

UK Corporate Capital Structure and Zombies: An Econometric Analysis

Sadegh Javaheriafif

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This Thesis is dedicated to my parents, Ebrahim and Zahra.

Abstract

This Thesis examines the determinants of corporate capital structure during a period characterised by significant changes in the overall economic conditions. Empirical studies of capital structure generally concentrate on identifying the firm-specific factors that managers should consider in making capital structure decisions, while ignoring the possible implications of the overall economic conditions that could affect the firms' financing decisions. Given that the 2007 Global Financial Crisis (GFC) was accompanied by an economic recession, this provides a unique opportunity to investigate the impact of the overall economic conditions on firm's capital structure.

There have been a number of unique factors to the 2007 GFC and the following economic recession that are not observed in previous economic downturns in the UK. These include near-zero interest rate (which was reduced by the Bank of England from a pre-crisis peak of 5.75% in July 2007 to 0.5% in March 2009), the extraordinary level of support to the troubled firms offered by the government (e.g., the Business Payment Support Service; the Asset Protection Scheme; and the Funding for Lending Scheme), and the unprecedented banks' forbearances on non-performing loans (e.g., granting waivers to breaches of pre-agreed loan covenants; switching to an interest-only loans; offering payment holidays; and rolling over the loan). These factors while protecting many viable businesses, may have contributed to the survival of some technically insolvent firms that would have defaulted otherwise. Recent evidence from insolvency practitioners have suggested the emergence of such "zombie" firms in the UK over the course of the GFC and the following economic recession.

Accordingly, the objective of this Thesis is fourfold. The main objective is to investigate the impact of the recent GFC and the firm-specific determinants of the capital structure on firms' leverage ratios. The second objective is to identify zombies, thirdly to develop an empirical model to identify the determinants of zombieness status, and fourthly to estimate their impact on the probability of becoming a zombie. The same dataset on the constituents of the FTSE 250 Index is utilised in achieving all these objectives.

Identifying zombies via a two-condition criteria, and using a population-averaged logit procedure, we show that the probability of becoming a zombie increases with the degree of financial leverage and viability of the business (as perceived by firm's top management). However, it is negatively affected by firm's profitability, cash-generating ability, and the ability to pay dividends. Our results thus show that there was a prevalence of zombie firms in the UK which evolved from the GFC.

Using data on the constituents of the FTSE 250 Index over the period 2004-2012 and estimating a two-step System GMM procedure, we find that the leverage ratio is positively affected by the tangibility of assets, the size of the firm, the amount of non-debt tax shields, growth opportunities and business risk, but declines with an increase in firm profitability. Furthermore, the recent GFC is found to exert a significant impact on firms' leverage ratio. The results also confirm that firms have target leverage ratios with a fairly fast speed of adjustment.

Applying the same estimation technique to a post-crisis model, we find that, despite the substantial differences in their ability to meet financial obligation, the leverage ratios of zombies and non-zombies do not seem to be determined differently. We further establish that except for business risk and growth opportunities, other commonly used firms-specific determinants of capital structure, maintain their empirical relevance over the post-crisis period.

