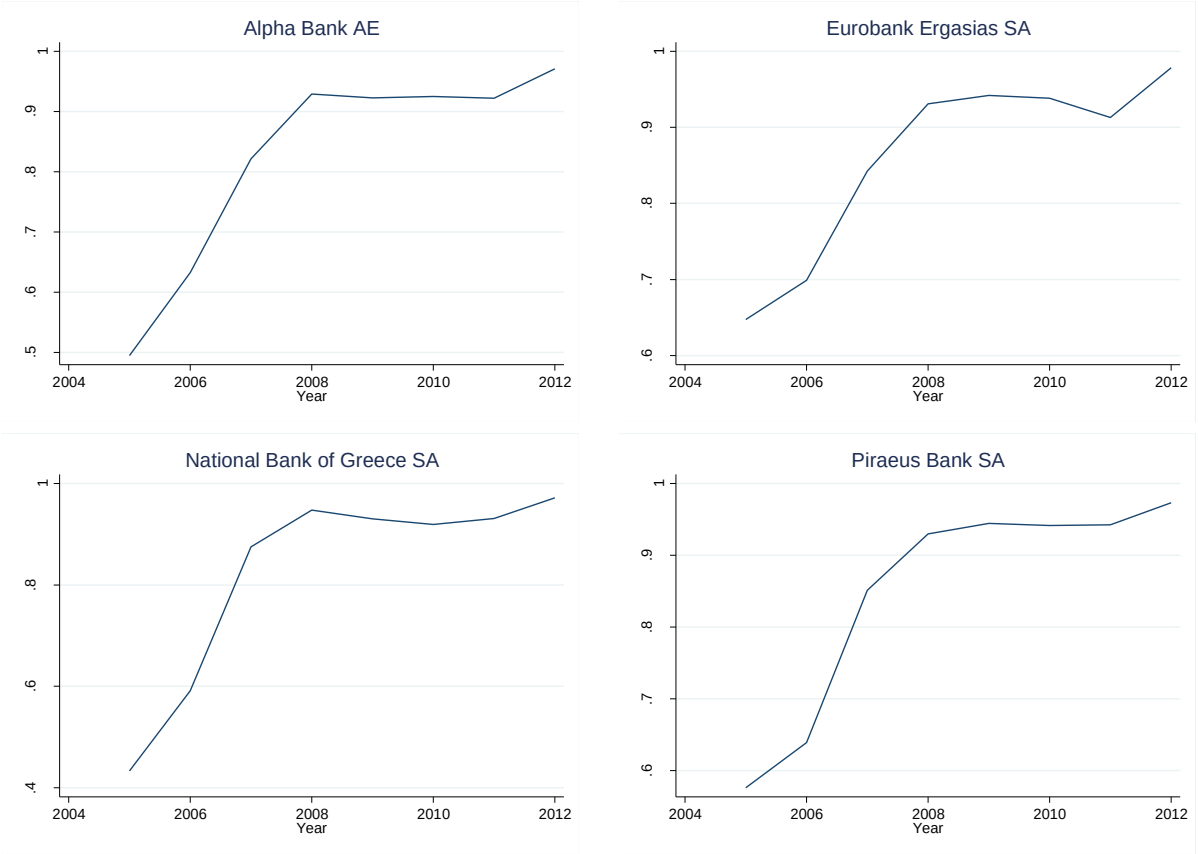
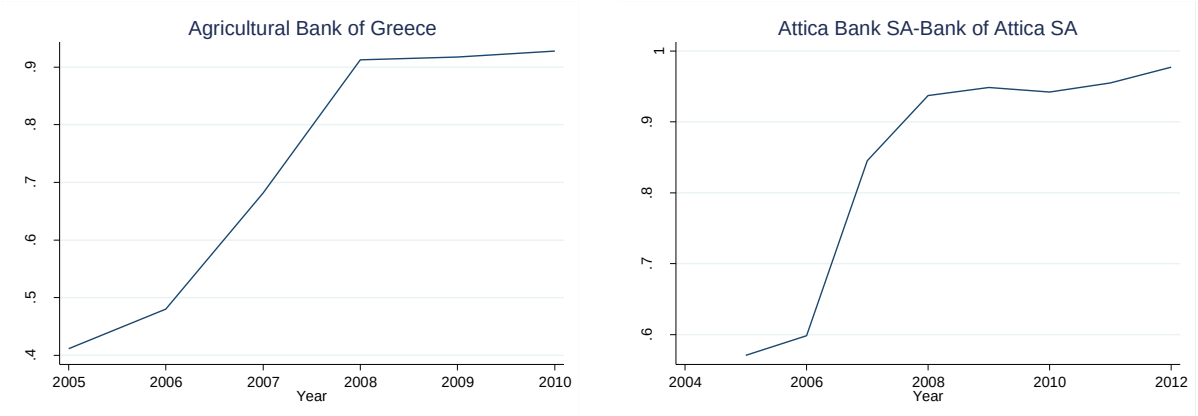
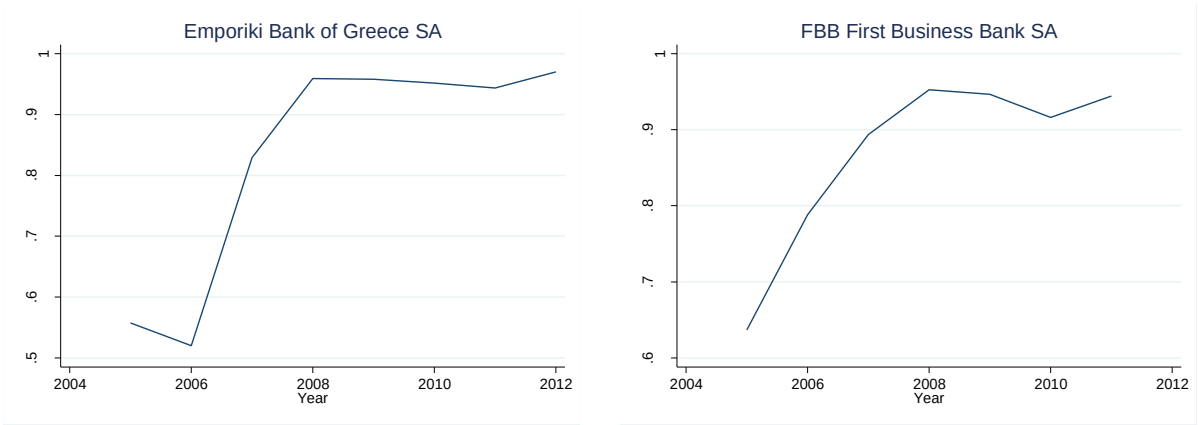

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Figure 9.3. Evolution of Cost Efficiency, Time Varying Model 3
Panel A – Core Banks