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List of Abbreviations

AB	–	Arellano-Bond
AB/BB	–	Arellano-Bover/Blundell-Bond
AH	–	Anderson-Hsiao
AIC	–	Akaike Information Criteria
AICR	–	Adjusted Interest Coverage Ratio
AME	–	Average Marginal Effect
AR	–	Auto Regressive
ASP	–	Asset Protection Scheme
BIC	–	Bayesian Information Criteria
BIS	–	Bank for International Settlements
BoE	–	Bank of England
BPLM	–	Breusch-Pagan Lagrange Multiplier
BPSS	–	Business Payment Support Service
CEO	–	Chief Executive Officer
CLT	–	Central Limit Theorem
CME	–	Conditional Marginal Effect
CPI	–	Consumer Price Index
CPM	–	Conditional Probability Model
CRA	–	Conditional Regression Analysis
CRE	–	Commercial Real Estate
DA	–	Discriminant Analysis
DBIS	–	Department for Business, Innovation, and Skills
DIFGMM	–	Difference System Generalized Method of Moments
ECM	–	Error Correction Model
FD	–	First Difference
FDIV	–	First Difference Instrumental Variables
FE	–	Fixed Effects
FLS	–	Funding for Lending Scheme
FSA	–	Financial Services Authority
GDP	–	Gross Domestic Product
GFC	–	Global Financial Crisis
GICS	–	Global Industry Classification Standard
GMM	–	Generalized Method of Moments
ICR	–	Interest Coverage Ratio
IV	–	Instrumental Variable
KD	–	Kernel Density
LIBOR	–	London Inter-Bank Offered Rate
LM	–	Lagrange Multiplier
LPM	–	Linear Probability Model
LTV	–	Loan to Value
MA	–	Moving Average
MDA	–	Multivariate Discriminant Analysis

MDM	–	Multivariate Discriminant Model
MDS	–	Multivariate Discriminant Score
ME	–	Marginal Effect
MEM	–	Marginal Effects at the Means
MFI	–	Monetary Financial Institution
ML	–	Maximum Likelihood
NNA	–	Neural Networks Analysis
OLS	–	Ordinary Least Squares
ONS	–	Office for National Statistics
PA	–	Population-Averaged
QQ	–	Quantiles on Quantiles
R3	–	Association of Business Recovery Professionals
RE	–	Random Effects
ROC	–	Receiver Operating Characteristic
RSS	–	Residual Sum of Squares
SK	–	Skewness-Kurtosis
SME	–	Small and Medium-sized Enterprise
SNP	–	Standardised Normal Probability
SW	–	Shapiro-Wilk
SYSGMM	–	System Generalized Method of Moments
UDA	–	Univariate Discriminant Analysis
UDM	–	Univariate Discriminant Model
VIF	–	Variance Inflation Factor

1. Introduction

The modern theory of capital structure began with the study of Modigliani and Miller's (1958) irrelevance theory. They argue that, under perfect capital markets conditions, the choice of capital structure is irrelevant to the firm's cost of capital and its overall value. However, the perfect market conditions never seem to hold in practice. This has led to the emergence of alternative theories of capital structure and a large body of empirical studies attempting to explain the choice of capital structure, while incorporating different market imperfections that were ignored in the Modigliani-Miller theorem.

However, the extensive empirical literature of capital structure mainly focuses on identifying the firm-specific variables that determine leverage ratios, while overlooking the possible impact of the overall economic conditions on firms' choice of capital structure (Antoniou *et al.*, 2008). Given that 2007 Global Financial Crisis (GFC) was followed by an economic recession, this provides a unique opportunity to investigate the impact of the overall economic conditions on firm's capital structure. Furthermore, investigating the impact of the GFC on the determination of capital structure can allow us to examine whether the prediction of the main theories regarding the firm-specific determinants of capital structure remain valid in a post-crisis environment.

That being said, there have been only a limited number of empirical studies addressing the impact of the recent GFC on the choice of leverage adopted by firms (e.g., Fosberg, 2012; Akbar *et al.*, 2013; Kahle and Stulz, 2013; and Iqbal and Kume, 2014). For instance, using pooled regression analysis and a large sample of US firms over the period 2001-2010, Fosberg (2012) attempts to capture the impact of the GFC on firms' leverage ratios. In particular, he tests the statistical significance of the difference between the coefficients on the annual time dummies included in a static model and finds that: while the GFC has a positive impact on leverage over the period 2006-2008, its impact reverses for the period 2009-2010. Consistent with these findings, Pattani *et al.* (2011) also show that aggregate debt issuance of UK firms continues to increase during the period 2008-2009 and then falls sharply to almost pre-crisis levels in 2010.