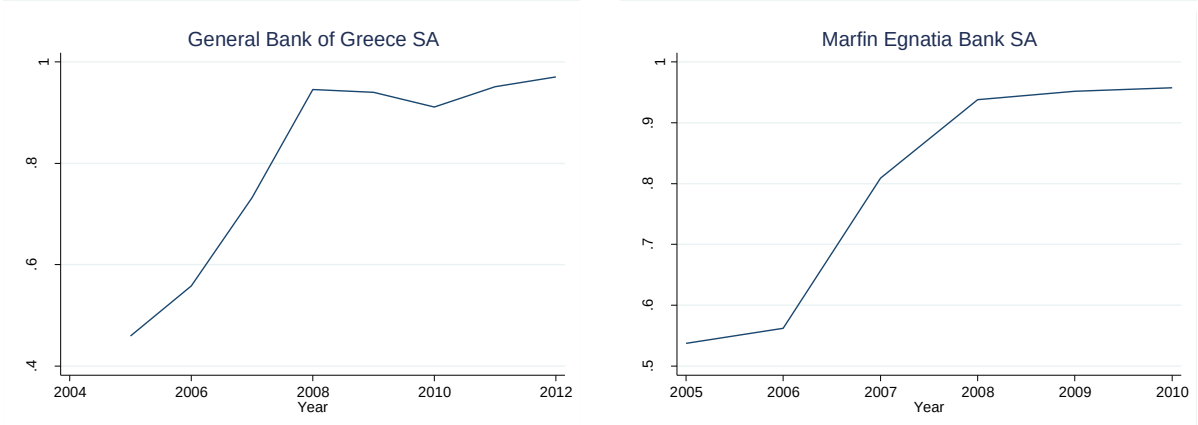


Evolution of Cost Efficiency, Time Varying Model 3
Panel B – Non Core Banks

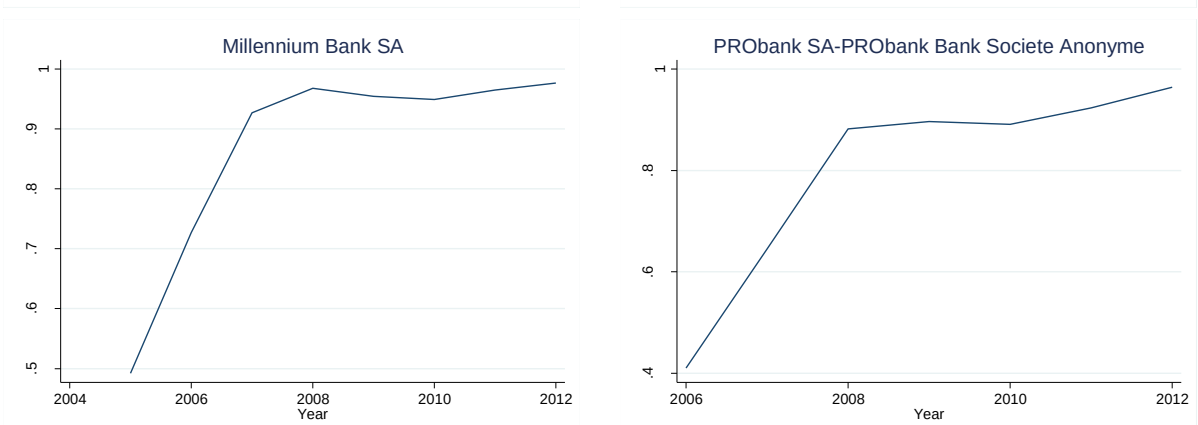



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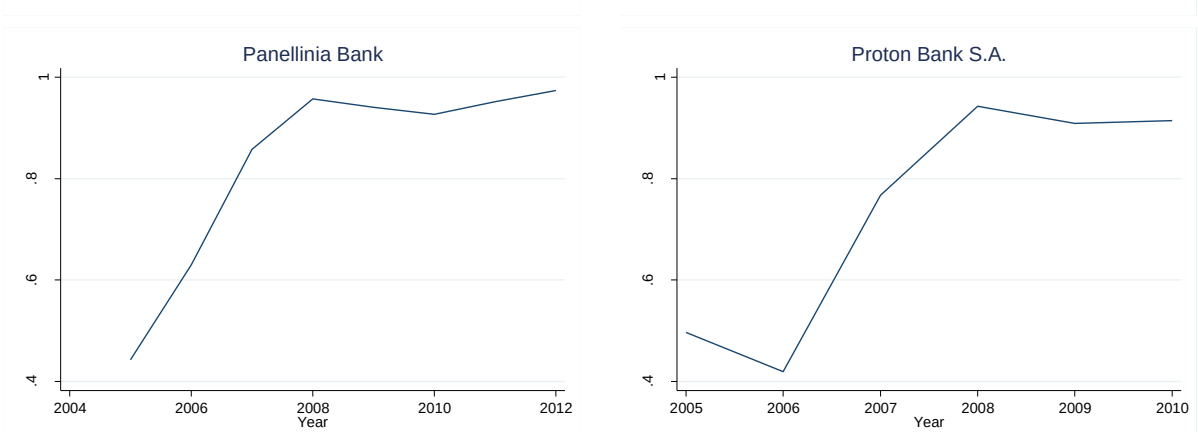
FBB First Business Bank SA
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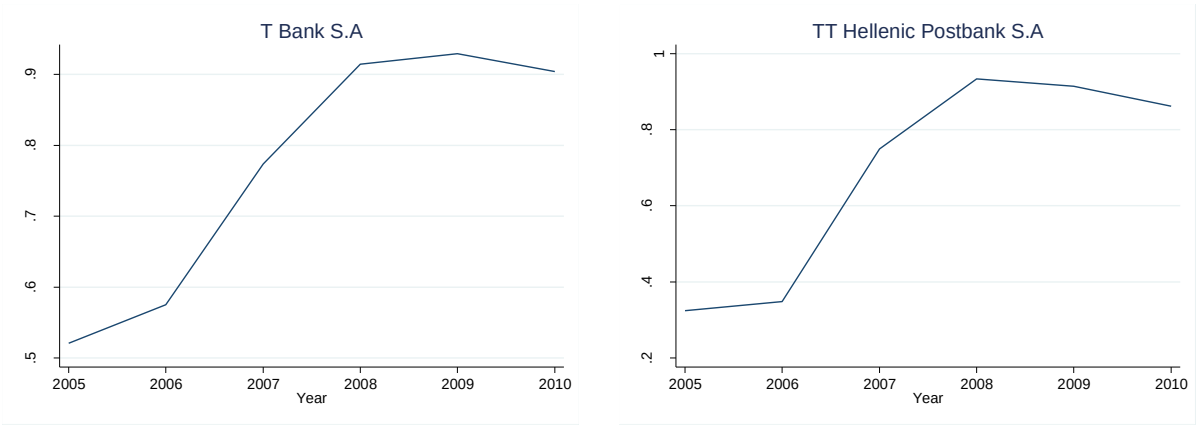
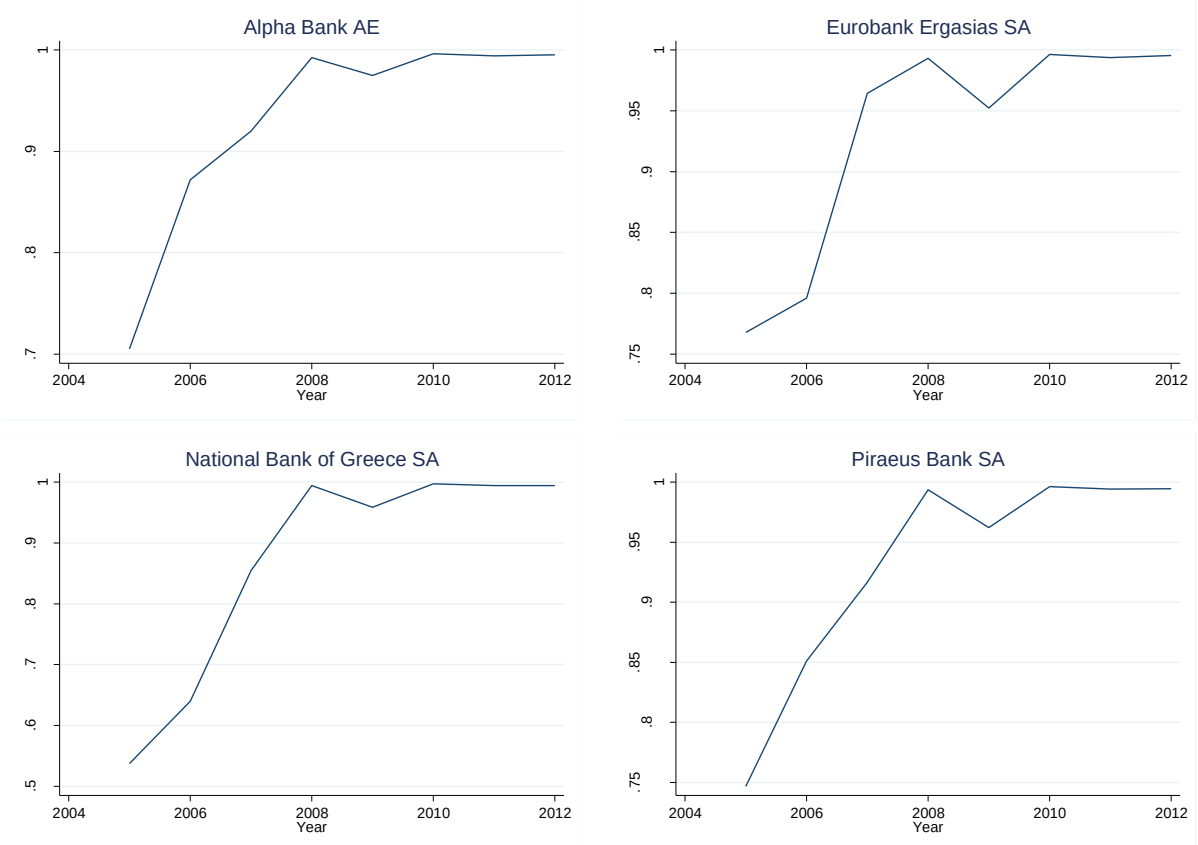
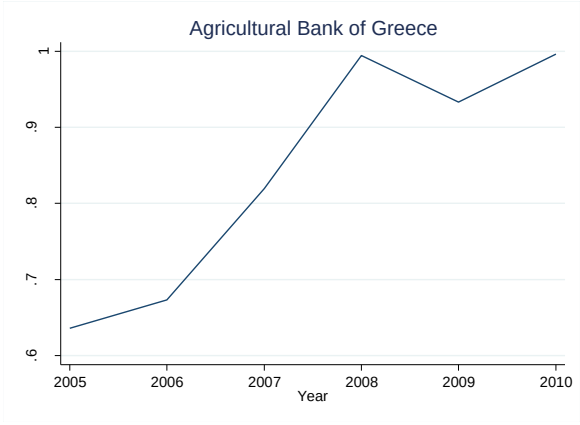
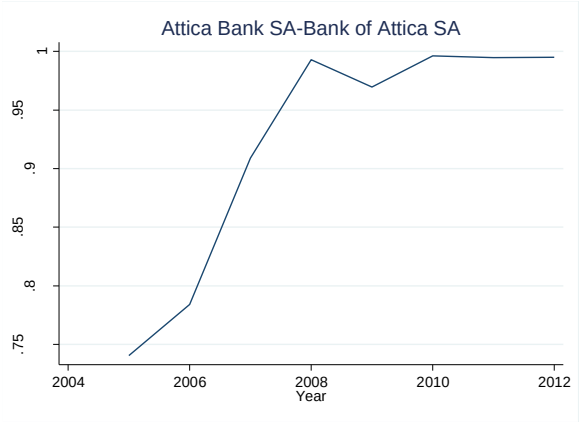


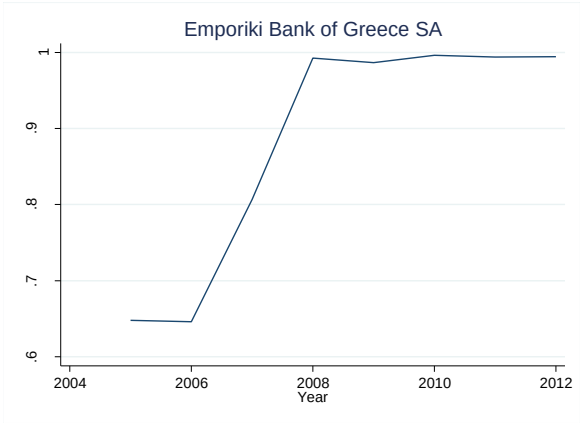
Figure 9.4. Evolution of Cost Efficiency, True Fixed Effects Model 1
Panel A – Core Banks

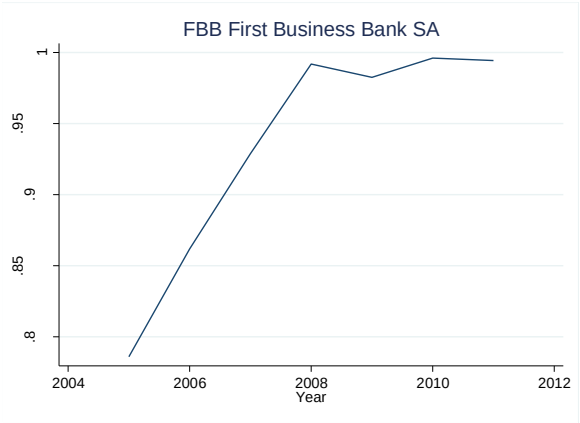


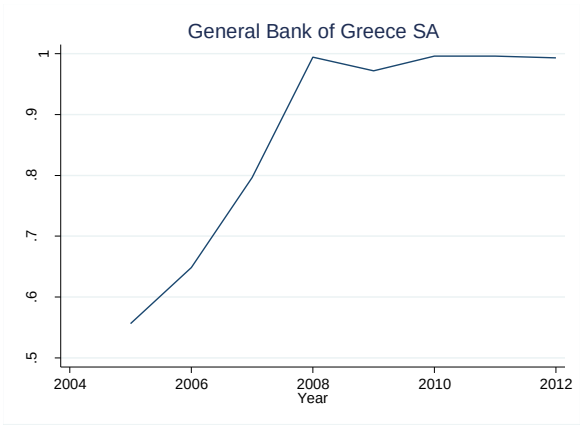
Evolution of Cost Efficiency, True Fixed Effects Model 1
Panel B – Non Core Banks

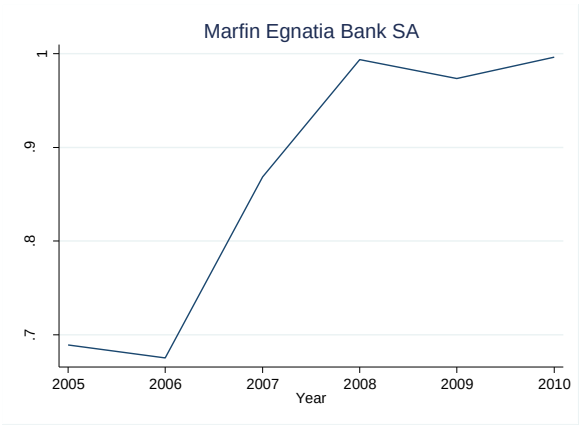


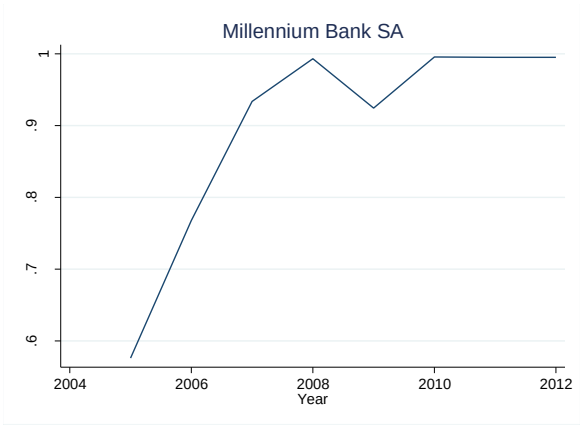


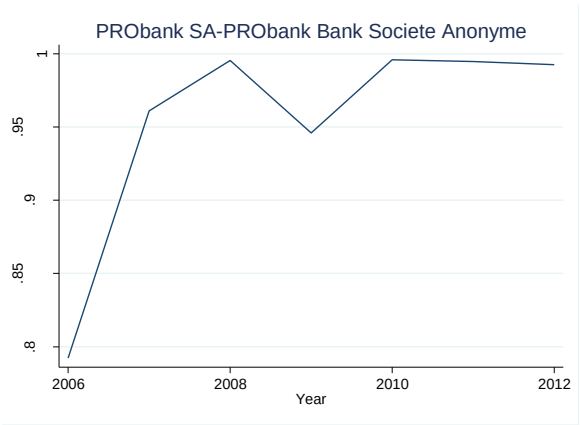


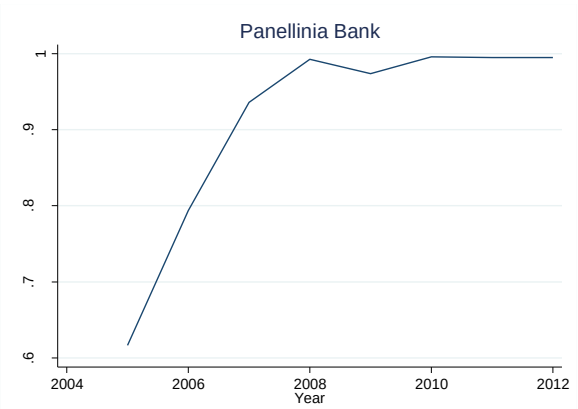


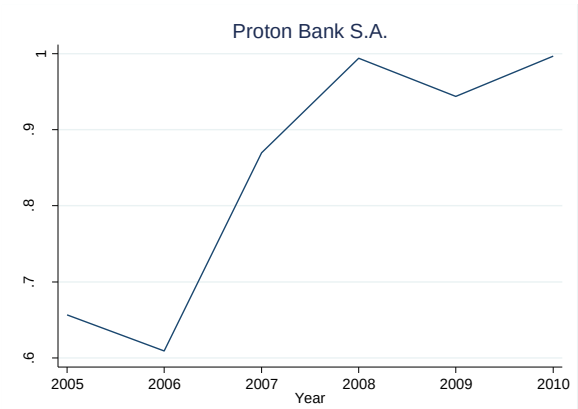


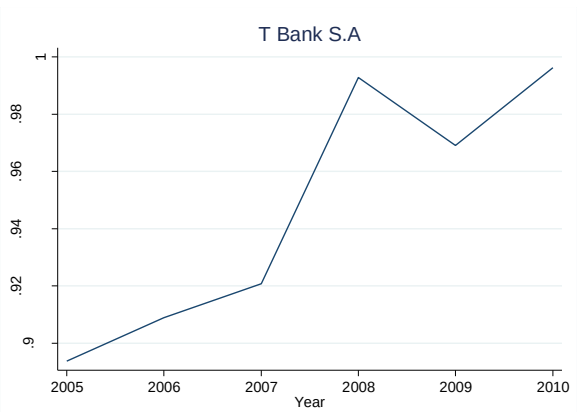







Panellinia Bank
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Proton Bank S.A.
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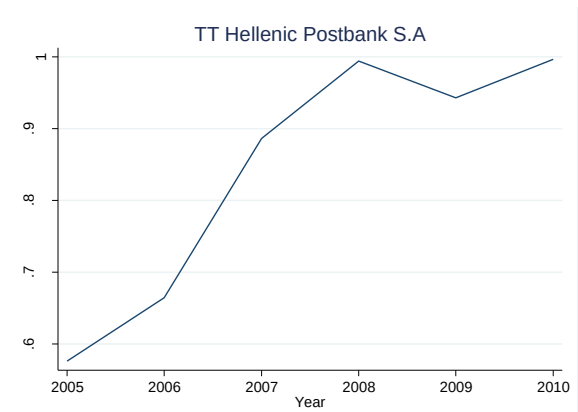
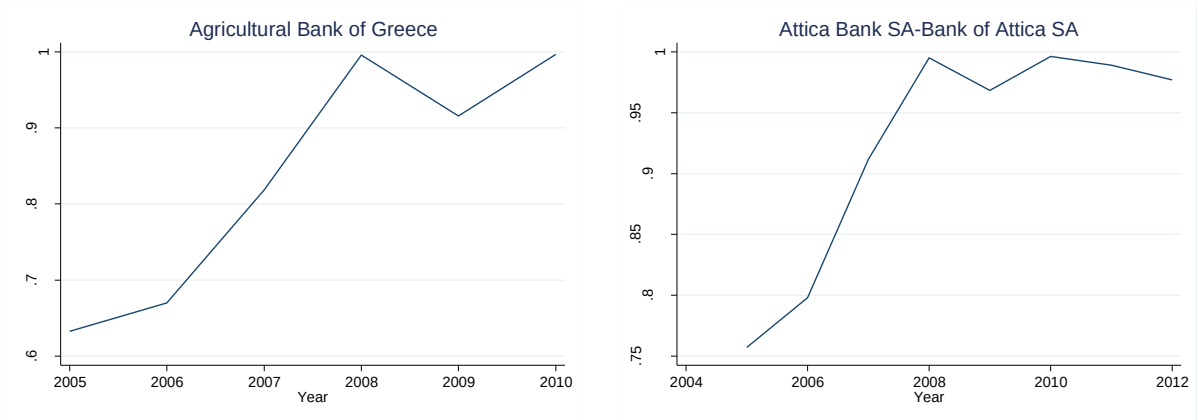
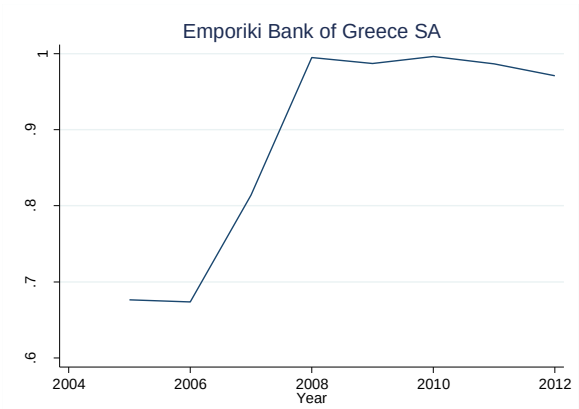