While Fosberg (2012) uses annual time dummies, Akbar *et al.* (2013) include a crisis period dummy in their fixed effect regression model to capture the impact of the GFC on leverage ratios of UK private firms. They also document a significant reduction in leverage ratios over the period 2007-2009 as opposed to the period 2004-2006. Finally, using a fixed effect regression model and two dummy variables for the crisis (2008-2009) and the post-crisis (2010-2011) period, Iqbal and Kume (2014) examine the impact of the recent GFC on the capital structure decision of listed non-financial firms in the UK. However, in contrast to the findings of Akbar *et al.* (2013), they find that the coefficient on the crisis dummy variable is positive and significant. Furthermore, their results fail to indicate a significant change in leverage ratios over the post-crisis period relative to 2006-2009.

Accordingly, while the significant impact of the GFC on firms' financing decisions is generally supported by the empirical literature, there seem to be major inconsistencies concerning the direction of the impact, depending on the sample and estimation approach. Moreover, the above studies are limited by their choice of estimation method and model specifications. That is, using simple OLS regressions and static models, previous estimates ignore the heterogeneity and endogeneity problems associated with panel data and assume away the dynamic nature of capital structure decisions. In addition, they do not take into account the existence of transaction costs involved in the adjustment process and thus, may not fully and accurately capture the determination of the firms' capital structures.

Changes in overall economic conditions are typically associated with fluctuations in corporate insolvency activities. Generally, aggregate insolvency tends to increase when in recessionary environments and decrease when the economy is growing (Desai and Montes, 1982; Goudie and Meeks, 1991; Liu 2004; Bonfim, 2009). However, the data from the Bank of England (BoE) and the Insolvency Service on GDP growth and aggregate corporate insolvency over the last three economic recessions indicate that, the UK aggregate corporate insolvency after the recent GFC and the consequent recession is nowhere close to where it should have been, having followed the trend in previous recessions.

The smaller-than-expected increase in aggregate corporate insolvency levels after the recent recession has been extensively investigated by government authorities, and

other professional bodies such as BoE and the Financial Services Authority (FSA). Findings indicate that record-low levels of interest rates, various government-sponsored support schemes, and the exceptional level of bank forbearance on non-performing loans are the main causes for the unusually high firm survivals after the recent recession (Arrowsmith *et al.,* 2013; BoE, 2013a; Barnett *et al.,* 2014b; and Nelson and Tanaka, 2014). However, while these factors may have protected some viable businesses suffering from temporary negative shocks and weak demands, they may have also led to the survival of some technically insolvent firms that would have otherwise defaulted.

Given that these half-dead or "zombie" firms have emerged after the recent GFC, and there have been evidence of their existence among UK firms (R3, 2012 & 2013), one must control for their existence and possible effects in any micro-level analysis that includes the period after the recent GFC[1]. Furthermore, zombies are unique in the sense that, they are neither fully insolvent (as are still active and in operation) nor in a solid financial standing (are unable to generate enough revenues to service their debts). Thus, their other financial characteristics such as capital structure may also be determined differently than those of non-zombies. Accordingly, these unique firms must be controlled for, when investigating the impact of the recent GFC on firms' capital structure, as failure to do so may lead to distorted and unreliable inferences regarding how different firms may determine their capital structures. However, to the best of our knowledge, there has not been any empirical attempt to identify zombies among the mid-cap firms in the UK and investigate their characteristics.

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

- investigate the impact of the recent GFC and the commonly used firm-specific determinants of the capital structure on firms' leverage ratios, using System Generalized Method of Moments (SYSGMM);
- Construct an indicator to identify zombie firms in our analysis sample and control for their impact on firms' financing decisions; and

[1] We define "zombies" as *surviving technically insolvent firms that are unable to generate enough revenues to even pay the interest expenses on their borrowings, let alone the repayment of the principal amount.*

- develop an empirical model to identify the determinants of zombieness status and estimate their impact on the probability of becoming a zombie.