TT Hellenic Postbank S.A
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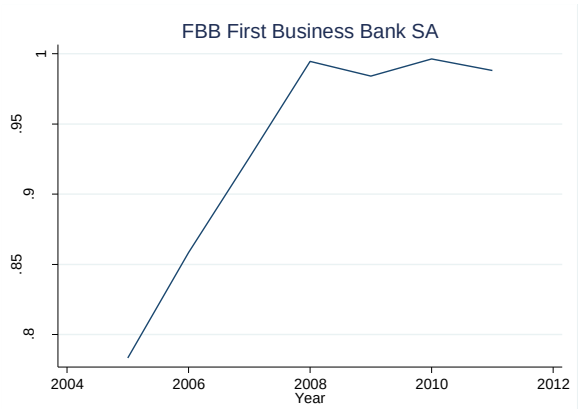
Figure 9.5. Evolution of Cost Efficiency, True Fixed Effects Model 2
Panel A – Core Banks

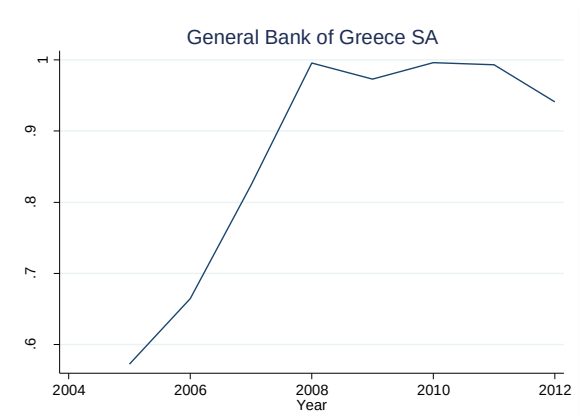


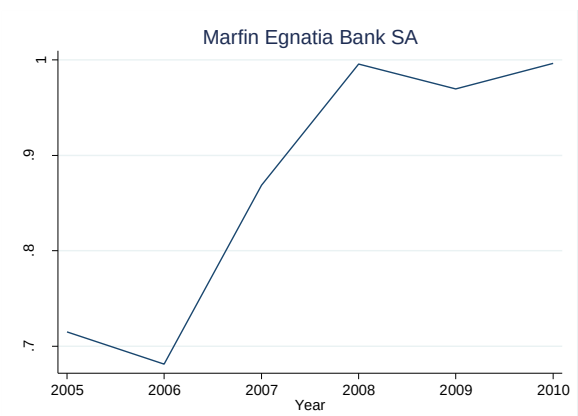
Evolution of Cost Efficiency, True Fixed Effects Model 2
Panel B – Non Core Banks

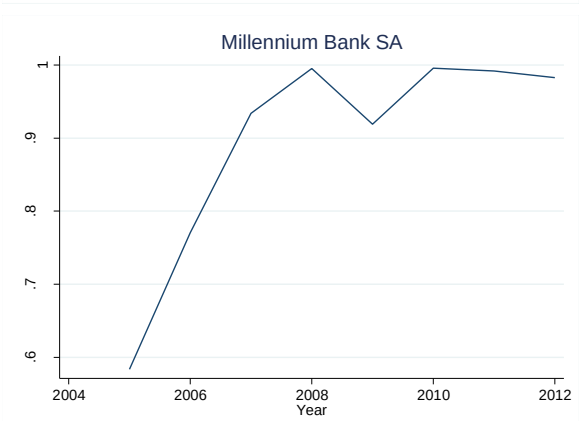


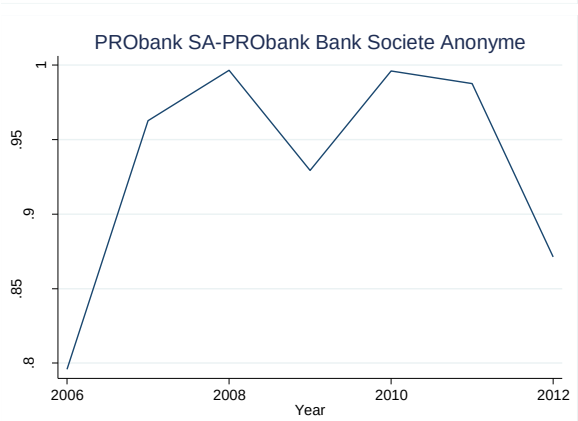

Emporiki Bank of Greece SA
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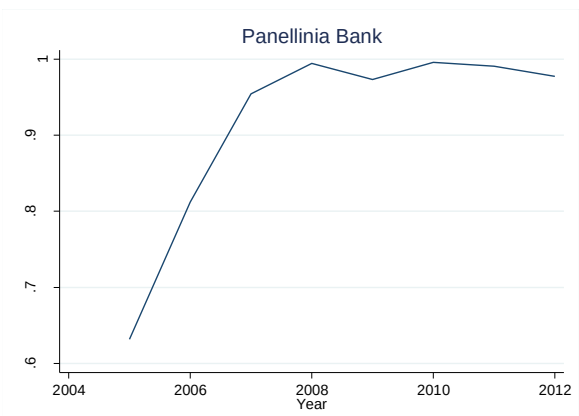

FBB First Business Bank SA
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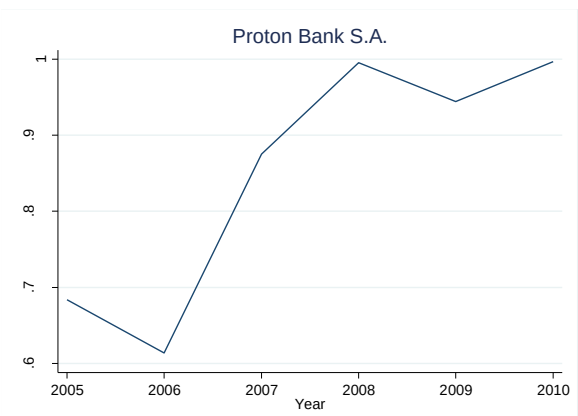

General Bank of Greece SA
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Marfin Egnatia Bank SA
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Millennium Bank SA
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PRObank SA-PRObank Bank Societe Anonyme
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Proton Bank S.A.
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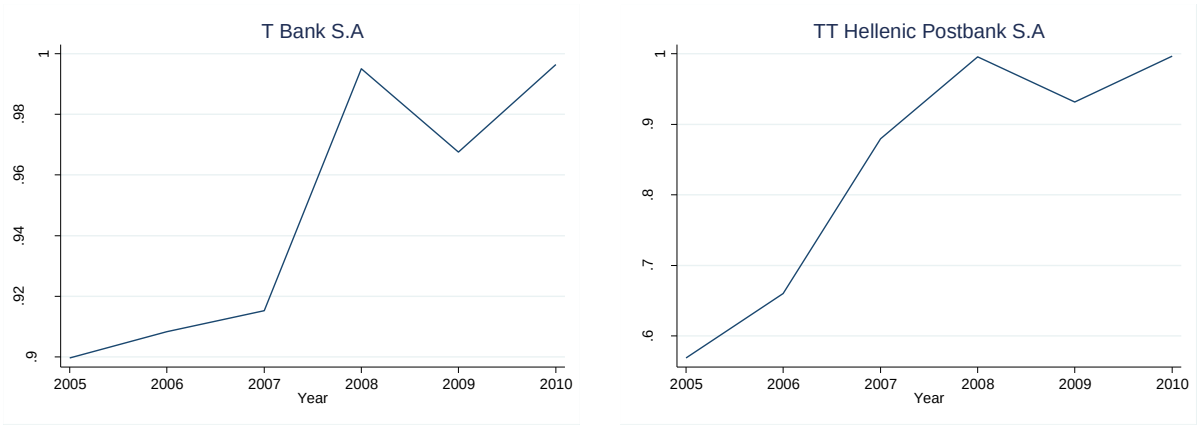
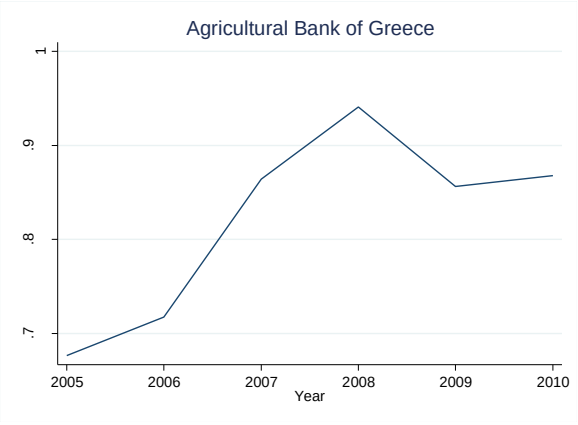
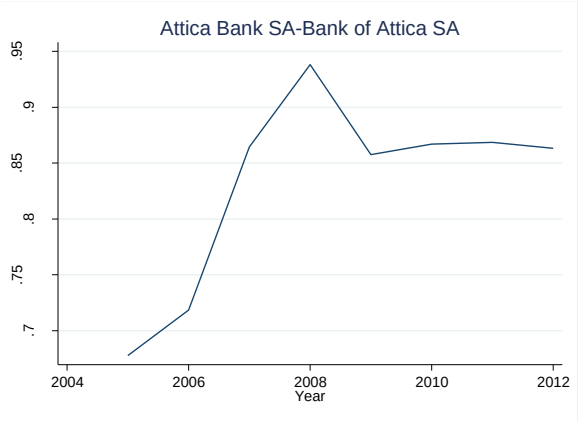


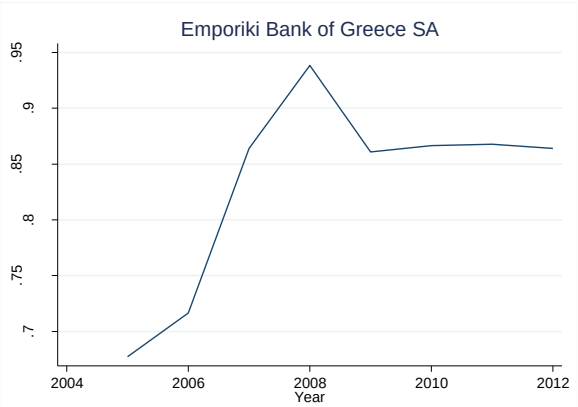
Figure 9.6. Evolution of Cost Efficiency, True Fixed Effects Model 3
Panel A – Core Banks

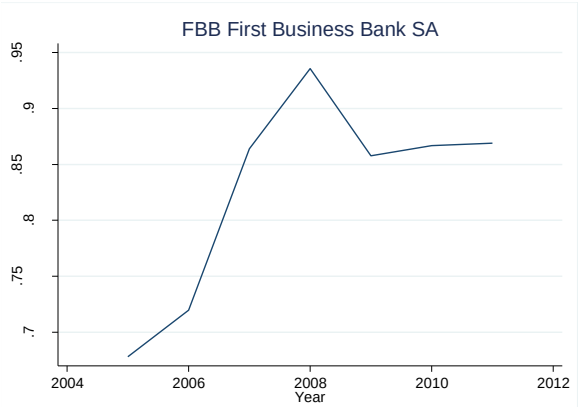


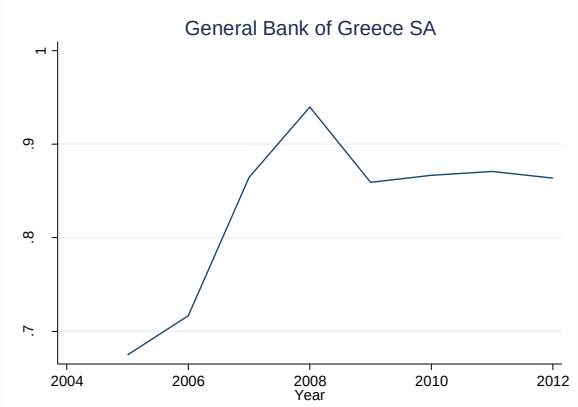
Evolution of Cost Efficiency, True Fixed Effects Model 3
Panel B – Non Core Banks