To address the above objectives we utilise a large panel data containing constituents of the FTSE 250 Index over the period 2004-2012. In order to facilitate the empirical analysis of capital structure, two distinct models are estimated: a "base model" for the period 2004-2012, and a "zombie model" for the period 2008-2012. Accordingly, the base model investigates the general impact of the recent GFC and a set of commonly used firm-specific determinants of capital structure on the sample firms' leverage ratios. Whereas, the zombie model is aimed to examine whether the capital structure of zombies and non-zombies are determined differently and evaluates the empirical relevance of commonly used firm-specific determinants of capital structure in a post-crisis environment.

Indeed, our empirical results provide support for the significant impact of the firm-specific determinants of capital structure and the recent GFC on firms' leverage ratios. The results further indicate that, the capital structure of zombies and non-zombies are not determined any differently. Furthermore, the included firm-specific determinants of capital structure generally seem to maintain their statistical significance when applied to a post-crisis context.

With regards to the investigation of the determinants of zombieness status, employing a range of econometric techniques, we find that, the viability of the business (as perceived by firms' top management), profitability, the degree of financial leverage, cash-generating ability, and the ability to pay dividends tend to exert a significant impact on the probability of becoming a zombie.

Finally, it should be emphasised that, while the empirical analysis of this Thesis is motivated by the limited and inconsistent empirical evidence regarding the impact of the recent GFC on firms' capital structures, it is not an investigation of the GFC per se. Accordingly, to keep the focus of this study on the determinants of capital structure we do not include an in-depth review of the causes and consequences of the GFC (moreover, reaching the mandatory word limit has also built in a constraint to include separate discussions concerning the GFC). Nevertheless, this subject has been extensively investigated by both academic researchers and practitioners (see, Barrell

and Davis, 2008; Acharya et al., 2009; BIS, 2009; IMF, 2009; and Sentence et al., 2012).

The rest of the Thesis is structured as follows. Chapter 2 provides the conceptual framework for our main analysis by reviewing the main theories and empirical literature on capital structure and the issue of zombies. This chapter is used to derive our choice of analysis variables. Chapter 3 presents our empirical framework by informing the choice of estimation method. Chapter 4 presents the main empirical findings and discuss the estimation results. Finally, Chapter 5 concludes the Thesis by reviewing the key results.

2. Review of Literature

2.1. Introduction

Firms generally tend to finance their operations and new investments either by using their internal funds, such as accumulated retained earnings and any undistributed capital, or by raising external finance. There are two main types of external finance available to firms: equity and debt. Most often, firms use a combination of the two and the choice between the aforementioned sources constitutes the capital structure decision.

Understanding the determinants of firms' capital structures is important as it affects their investment decisions, which in turn translate into their performance and valuation (Brealey *et al.*, 2006). Firms' capital structure and the relevant implications arising thereafter has been one of the most popular fields of research in corporate finance. There are extensive number of theoretical and empirical studies of capital structure where they have attempted to provide alternative theoretical explanations for the proportions of debt and equity of firms and empirically test the determinants of capital structure as proposed by different theories, respectively.

The aim of the Thesis is to conduct an empirical analysis and not to develop a new theoretical framework, and since theories of capital structure have been reviewed in detail in a number of frequently cited (see, Harris and Raviv, 1991; Myers, 2003; and Frank and Goyal, 2009), we only discuss the descriptive aspects of the main versions of the theories without extending our discussion to cover the mathematical proofs surrounding the said theories and their subsequent versions and extensions. Accordingly, we assign more weight to the empirical literature than the theoretical literature, in order to develop a conceptual framework for our empirical analysis and inform the choice of variables used in our model[2].

[2] The capital structure literature is vast, containing hundreds of papers. Inevitably, we have left out a great deal. For excellent surveys on capital structure theories and empirical findings, see: Myers (1984); Harris and Raviv (1991); Myers (2003); Strebulaev (2007); and Frank and Goyal (2009). Furthermore, Migo (2010) provides a detailed presentation of the basic models and equations of some of the main theories of capital structure.