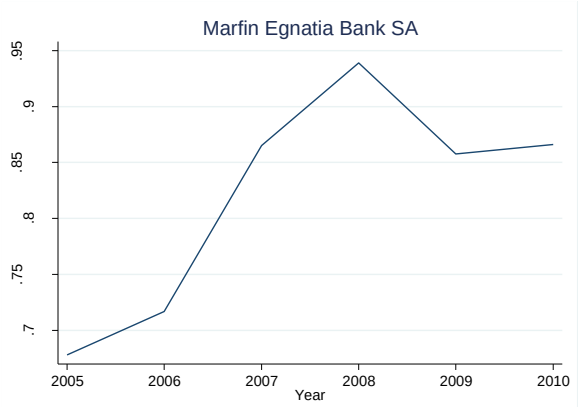


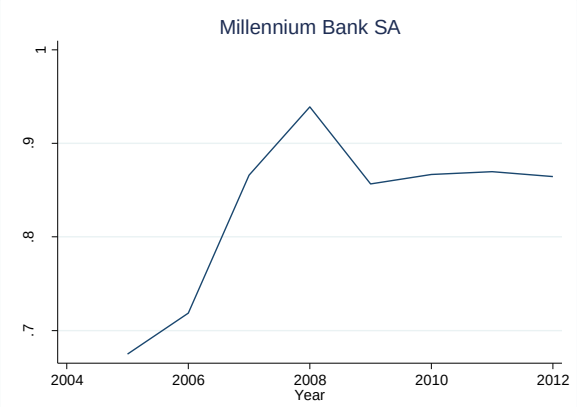


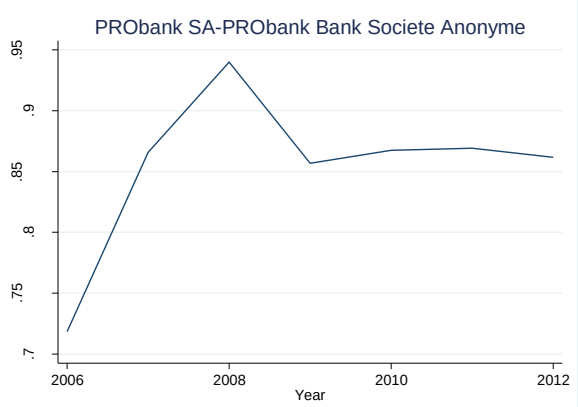


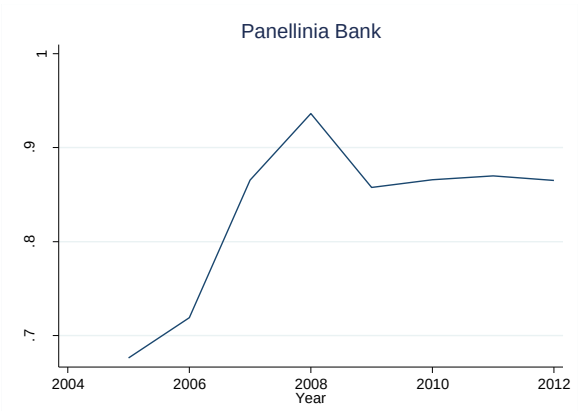


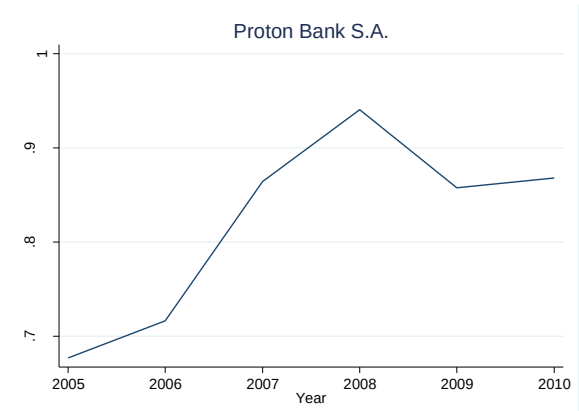


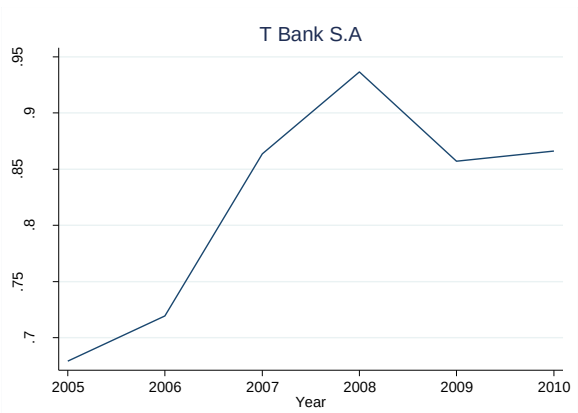







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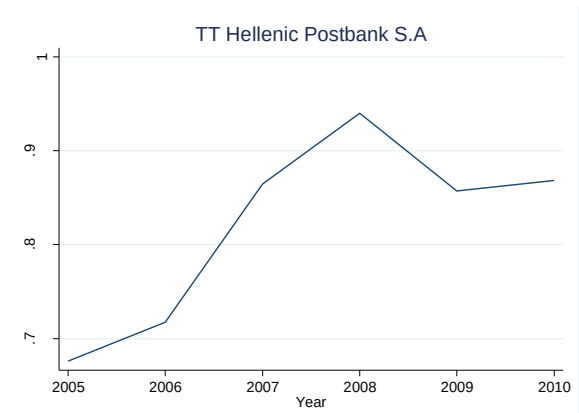

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Table 9.9. Evolution of Cost Efficiency, Time Varying Model 1

Bank	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Alpha Bank AE	0.48	0.63	0.82	0.93	0.91	0.93	0.92	0.97
Eurobank Ergasias SA	0.64	0.7	0.84	0.93	0.93	0.94	0.91	0.97
National Bank of Greece SA	0.42	0.58	0.87	0.95	0.92	0.92	0.93	0.97
Piraeus Bank SA	0.57	0.64	0.86	0.93	0.94	0.94	0.94	0.97
Agricultural Bank of Greece	0.42	0.49	0.7	0.92	0.91	0.93		
Attica Bank SA-Bank of Attica SA	0.57	0.61	0.85	0.94	0.95	0.95	0.95	0.98
Emporiki Bank of Greece SA	0.56	0.53	0.83	0.96	0.96	0.96	0.94	0.97
FBB First Business Bank SA	0.65	0.8	0.9	0.96	0.94	0.92	0.94	
General Bank of Greece SA	0.46	0.56	0.74	0.95	0.94	0.92	0.95	0.97
Marfin Egnatia Bank SA	0.55	0.56	0.81	0.94	0.95	0.96		
Millennium Bank SA	0.5	0.74	0.93	0.97	0.95	0.95	0.96	0.98
PRObank SA-PRObank Bank Societe Anonyme	0.42	0.66	0.9	0.88	0.9	0.92	0.96	
Panellinia Bank	0.45	0.64	0.87	0.96	0.94	0.93	0.95	0.97
Proton Bank S.A.	0.49	0.45	0.78	0.95	0.9	0.92		
T Bank S.A	0.54	0.6	0.8	0.92	0.92	0.91		
TT Hellenic Postbank S.A	0.33	0.36	0.75	0.94	0.91	0.88		

Where, TVM1: Time Varying Model 1, without a risk metric.

Table 9.10. Evolution of Cost Efficiency, Time Varying Model 2

Banks	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Alpha Bank AE	0.47	0.61	0.77	0.92	0.87	0.93	0.93	0.97
Eurobank Ergasias SA	0.64	0.68	0.81	0.93	0.91	0.94	0.9	0.97
National Bank of Greece SA	0.38	0.61	0.86	0.94	0.9	0.94	0.93	0.97
Piraeus Bank SA	0.57	0.63	0.84	0.94	0.91	0.95	0.93	0.97
Agricultural Bank of Greece	0.43	0.51	0.66	0.91	0.85	0.94		
Attica Bank SA-Bank of Attica SA	0.55	0.6	0.83	0.95	0.93	0.95	0.96	0.98
Emporiki Bank of Greece SA	0.53	0.5	0.79	0.96	0.94	0.96	0.95	0.97
FBB First Business Bank SA	0.64	0.78	0.88	0.95	0.92	0.93	0.94	
General Bank of Greece SA	0.45	0.55	0.75	0.95	0.91	0.91	0.95	0.97
Marfin Egnatia Bank SA	0.54	0.57	0.8	0.94	0.92	0.96		
Millennium Bank SA	0.49	0.73	0.93	0.97	0.94	0.95	0.96	0.98
PRObank SA-PRObank Bank Societe Anonyme	0.41	0.62	0.88	0.81	0.9	0.92	0.97	
Panellinia Bank	0.43	0.63	0.86	0.95	0.91	0.93	0.95	0.98
Proton Bank S.A.	0.49	0.45	0.75	0.95	0.83	0.92		
T Bank S.A	0.52	0.58	0.77	0.92	0.88	0.91		
TT Hellenic Postbank S.A	0.32	0.35	0.72	0.94	0.86	0.89		

Where, TVM2: Time Varying Model 2, with Total Equity as netput, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.

Table 9.11. Evolution of Cost Efficiency, Time Varying Model 3

Banks	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Alpha Bank AE	0.49	0.63	0.82	0.92	0.92	0.92	0.92	0.97
Eurobank Ergasias SA	0.64	0.69	0.84	0.93	0.94	0.93	0.91	0.97
National Bank of Greece SA	0.43	0.59	0.87	0.94	0.93	0.91	0.93	0.97
Piraeus Bank SA	0.57	0.63	0.85	0.93	0.94	0.94	0.94	0.97
Agricultural Bank of Greece	0.41	0.48	0.68	0.91	0.92	0.93		
Attica Bank SA-Bank of Attica SA	0.57	0.6	0.85	0.94	0.95	0.94	0.96	0.98
Emporiki Bank of Greece SA	0.56	0.52	0.83	0.96	0.96	0.95	0.94	0.97
FBB First Business Bank SA	0.64	0.79	0.89	0.95	0.95	0.92	0.94	
General Bank of Greece SA	0.46	0.56	0.73	0.95	0.94	0.91	0.95	0.97
Marfin Egnatia Bank SA	0.54	0.56	0.81	0.94	0.95	0.96		
Millennium Bank SA	0.49	0.73	0.93	0.97	0.95	0.95	0.97	0.98
PRObank SA-PRObank Bank Societe Anonyme	0.41	0.65	0.88	0.9	0.89	0.92	0.96	
Panellinia Bank	0.44	0.63	0.86	0.96	0.94	0.93	0.95	0.97
Proton Bank S.A.	0.5	0.42	0.77	0.94	0.91	0.91		
T Bank S.A	0.52	0.57	0.77	0.91	0.93	0.9		
TT Hellenic Postbank S.A	0.32	0.35	0.75	0.93	0.91	0.86		

Where, TVM3: Time Varying Model 3, with Loan Loss Provisions as netput.

Table 9.12. Evolution of Cost Efficiency, True Fixed Effects Model 1

Banks	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Alpha Bank AE	0.705	0.872	0.92	0.993	0.975	0.996	0.994	0.995
Eurobank Ergasias SA	0.768	0.796	0.964	0.993	0.952	0.996	0.994	0.995
National Bank of Greece SA	0.537	0.64	0.854	0.994	0.959	0.997	0.994	0.994
Piraeus Bank SA	0.747	0.851	0.917	0.994	0.962	0.996	0.994	0.995
Agricultural Bank of Greece	0.636	0.673	0.819	0.995	0.933	0.996		
Attica Bank SA-Bank of Attica SA	0.741	0.784	0.909	0.993	0.97	0.996	0.995	0.995
Emporiki Bank of Greece SA	0.648	0.646	0.807	0.993	0.987	0.996	0.994	0.995
FBB First Business Bank SA	0.786	0.862	0.929	0.992	0.982	0.996	0.994	
General Bank of Greece SA	0.556	0.648	0.796	0.994	0.972	0.996	0.996	0.993
Marfin Egnatia Bank SA	0.689	0.675	0.869	0.994	0.974	0.996		
Millennium Bank SA	0.576	0.768	0.934	0.993	0.924	0.996	0.995	0.995
PRObank SA-PRObank Bank Societe Anonyme	0.792	0.961	0.995	0.946	0.996	0.995	0.993	
Panellinia Bank	0.617	0.794	0.936	0.992	0.974	0.996	0.995	0.995
Proton Bank S.A.	0.656	0.609	0.87	0.994	0.944	0.997		
T Bank S.A	0.894	0.909	0.921	0.993	0.969	0.996		
TT Hellenic Postbank S.A	0.576	0.664	0.887	0.994	0.943	0.997		

Table 9.13. Evolution of Cost Efficiency, True Fixed Effects Model 2

Banks	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Alpha Bank AE	0.726	0.877	0.92	0.995	0.975	0.996	0.987	0.98
Eurobank Ergasias SA	0.8	0.809	0.965	0.995	0.954	0.996	0.984	0.981
National Bank of Greece SA	0.571	0.642	0.889	0.996	0.939	0.997	0.988	0.942
Piraeus Bank SA	0.773	0.871	0.907	0.995	0.962	0.996	0.987	0.973
Agricultural Bank of Greece	0.632	0.67	0.818	0.996	0.916	0.997		
Attica Bank SA-Bank of Attica SA	0.757	0.798	0.912	0.995	0.968	0.996	0.989	0.977
Emporiki Bank of Greece SA	0.676	0.674	0.814	0.995	0.987	0.996	0.987	0.971
FBB First Business Bank SA	0.783	0.858	0.926	0.994	0.984	0.996	0.988	
General Bank of Greece SA	0.573	0.665	0.824	0.996	0.973	0.996	0.993	0.941
Marfin Egnatia Bank SA	0.715	0.681	0.869	0.996	0.97	0.996		
Millennium Bank SA	0.584	0.77	0.934	0.995	0.919	0.996	0.992	0.983
PRObank SA-PRObank Bank Societe Anonyme	0.796	0.963	0.996	0.929	0.996	0.988	0.871	
Panellinia Bank	0.632	0.812	0.954	0.995	0.973	0.996	0.991	0.977
Proton Bank S.A.	0.684	0.614	0.875	0.996	0.945	0.997		
T Bank S.A	0.9	0.908	0.915	0.995	0.968	0.996		
TT Hellenic Postbank S.A	0.569	0.66	0.88	0.996	0.931	0.997		

Table 9.14. Evolution of Cost Efficiency, True Fixed Effects Model 3

Banks	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Alpha Bank AE	0.677	0.72	0.865	0.937	0.858	0.867	0.869	0.864
Eurobank Ergasias SA	0.678	0.718	0.866	0.938	0.857	0.867	0.868	0.864
National Bank of Greece SA	0.676	0.717	0.865	0.94	0.858	0.869	0.869	0.863
Piraeus Bank SA	0.677	0.719	0.864	0.938	0.857	0.867	0.869	0.864
Agricultural Bank of Greece	0.677	0.717	0.864	0.941	0.856	0.868		
Attica Bank SA-Bank of Attica SA	0.678	0.718	0.865	0.938	0.858	0.867	0.869	0.863
Emporiki Bank of Greece SA	0.677	0.717	0.864	0.938	0.861	0.867	0.868	0.864
FBB First Business Bank SA	0.678	0.72	0.864	0.936	0.858	0.867	0.869	
General Bank of Greece SA	0.675	0.717	0.864	0.94	0.859	0.867	0.871	0.864
Marfin Egnatia Bank SA	0.678	0.717	0.865	0.939	0.858	0.866		
Millennium Bank SA	0.675	0.719	0.866	0.939	0.857	0.867	0.87	0.865
PRObank SA-PRObank Bank Societe Anonyme	0.718	0.866	0.94	0.857	0.867	0.869	0.862	
Panellinia Bank	0.676	0.719	0.865	0.936	0.858	0.866	0.87	0.865
Proton Bank S.A.	0.677	0.716	0.864	0.941	0.858	0.868		
T Bank S.A	0.679	0.719	0.864	0.936	0.857	0.866		
TT Hellenic Postbank S.A	0.676	0.717	0.865	0.94	0.857	0.868		