Reviewing the literature, we emphasise the Modigliani-Miller irrelevance theory, the trade-off theory, the agency theory and the pecking order theory of capital structure. While the Modigliani-Miller theory proposes that, under perfect capital market conditions, the choice of capital structure is irrelevant to the firms' overall value, other theories have raised concerns regarding the validity of the perfect market assumption and hence reject the irrelevance of capital structure proposition. For instance, the trade-off theory states that, there exists an optimal capital structure that maximises firm value by balancing the marginal tax advantages of debt against the marginal bankruptcy costs associated with debt financing. On the other hand, agency theory proposes that optimal capital structure is determined by minimising total agency costs associated with the use of debt and equity. Finally, pecking order theory suggests that, information asymmetries problems associated with external financing lead firms to have a preference towards internal financing. Similarly, because of the smaller adverse selection problems associated with debt issues relative to equity issues, if external financing is required, debt is always preferred to equity.

Despite their widespread acceptance, these theoretical predications may not exactly correspond to the financing behaviour of firms in practice. This is because, these predictions are based on simplified models that assume away many of the real life complications such as transaction costs, market conditions, firm's financial health, risk attitude of investors, and the overall economic conditions in which firms operate. Accordingly, in order to enhance our understanding of the determination of capital structure in practice and inform our choice of analysis variables, we provide a critical review of the empirical literature of capital structure.

Reviewing the choice of estimation model and measure of capital structure, we find that the choice of capital structure measure varies significantly, depending on the objective of the analysis. Thus, using the 3 common selection criteria in the literature (i.e., nature of financial obligation, time-horizon of the liability; and the basis of valuation), we choose the book debt-to-capital leverage ratio as our measure of capital structure. Furthermore, there has been significant support for the existence of a target leverage and the gradual adjustment behaviour of firms amongst empirical studies. This in turn, suggests the estimation of a dynamic model of capital structure including a 1-period lagged value of the capital structure measure.

In the course of reviewing the potential firm-specific determinants of capital structure, we emphasise growth opportunities, size, tangibility, profitability, non-debt tax shields and business risk, as they seem to have appeared more frequently as significant firm-specific determinants of capital structure than other variables. Overall, the general consensus among empirical studies concerning capital structure are; leverage increases with firm size and asset tangibility, and decreases with growth opportunities, profitability, non-debt tax shields and business risk. Accordingly, to capture the impact of these commonly used firm-specific determinants of capital structure, we identify appropriate proxy variables for growth opportunities; firm size; degree of asset tangibility; profitability; non-debt tax shields; and business risk to be used in our estimation model of capital structure.

Next, we review the empirical findings on the impact of the recent Global Financial Crisis (GFC) on firms' capital structure. We find that, despite general inconsistencies concerning the *direction* of the impact of the recent GFC on firms' leverage ratios, all the reviewed studies provide supporting evidence for the *significance* of the impact. Furthermore, the critical evaluation of alternative methods that have been used by previous studies suggest that inclusion of a set of annual time dummy variables seems to be the most appropriate approach to capture the impact of the recent GFC on firms' capital structure. Finally, introducing the issue of zombies in the context of capital structure, we propose that the zombieness status may be a possible determinant of capital structure. Therefore, we will also include a dummy variable (equal to 1 if zombie, 0 otherwise) to capture the variation in capital structure that is attributable to zombie-specific characteristics.

The rest of the chapter is structured as follows. Section 2.2 provide a review of the main theories of capital and discuss their properties. Section 2.3 reviews the key empirical findings of the literature regarding the appropriate measure of capital structure, the existence of a target capital structure, the most commonly used firm-specific determinants of capital structure, the impact of the recent GFC on firms' financing decisions, and the issue of zombies. Finally, Section 2.4 concludes this chapter.