Table 9.15. Evolution of Cost Efficiency, COLS, Model 1

Banks	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Alpha Bank AE	0.43	0.52	0.5	0.49	0.46	0.46	0.43	0.51
Eurobank Ergasias SA	0.54	0.57	0.57	0.53	0.52	0.54	0.44	0.62
National Bank of Greece SA	0.41	0.56	0.65	0.6	0.51	0.47	0.49	0.48
Piraeus Bank SA	0.47	0.52	0.56	0.52	0.52	0.52	0.58	0.53
Agricultural Bank of Greece	0.38	0.4	0.41	0.5	0.43	0.5		
Attica Bank SA-Bank of Attica SA	0.46	0.48	0.62	0.66	0.65	0.57	0.57	0.62
Emporiki Bank of Greece SA	0.44	0.4	0.58	0.71	0.86	0.75	0.65	0.49
FBB First Business Bank SA	0.58	0.6	0.73	0.73	0.67	0.54	0.64	
General Bank of Greece SA	0.27	0.32	0.41	0.67	0.49	0.43	0.58	0.5
Marfin Egnatia Bank SA	0.46	0.53	0.81	0.73	0.75	0.78		
Millennium Bank SA	0.47	0.71	0.92	0.98	0.84	0.88	1	0.77
PRObank SA-PRObank Bank Societe Anonyme	0.36	0.43	0.51	0.44	0.4	0.45	0.45	
Panellinia Bank	0.4	0.58	0.69	0.76	0.56	0.59	0.63	0.51
Proton Bank S.A.	0.51	0.26	0.5	0.61	0.46	0.61		
T Bank S.A	0.46	0.49	0.53	0.51	0.5	0.41		
TT Hellenic Postbank S.A	0.21	0.23	0.39	0.53	0.44	0.34		

Where, COLS represents: Corrected Ordinary Least Squares.

Table 9.16. Evolution of Cost Efficiency, COLS, Model 2

Banks	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Alpha Bank AE	0.42	0.51	0.47	0.45	0.46	0.46	0.47	0.51
Eurobank Ergasias SA	0.55	0.57	0.56	0.52	0.54	0.56	0.42	0.56
National Bank of Greece SA	0.38	0.59	0.63	0.55	0.55	0.53	0.49	0.44
Piraeus Bank SA	0.48	0.52	0.57	0.55	0.5	0.55	0.54	0.53
Agricultural Bank of Greece	0.4	0.42	0.4	0.48	0.41	0.51		
Attica Bank SA-Bank of Attica SA	0.45	0.47	0.62	0.68	0.66	0.58	0.58	0.63
Emporiki Bank of Greece SA	0.42	0.37	0.55	0.7	0.82	0.74	0.64	0.49
FBB First Business Bank SA	0.58	0.58	0.7	0.71	0.69	0.57	0.62	
General Bank of Greece SA	0.26	0.32	0.43	0.68	0.49	0.41	0.58	0.48
Marfin Egnatia Bank SA	0.46	0.55	0.84	0.72	0.74	0.75		
Millennium Bank SA	0.46	0.69	0.93	1	0.82	0.86	0.97	0.74
PRObank SA-PRObank Bank Societe Anonyme	0.36	0.42	0.5	0.43	0.41	0.44	0.44	
Panellinia Bank	0.39	0.57	0.7	0.7	0.56	0.58	0.62	0.52
Proton Bank S.A.	0.52	0.26	0.49	0.62	0.44	0.59		
T Bank S.A	0.45	0.48	0.53	0.51	0.5	0.4		
TT Hellenic Postbank S.A	0.21	0.23	0.39	0.55	0.45	0.35		

Where, COLS represents: Corrected Ordinary Least Squares.

Table 9.17. Evolution of Cost Efficiency, COLS, Model 3

Banks	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Alpha Bank AE	0.42	0.52	0.5	0.48	0.46	0.46	0.43	0.5
Eurobank Ergasias SA	0.53	0.56	0.57	0.53	0.51	0.53	0.45	0.61
National Bank of Greece SA	0.4	0.57	0.66	0.59	0.5	0.47	0.48	0.48
Piraeus Bank SA	0.47	0.52	0.56	0.51	0.5	0.52	0.58	0.53
Agricultural Bank of Greece	0.38	0.41	0.42	0.5	0.43	0.49		
Attica Bank SA-Bank of Attica SA	0.43	0.47	0.61	0.64	0.64	0.57	0.55	0.62
Emporiki Bank of Greece SA	0.44	0.39	0.57	0.7	0.84	0.74	0.64	0.48
FBB First Business Bank SA	0.61	0.63	0.76	0.74	0.65	0.51	0.64	
General Bank of Greece SA	0.26	0.32	0.4	0.69	0.49	0.42	0.56	0.49
Marfin Egnatia Bank SA	0.46	0.51	0.8	0.73	0.75	0.78		
Millennium Bank SA	0.46	0.71	0.91	1	0.84	0.85	0.92	0.75
PRObank SA-PRObank Bank Societe Anonyme	0.35	0.42	0.5	0.41	0.4	0.42	0.45	
Panellinia Bank	0.4	0.58	0.69	0.76	0.55	0.56	0.59	0.5
Proton Bank S.A.	0.5	0.3	0.51	0.61	0.42	0.56		
T Bank S.A	0.51	0.54	0.57	0.51	0.47	0.4		
TT Hellenic Postbank S.A	0.2	0.24	0.39	0.51	0.45	0.35		

Where, COLS represents: Corrected Ordinary Least Squares.

Table 9.18. Evolution of Cost Efficiency, MOLS exponential, Model 1

Banks	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Alpha Bank AE	0.59	0.73	0.7	0.68	0.64	0.65	0.6	0.71
Eurobank Ergasias SA	0.76	0.8	0.8	0.74	0.72	0.75	0.62	0.87
National Bank of Greece SA	0.58	0.79	0.91	0.83	0.71	0.65	0.68	0.68
Piraeus Bank SA	0.66	0.72	0.79	0.73	0.73	0.73	0.8	0.74
Agricultural Bank of Greece	0.53	0.56	0.57	0.69	0.6	0.7		
Attica Bank SA-Bank of Attica SA	0.64	0.66	0.87	0.92	0.91	0.8	0.79	0.87
Emporiki Bank of Greece SA	0.61	0.55	0.81	0.99	1	1	0.9	0.68
FBB First Business Bank SA	0.82	0.84	1	1	0.94	0.75	0.89	
General Bank of Greece SA	0.37	0.45	0.57	0.93	0.69	0.6	0.82	0.69
Marfin Egnatia Bank SA	0.65	0.74	1	1	1	1		
Millennium Bank SA	0.65	0.99	1	1	1	1	1	1
PRObank SA-PRObank Bank Societe Anonyme	0.5	0.6	0.71	0.61	0.56	0.62	0.62	
Panellinia Bank	0.56	0.8	0.96	1	0.78	0.82	0.87	0.71
Proton Bank S.A.	0.72	0.36	0.7	0.86	0.64	0.84		
T Bank S.A	0.64	0.69	0.74	0.72	0.7	0.57		
TT Hellenic Postbank S.A	0.29	0.33	0.55	0.74	0.61	0.47		

Where MOLSexp represents: Modified Ordinary Least Squares where the ineffiinecy component follows an exponential distribution.

Table 9.19. Evolution of Cost Efficiency, MOLS exponential, Model 2

Banks	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Alpha Bank AE	0.59	0.72	0.66	0.64	0.64	0.65	0.66	0.72
Eurobank Ergasias SA	0.78	0.8	0.78	0.73	0.75	0.79	0.6	0.79
National Bank of Greece SA	0.54	0.83	0.89	0.77	0.77	0.74	0.69	0.62
Piraeus Bank SA	0.68	0.73	0.8	0.78	0.7	0.77	0.76	0.75
Agricultural Bank of Greece	0.56	0.59	0.57	0.68	0.57	0.71		
Attica Bank SA-Bank of Attica SA	0.63	0.66	0.87	0.95	0.92	0.81	0.81	0.89
Emporiki Bank of Greece SA	0.59	0.52	0.77	0.98	1	1	0.9	0.69
FBB First Business Bank SA	0.81	0.82	0.99	1	0.97	0.8	0.87	
General Bank of Greece SA	0.37	0.45	0.61	0.96	0.69	0.58	0.81	0.67
Marfin Egnatia Bank SA	0.64	0.77	1	1	1	1		
Millennium Bank SA	0.64	0.97	1	1	1	1	1	1
PRObank SA-PRObank Bank Societe Anonyme	0.5	0.59	0.7	0.61	0.57	0.62	0.62	
Panellinia Bank	0.55	0.81	0.98	0.98	0.79	0.82	0.87	0.73
Proton Bank S.A.	0.73	0.36	0.69	0.87	0.62	0.83		
T Bank S.A	0.63	0.68	0.75	0.72	0.7	0.56		
TT Hellenic Postbank S.A	0.29	0.33	0.54	0.77	0.63	0.49		

Where MOLS exponential represents: Modified Ordinary Least Squares where the ineffiinecy component follows an exponential distribution.

Table 9.20. Evolution of Cost Efficiency, MOLS exponential, Model 3

Banks	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Alpha Bank AE	0.59	0.73	0.71	0.68	0.65	0.65	0.61	0.71
Eurobank Ergasias SA	0.75	0.79	0.8	0.74	0.72	0.75	0.63	0.86
National Bank of Greece SA	0.4	0.57	0.66	0.59	0.5	0.47	0.48	0.48
Piraeus Bank SA	0.47	0.52	0.56	0.51	0.5	0.52	0.58	0.53
Agricultural Bank of Greece	0.53	0.57	0.59	0.7	0.6	0.69		
Attica Bank SA-Bank of Attica SA	0.61	0.66	0.86	0.91	0.91	0.81	0.77	0.88
Emporiki Bank of Greece SA	0.61	0.54	0.81	0.98	1	1	0.9	0.68
FBB First Business Bank SA	0.86	0.88	1	1	0.91	0.72	0.89	
General Bank of Greece SA	0.37	0.45	0.57	0.97	0.69	0.6	0.79	0.69
Marfin Egnatia Bank SA	0.65	0.72	1	1	1	1		
Millennium Bank SA	0.65	1	1	1	1	1	1	1
PRObank SA-PRObank Bank Societe Anonyme	0.49	0.59	0.7	0.57	0.56	0.58	0.63	0
Panellinia Bank	0.56	0.81	0.97	1	0.77	0.79	0.82	0.71
Proton Bank S.A.	0.71	0.42	0.72	0.85	0.59	0.78		
T Bank S.A	0.71	0.76	0.8	0.72	0.66	0.57		
TT Hellenic Postbank S.A	0.28	0.33	0.55	0.72	0.63	0.5		

Where MOLS exponential represents: Modified Ordinary Least Squares where the inefficiency component follows an exponential distribution

Table 9.21. Evolution of Cost Efficiency, MOLS half-normal, Model 1

Banks	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Alpha Bank AE	0.63	0.78	0.75	0.73	0.68	0.69	0.64	0.76
Eurobank Ergasias SA	0.81	0.85	0.85	0.79	0.77	0.8	0.66	0.92
National Bank of Greece SA	0.62	0.84	0.97	0.89	0.75	0.69	0.72	0.72
Piraeus Bank SA	0.7	0.77	0.84	0.78	0.77	0.78	0.86	0.79
Agricultural Bank of Greece	0.57	0.6	0.61	0.74	0.64	0.74		
Attica Bank SA-Bank of Attica SA	0.68	0.71	0.93	0.98	0.96	0.85	0.84	0.92
Emporiki Bank of Greece SA	0.65	0.59	0.86	1	1	1	0.96	0.72
FBB First Business Bank SA	0.87	0.89	1	1	1	0.8	0.95	
General Bank of Greece SA	0.4	0.48	0.6	0.99	0.73	0.64	0.87	0.74
Marfin Egnatia Bank SA	0.69	0.79	1	1	1	1		
Millennium Bank SA	0.69	1	1	1	1	1	1	1
PRObank SA-PRObank Bank Societe Anonyme	0.53	0.64	0.76	0.65	0.6	0.66	0.66	
Panellinia Bank	0.6	0.85	1	1	0.83	0.88	0.93	0.75
Proton Bank S.A.	0.76	0.38	0.74	0.91	0.68	0.9		
T Bank S.A	0.69	0.73	0.79	0.76	0.75	0.61		
TT Hellenic Postbank S.A	0.31	0.35	0.58	0.79	0.65	0.5		

Where MOLS half-normal: Modified Ordinary Least Squares where the inefficiency component follows a half-normal.