2.2. Theories of Capital Structure

In this section, we review some of the major theories of capital structure to provide a framework for our subsequent empirical analysis. We focus on the most prominent and frequently discussed theories. Reviewing the literature, we emphasise the Modigliani-Miller irrelevance theory, the static and dynamic versions of the trade-off theory, the agency theory and the pecking order theory of capital structure[3].

2.2.1. The Modigliani-Miller Irrelevance Theory

The modern theory of capital structure began with the study of Modigliani and Miller (1958), which argues that, under "perfect" capital markets condition, the choice of capital structure is irrelevant to the firm's cost of capital and overall value[4]. The Modigliani-Miller (hereafter MM) irrelevance theory consists of two main propositions. Proposition 1 claims that a firm's value is independent of the proportions of debt and equity it uses to finance its total assets. Proposition 2 states that, the firm's Weighted Average Cost of Capital (WACC) used as the discount rate for valuation is also independent of its capital structure. This suggests that, firms are not able to reduce cost of capital by substituting "cheap" debt for "expensive" equity. That is, the reduction in the cost of capital due to larger debt component is offset by the increase in the cost of remaining equity, hence the constant WACC[5]. The simple analogy commonly used to explain the MM propositions is that, the overall value of a pizza (value of the firm) does not depend on how it is sliced (how the firm finances its

[3] Other major theories include the signaling theory of capital structure (Ross, 1977) and the market timing theory of capital structure (Baker and Wurgler, 2002). For excellent surveys on the capital structure theories and the empirical findings, see Myers (1984), Harris and Raviv (1991), Myers (2003) and Frank and Goyal (2009).

[4] Myers (2003) notes that, the "perfect" condition requires that capital markets are not only competitive and frictionless, but also complete, so that the risk characteristics of every security issued by the firm can be matched in capital markets by the purchase of another existing security or a dynamic trading strategy. Furthermore, the assumption of competitive and frictionless capital markets implies that, there are no taxes, no transaction costs, no bankruptcy risk (i.e., debt is risk-free), and that individual investors are able to borrow and lend on their own at the same rate as firms do to obtain the preferred leverage level that is not offered by firms (Modigliani and Miller, 1958).

[5] $WACC = r_A = r_D \frac{D}{V} + r_E \frac{E}{V}$, where WACC is the hurdle rate for capital investments by the firm and its valuation and D, E and V are debt, equity and firm value, respectively. r_D and r_E are the cost of debt and the cost of equity, respectively.

investments), as long as the overall size of the pizza remains the same (total assets of the firm is constant).

A major issue with the MM irrelevance theory is that it is only valid under the assumption of perfect capital markets, which almost never holds in practice. Nonetheless, even though the MM theorem is too restrictive to apply in practice, it specifies under what conditions capital structure does not affect firm's value. As Miller (1989: p. 7) notes: "*... showing what doesn't matter can also show, by implication, what does*". Accordingly, the existence of different market imperfections such as, bankruptcy risk, transaction costs, corporate taxes, costs of financial distress, information asymmetries, and conflicts of interest among stakeholders have led to the emergence of alternative and more practically applicable theories of capital structure. These theories have been developed to explain the choice of capital structure and its determinants while incorporating different market imperfections that were ignored in the MM theorem.

2.2.2. The Trade-off Theory

A short while after their seminal paper generated significant debates among finance academics and practitioners, Modigliani and Miller (1963) developed a modified version of their irrelevance theory. They attempted to give a more practical edge to the original theory by allowing it to accommodate income taxes and the tax advantage of debt financing. Generally, given the tax deductibility of interest payments, larger debt component in capital structures would increase firm value by reducing corporate tax expenses (Modigliani and Miller, 1963). However, the linear nature of the firm's objective function and more importantly the lack of any offsetting costs of debt in Modigliani and Miller's (1963) model would imply maximum (100%) debt financing by firms[6]. Their fundamental argument that the tax advantage of debt would lead to higher debt to equity ratios was also confirmed by other studies. For instance,

[6] They also note that, the existence of tax advantage for debt financing does not necessarily mean that firms should at all times have the maximum possible debt to equity ratios, however, they argue that some external factors that cannot be incorporated into their model might cause the less-than-maximum amount of debt in firms' capital structures. For instance, they note that firms may not always operate at the maximum possible amount of debt in their capital structure because sometimes other forms of financing, such as retained earnings, may be cheaper even when considering the tax advantage of debt financing, or in most cases lenders may impose strict limitations on the maximum amount a firm can borrow relative to its equity. For more details, see Modigliani and Miller (1963).