Table 9.22. Evolution of Cost Efficiency, MOLS half-normal, Model 2

Banks	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Alpha Bank AE	0.63	0.76	0.71	0.68	0.68	0.69	0.71	0.77
Eurobank Ergasias SA	0.83	0.85	0.83	0.77	0.8	0.84	0.63	0.84
National Bank of Greece SA	0.58	0.89	0.94	0.82	0.82	0.79	0.73	0.66
Piraeus Bank SA	0.72	0.77	0.86	0.83	0.74	0.82	0.81	0.79
Agricultural Bank of Greece	0.59	0.63	0.6	0.72	0.61	0.75		
Attica Bank SA-Bank of Attica SA	0.67	0.71	0.93	1	0.98	0.86	0.86	0.94
Emporiki Bank of Greece SA	0.63	0.56	0.82	1	1	1	0.96	0.73
FBB First Business Bank SA	0.86	0.87	1	1	1	0.85	0.92	
General Bank of Greece SA	0.39	0.48	0.65	1	0.73	0.62	0.86	0.71
Marfin Egnatia Bank SA	0.69	0.82	1	1	1	1		
Millennium Bank SA	0.69	1	1	1	1	1	1	1
PRObank SA-PRObank Bank Societe Anonyme	0.54	0.63	0.75	0.65	0.61	0.66	0.66	
Panellinia Bank	0.59	0.86	1	1	0.84	0.87	0.92	0.78
Proton Bank S.A.	0.78	0.39	0.74	0.92	0.66	0.89		
T Bank S.A	0.67	0.72	0.8	0.76	0.74	0.6		
TT Hellenic Postbank S.A	0.31	0.35	0.58	0.82	0.68	0.52		

Where MOLS half-normal: Modified Ordinary Least Squares where the inefficiency component follows a half-normal.

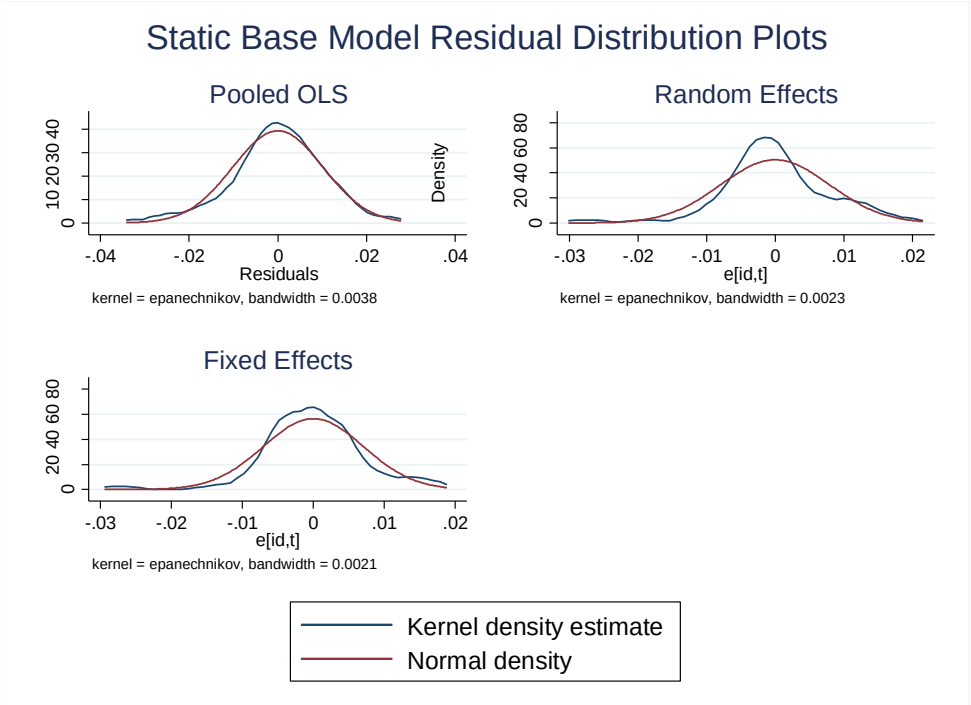
Table 9.23. Evolution of Cost Efficiency, MOLS half-normal, Model 3

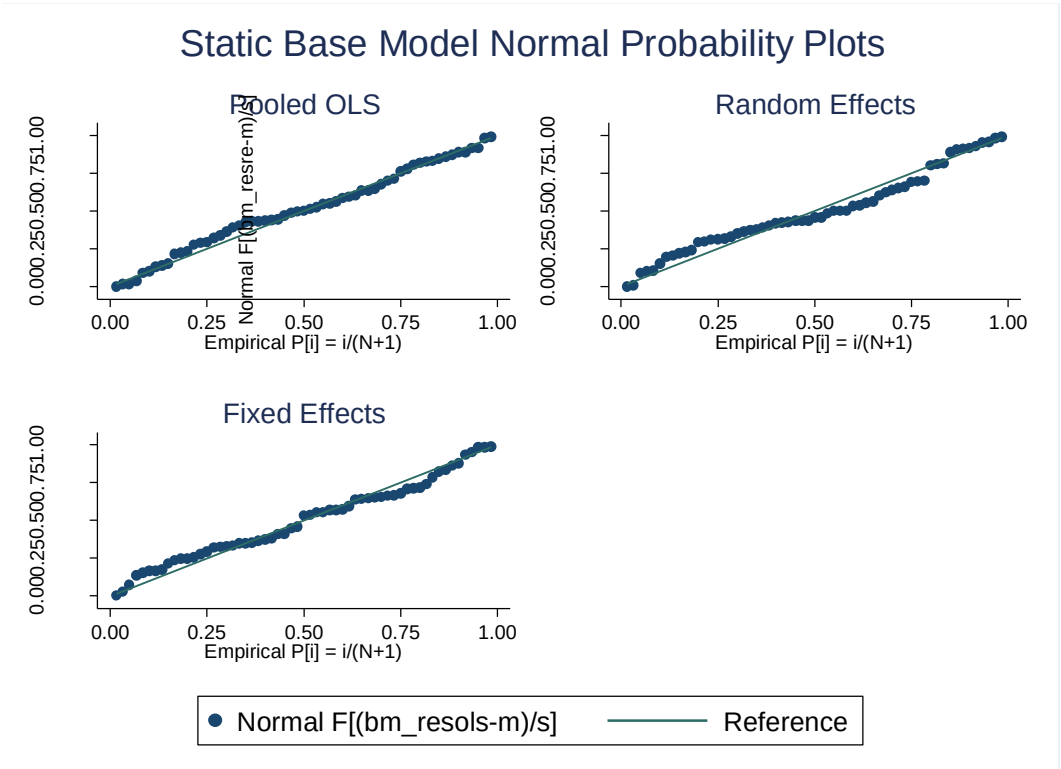
Banks	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*
Alpha Bank AE	0.63	0.78	0.75	0.72	0.69	0.69	0.64	0.76
Eurobank Ergasias SA	0.79	0.84	0.85	0.79	0.77	0.8	0.67	0.92
National Bank of Greece SA	0.6	0.85	0.99	0.88	0.75	0.7	0.73	0.72
Piraeus Bank SA	0.7	0.77	0.84	0.76	0.76	0.77	0.87	0.79
Agricultural Bank of Greece	0.57	0.61	0.63	0.74	0.64	0.73		
Attica Bank SA-Bank of Attica SA	0.65	0.7	0.91	0.96	0.96	0.86	0.82	0.93
Emporiki Bank of Greece SA	0.65	0.58	0.86	1	1	1	0.96	0.72
FBB First Business Bank SA	0.91	0.94	1	1	0.97	0.77	0.95	
General Bank of Greece SA	0.4	0.48	0.6	1	0.73	0.63	0.84	0.74
Marfin Egnatia Bank SA	0.69	0.76	1	1	1	1		
Millennium Bank SA	0.69	1	1	1	1	1	1	1
PRObank SA-PRObank Bank Societe Anonyme	0.52	0.63	0.75	0.61	0.59	0.62	0.67	
Panellinia Bank	0.59	0.86	1	1	0.82	0.84	0.88	0.75
Proton Bank S.A.	0.75	0.44	0.77	0.91	0.63	0.83		
T Bank S.A	0.76	0.81	0.86	0.77	0.71	0.6		
TT Hellenic Postbank S.A	0.3	0.36	0.59	0.77	0.67	0.53		

Where MOLS half-normal: Modified Ordinary Least Squares where the inefficiency component follows a half-normal.

Appendix C

Figure 10.1. Static Base Model – Residual Diagnostics





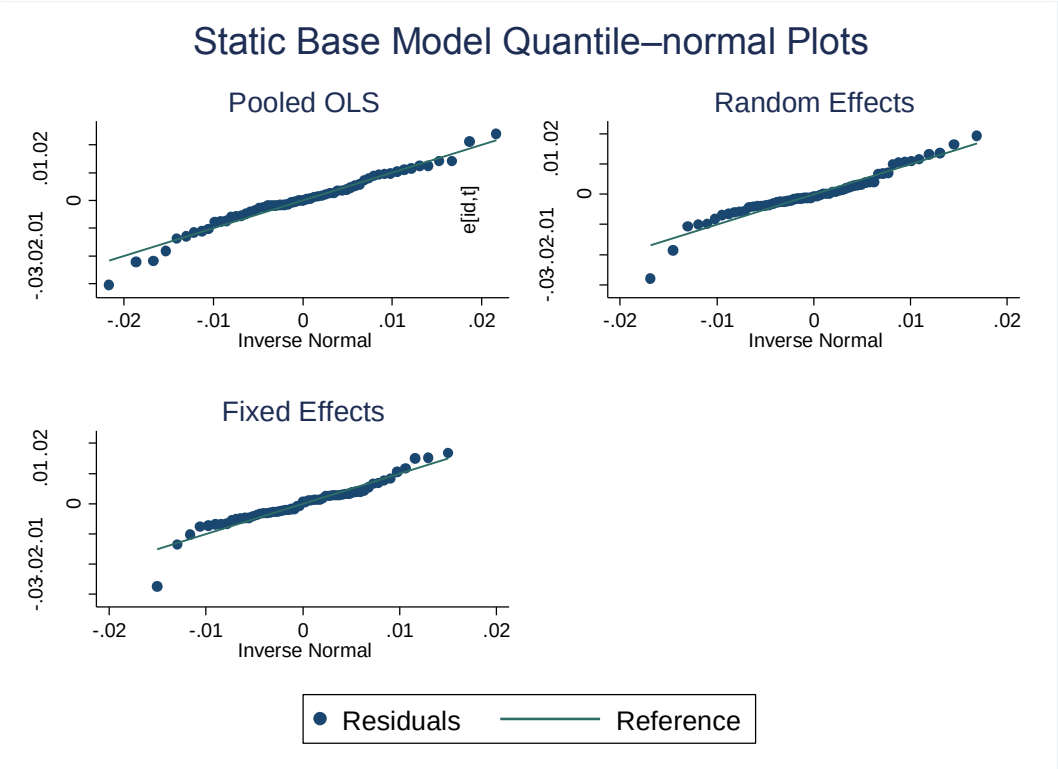
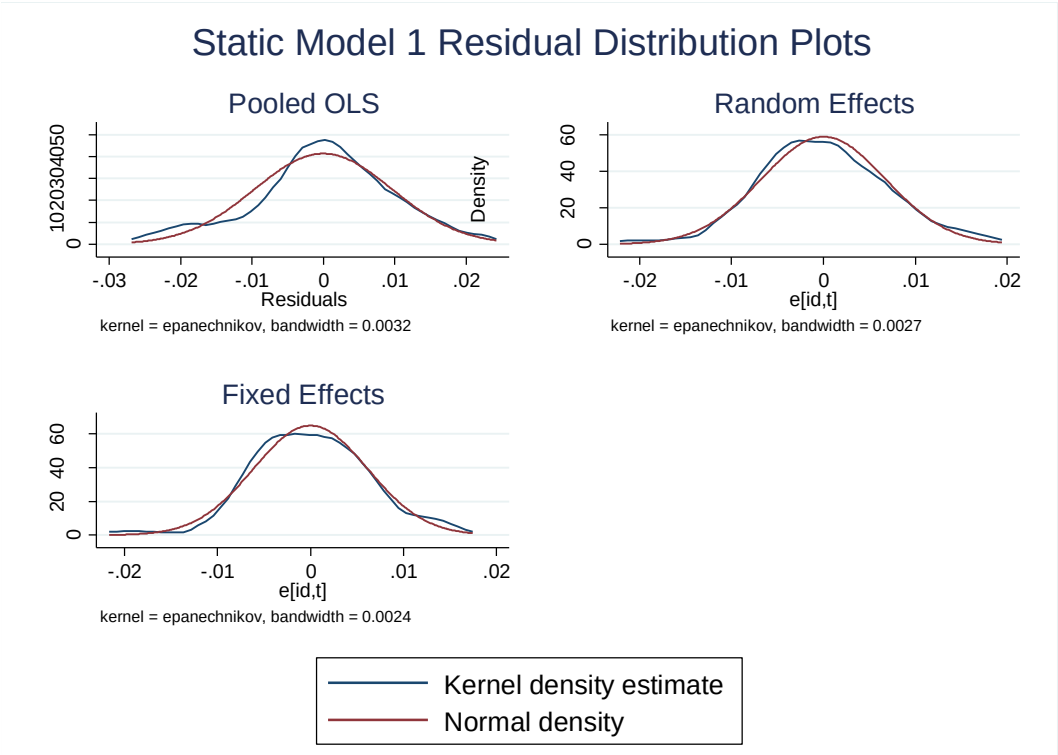
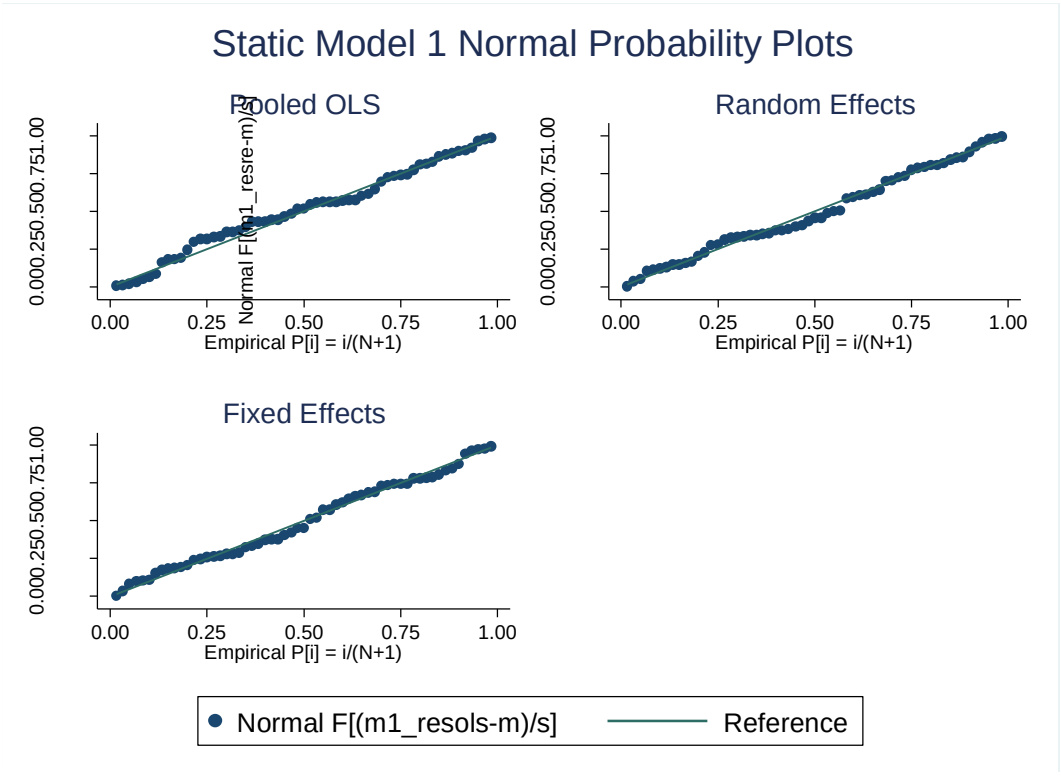


Figure 10.2. Static Model 1 – Residual Diagnostics




Static Model 1 Normal Probability Plots
Pooled OLS
Random Effects
Fixed Effects
Normal F[(m1_resre-m)/s]
0.000.250.500.751.00
0.00
0.25
0.50
0.75
1.00
Empirical P[i] = i/(N+1)
Normal F[(m1_resols-m)/s]
Reference

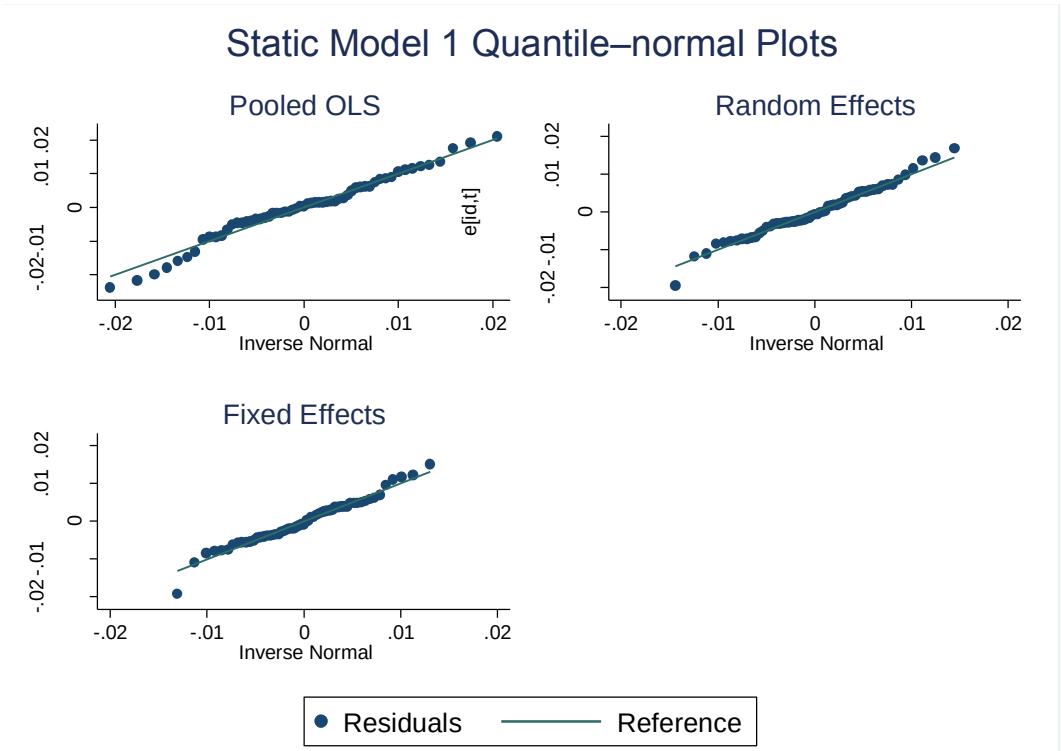
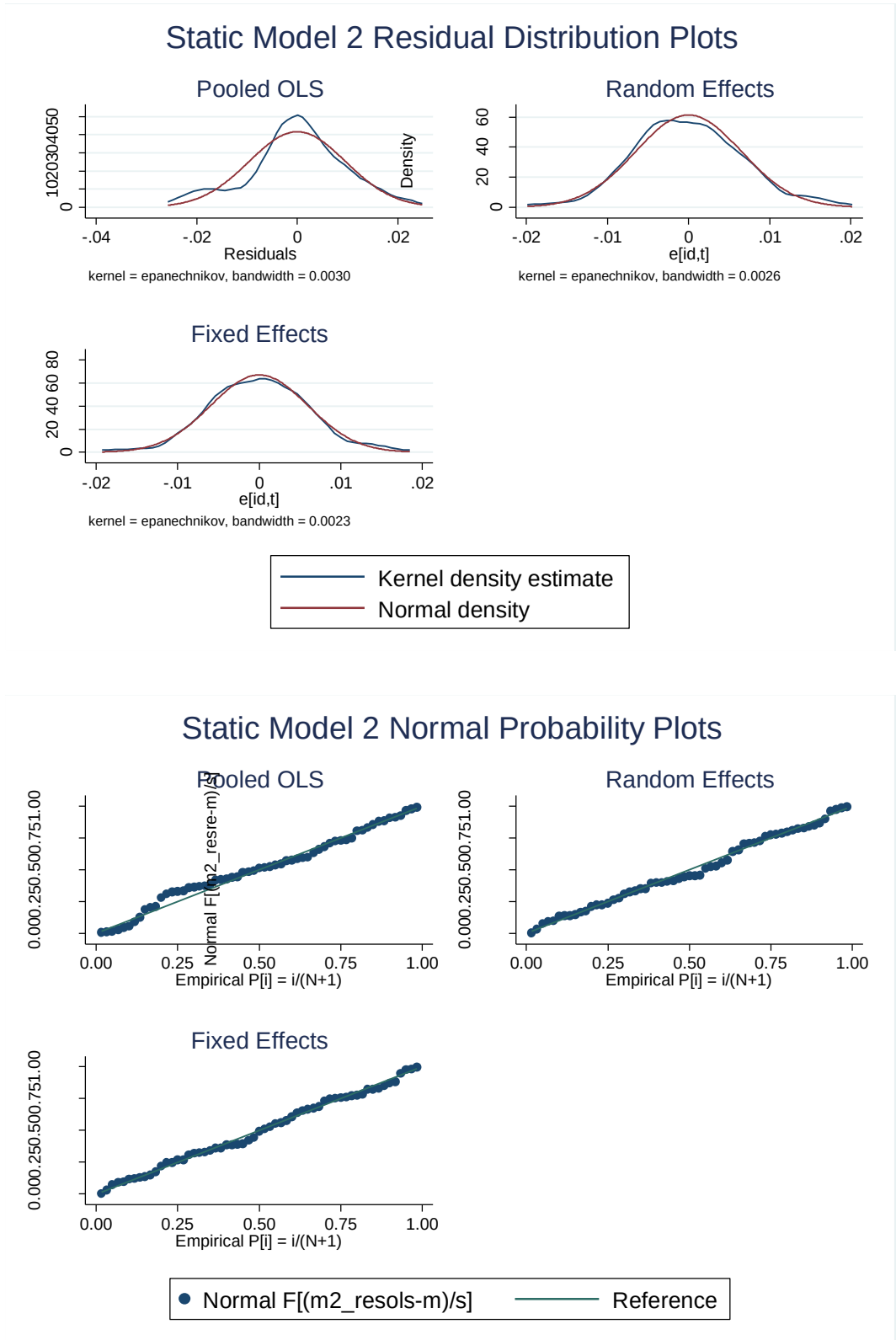

Static Model 1 Quantile–normal Plots
Pooled OLS
Random Effects
Fixed Effects
e[id,t]
-.02
-.01
0
.01
.02
Inverse Normal
Residuals
Reference

Figure 10.3. Static Model 2 – Residual Diagnostics



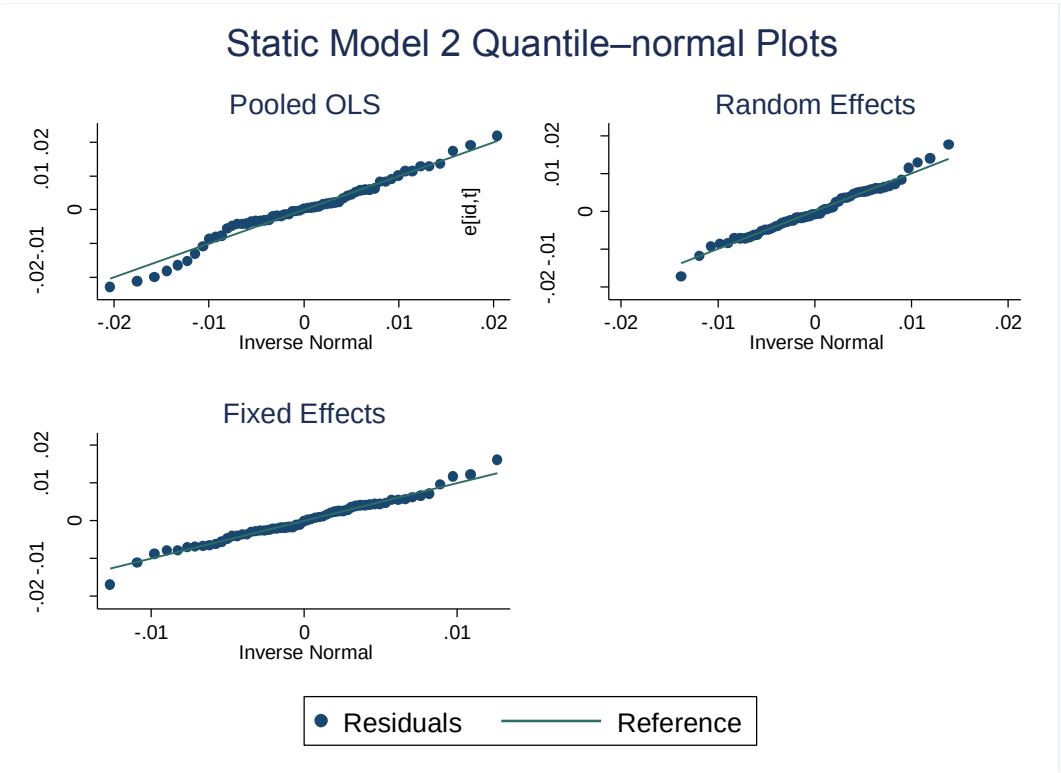
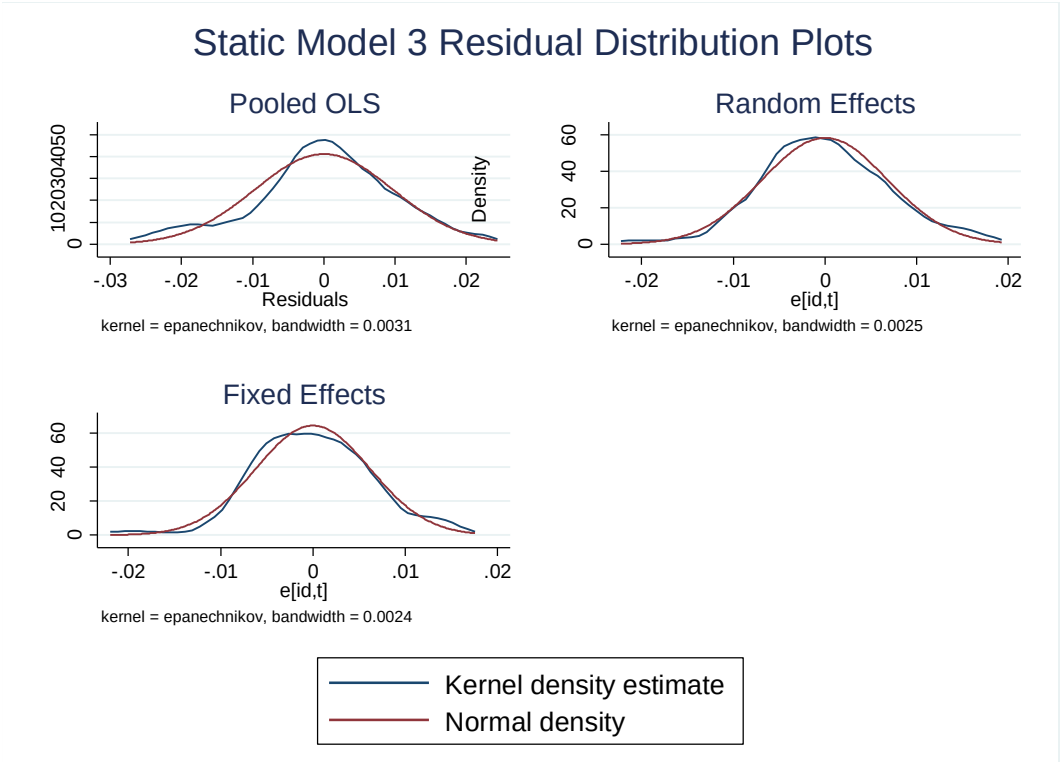
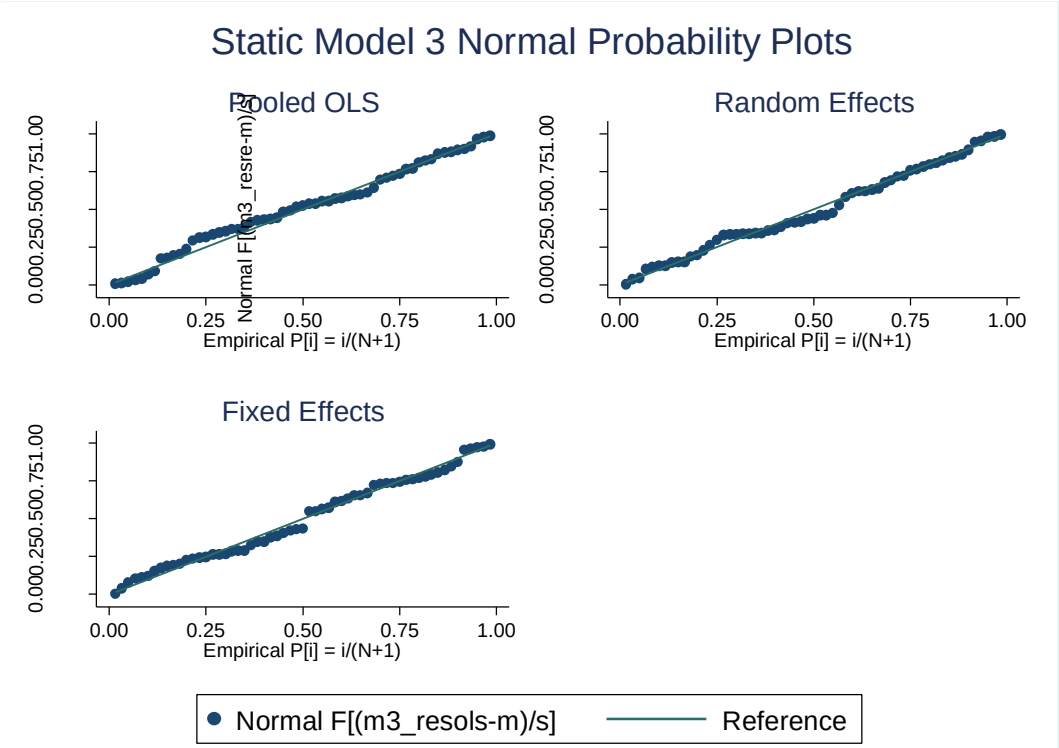


Figure 10.4. Static Model 3 – Residual Diagnostics




Static Model 3 Normal Probability Plots
Pooled OLS
Random Effects
Fixed Effects
Normal F[(m3_resre-m)/s]
0.000.250.500.751.00
0.00 0.25 0.50 0.75 1.00
Empirical P[i] = i/(N+1)
Normal F[(m3_resols-m)/s]
Reference

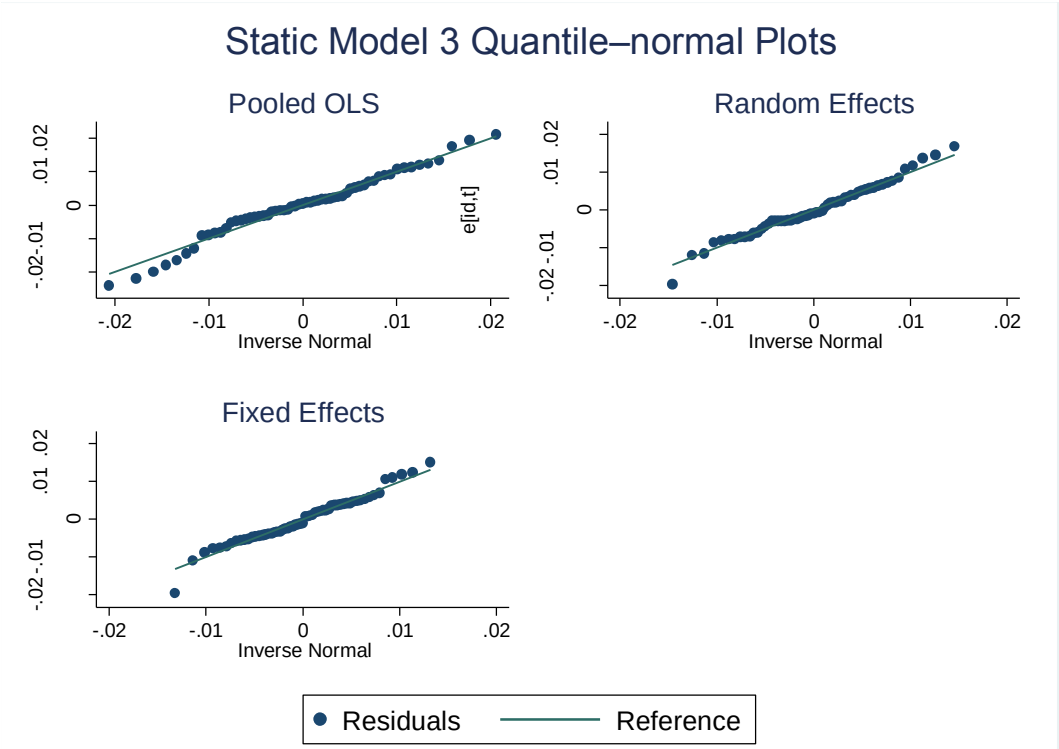

Static Model 3 Quantile–normal Plots
Pooled OLS
Random Effects
Fixed Effects
e[id,t]
-.02 -.01 0 .01 .02
Inverse Normal
Residuals
Reference

Table 10.1. Dynamic Model Autoregressive Diagnostics - DBM

Dependent variable LLP_{it}/TA_{it}				
	Pooled OLS	*Random Effects*	*Fixed Effects*	*SGMM*
LLP_{it-1}/TA_{it-1}	0.058	0.051	-0.003	0.141*
	(0.071)	(0.071)	(0.092)	(0.075)
CE_{it}/TA_{it}	-0.022	-0.025	-0.077	-0.129**
	(0.044)	(0.036)	(0.047)	(0.059)
NI_{it}/TA_{it}	-1.042***	-1.044***	-0.970***	-1.106***
	(0.114)	(0.100)	(0.099)	(0.123)
NPL_{it}/GL_{it}	-0.051	-0.032	0.053	-0.038
	(0.031)	(0.028)	(0.036)	(0.040)
$GDPgr$	0.000	0.001	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.001)
Un	0.000	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
constant	0.016**	0.016***	0.022**	0.031**
	(0.006)	(0.006)	(0.009)	*(0.008)
Observations	48	48	48	48
R^2	0.917		0.947	

This table reports the Windmeijer (2005) robust standard errors in parentheses for SGMM and the Huber/White robust standard errors for the OLS and FE and RE estimators. Where, DMB is the Dynamic base model as in equation (5.22). LLP_{it-1}/TA_{it-1} *represents the autoregressive term;* TCE_{it}/TA_{is} *represents Total Common Equity scaled by total assets at period* t*;* NI_{it}/TA_{it} *represents Net Income scaled by total assets at period* t*;* NPL_{it}/GL_{it} *represents Non-Performing Loans to gross loans, at time* t*;* $GDPgr$ *represents the annual change of Gross Domestic Product (%); Un represents the unemployment rate.*

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10.2. Dynamic Model Autoregressive Diagnostics - DM1

Dependent variable LLP_{it}/TA_{it}				
	Pooled OLS	*Random Effects*	*Fixed Effects*	*SGMM*
LLP_{it-1}/TA_{it-1}	0.098*	0.118**	0.124	0.189***
	(0.056)	(0.056)	(0.074)	(0.060)
CE_{it}/TA_{it}	-0.044	-0.046	-0.071*	-0.153**
	(0.040)	(0.040)	(0.036)	(0.076)
$GDPgr$	-0.001	-0.002**	-	-0.002
	(0.001)	(0.001)	0.002***(0.000)	(0.002)
Un	-0.000	-0.001**	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
NI_{it}/TA_{it}	-1.034***	-1.052***	-1.032***	-1.037***
	(0.094)	(0.080)	(0.078)	(0.095)
$TVM1-4Z$	-0.066*	-0.077**	-0.086**	-0.087*
	*(0.026)	*(0.018)	*(0.019)	(0.048)
NPL_{it}/GL_{it}	-0.061**	-0.055*	-0.028	-0.032
	(0.023)	*(0.023)	(0.042)	(0.023)
constant	0.079**	0.091***	0.107***	0.116**
	*(0.026)	(0.019)	(0.018)	*(0.039)
N	48	48	48	48
R^2	0.930		0.963	

This table reports the Windmeijer (2005) robust standard errors in parentheses for SGMM and the Huber/White robust standard errors for the OLS and FE and RE estimators. Where, DM1 is the augmented dynamic model as in equation (5.23), including $TVM1-4Z$. LLP_{it-1}/TA_{it-1} *represents the autoregressive term;* TCE_{it}/TA_{is} *represents Total Common Equity scaled by total assets at period* t*;* NI_{it}/TA_{it} *represents Net Income scaled by total assets at period* t*;* NPL_{it}/GL_{it} *represents Non-Performing Loans to gross loans, at time* t*;* $GDPgr$ *represents the annual change of Gross Domestic Product (%); Un represents the unemployment rate;* $TVM1-4Z$*: Time Varying Model 1, without a risk metric; 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio.*

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10.3 .Dynamic Model Autoregressive Diagnostics - DM2

Dependent variable LLP_{it}/TA_{it}				
	Pooled OLS	*Random Effects*	*Fixed Effects*	*SGMM*
LLP_{it-1}/TA_{it-1}	0.092	0.116**	0.126	0.133
	(0.056)	(0.055)	(0.072)	(0.083)
CE_{it}/TA_{it}	-0.042	-0.040	-0.057	-0.155**
	(0.038)	(0.038)	(0.035)	(0.075)
$GDPgr$	-0.001	-0.002***	-0.003**	-0.002*
	(0.001)	(0.001)	*(0.001)	(0.001)
Un	-0.000	-0.001**	-0.001***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.001)
NI_{it}/TA_{it}	-1.035***	-1.056***	-1.043***	-1.013***
	(0.091)	(0.069)	(0.060)	(0.086)
$TVM2-4Z$	-0.065**	-0.082***	-0.091***	-0.091***
	(0.024)	(0.019)	(0.021)	(0.035)
NPL_{it}/GL_{it}	-0.061***	-0.055**	-0.034	-0.015
	(0.022)	(0.022)	(0.042)	(0.037)
constant	0.076***	0.093**	0.107***	0.117***
	(0.023)	*(0.018)	(0.019)	(0.029)
N	48	48	48	48
R^2	0.931		0.967	

This table reports the Windmeijer (2005) robust standard errors in parentheses for SGMM and the Huber/White robust standard errors for the OLS and FE and RE estimators. Where, DM2 is the augmented dynamic model as in equation (5.23), including,$TVM2-4Z$. LLP_{it-1}/TA_{it-1} represents the autoregressive term; TCE_{it}/TA_{is} represents Total Common Equity scaled by total assets at period t; NI_{it}/TA_{it} represents Net Income scaled by total assets at period t; NPL_{it}/GL_{it} represents Non-Performing Loans to gross loans, at time t; $GDPgr$ represents the annual change of Gross Domestic Product (%); Un represents the unemployment rate; $TVM2-4Z$: Time Varying Model 2, with Equity as a risk metric; 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio.

Standard errors in parentheses

** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Table 10.4. Dynamic Model Autoregressive Diagnostics - DM3

Dependent variable LLP_{it}/TA_{it}				
	Pooled OLS	*Random Effects*	*Fixed Effects*	*SGMM*
LLP_{it-1}/TA_{it-1}	0.096	0.116**	0.126	0.191**
	(0.057)	(0.055)	(0.072)	(0.080)
CE_{it}/TA_{it}	-0.044	-0.047	-0.075*	-0.165*
	(0.041)	(0.042)	(0.038)	*(0.072)
$GDPgr$	-0.001	-0.002**	-0.002***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Un	-0.000	-0.001**	-0.002***	-0.002***
	(0.001)	(0.000)	(0.000)	(0.001)
NI_{it}/TA_{it}	-1.033***	-1.052***	-1.032***	-1.106***
	(0.096)	(0.082)	(0.080)	(0.097)
$TVM3-4Z$	-0.060**	-0.072***	-0.083***	-0.062**
	(0.026)	(0.019)	(0.019)	(0.031)
NPL_{it}/GL_{it}	-0.060**	-0.054**	-0.028	-0.044*
	(0.024)	(0.023)	(0.041)	(0.024)
constant	0.074***	0.086***	0.104***	0.094***
	(0.026)	(0.021)	(0.018)	(0.032)
N	48	48	48	48
R^2	0.929		0.962	

This table reports the Windmeijer (2005) robust standard errors in parentheses for SGMM and the Huber/White robust standard errors for the OLS and FE and RE estimators. Where, DM3 is the augmented dynamic model as in equation (5.23), including $TVM3-4Z$. LLP_{it-1}/TA_{it-1} *represents the autoregressive term;* TCE_{it}/TA_{is} *represents Total Common Equity scaled by total assets at period* t*;* NI_{it}/TA_{it} *represents Net Income scaled by total assets at period* t*;* NPL_{it}/GL_{it} *represents Non-Performing Loans to gross loans, at time* t*;* $GDPgr$ *represents the annual change of Gross Domestic Product (%); Un represents the unemployment rate;* $TVM3-4Z$ *Time Varying Model 1, with LLP as a risk metric; 4Z: Gross Domestic Product (% change), Unemployment rate (% change), Inflation rate (% change), top five Concentration Ratio.*

Standard errors in parentheses

** p < 0.10, ** p < 0.05, *** p < 0.01*

Table 10.5. Additional Dynamic Models Diagnostics

	DBM		*DM1*	
	OLS	FE	OLS	FE
Bank Specific	0.058	-.061	0.08	0.02
All – Levels	0.057	-.003	0.097	0.124
All - Index	0.095	.051	0.112	0.104
	DM2		*DM3*	
Bank Specific	0.08	0.03	0.08	0.02
All – Levels	0.091	0.125	0.095	0.126
All - Index	0.110	0.108	0.112	0.105

Where, DMB is the Dynamic base model as in equation (5.22) and DM1, DM2, DM3 are the augmented dynamic models as in equation (5.23), including $TVM1-4Z$, $TVM2-4Z$ *and* $TVM3-4Z$ *respectively. This table reports the coefficient of the lag dependent variable of models as specified in equations (5.22) and (5.23) as estimated via the Huber/White robust standard errors for the OLS and FE estimators.*