Hirshleifer (1966) and Robichek and Myers (1966) using state-preference modelling prove that, in the existence of income taxes and absence of bankruptcy, any attempt to reduce taxes will have a positive impact on firm value[7].

2.2.2.1. The Static Trade-off Theory

Kraus and Litzenberger (1973), on the other hand, argue that, both the tax advantage of debt and the bankruptcy costs associated with increased debt obligations should be considered in the determination of a firm's capital structure. That is, as firms continue to increase their debt obligations to benefit from greater interest tax shields, the risk of bankruptcy and its associated costs would increase too. Although others had previously noted the existence of a trade-off between benefits and costs of debt, Kraus and Litzenberger (1973) were among the first to formally introduce the trade-off theory of capital structure by incorporating tax advantage of debt and the associated bankruptcy costs into a static state-preference framework[8]. In their state-preference model, the firm's capital structure determines the states in which it receives the tax shields as well as the states in which the firm incurs bankruptcy costs, and the optimal capital structure is obtained at the debt level for which the resulting division of states yields the maximum market value of the firm[9]. Accordingly, the trade-off theory proposes that the optimal debt ratio that maximises firm value is determined by balancing the tax advantages of debt against the bankruptcy costs associated with debt financing.

The static trade-off theory is essentially a single-period model and therefore, by construction, assumes that leverage is always at the solution (i.e., target optimal level). The single-period framework as well as the assumption of no transaction costs of the Kraus and Litzenberger (1973) theory implies that, target ratio adjustment is costless and hence firms could adjust their leverage ratio instantaneously. However, firms in

[7] The term 'bankruptcy', which is commonly used in the US is the equivalent of the term 'insolvency', which is commonly used in the UK. They both refer to circumstances where firm is unable to pay its financial obligations. For consistency with the existing literature of capital structure, we will also use the term 'bankruptcy' in the remaining of this Thesis.

[8] For instance, Robichek and Myers (1965) note that, the optimization of capital structure involves a tradeoff between "*the present value of the tax rebate associated with a marginal increase in leverage … [and] the present value of the marginal cost of the disadvantages of leverage*" (Robichek and Myers, 1965: p. 20).

[9] Firms tend to increase their debt levels until the tax shield due to deductibility of interest expenses equals the marginal cost of debt, including the premium due to the increasing probability of bankruptcy as debt increases. For a detailed presentation of the static trade-off theory, see Bradley *et al.* (1984).

the real world operate over many periods and when taking into account transaction costs and other forms of market imperfections, their capital structure may not exactly correspond to the optimal level (Jalilvand and Harris, 1984). Consequently, the static trade-off theory fails to address the target adjustment behaviour of firms. Furthermore, the notion of retained earnings cannot be accommodated in a single-period model. Thus, the static trade-off theory also fails to control for the building up of inside equity (through accumulation of retained earnings) and is, therefore, unable to explain the lower leverage ratio of profitable firm caused by building up retained earnings.

2.2.2.2. The Dynamic Trade-off Theory

Failure of the static trade-off theory to address the issues above led to the introduction of the dynamic trade-off theory of capital structure by Fischer *et al.* (1989). They attempted to improve the static trade-off theory by modelling capital structure in a continuous-time framework and allow for temporary deviations from target ratio by introducing target adjustment transaction costs[10]. Consequently, the dynamic trade-off theory is able to control for temporary deviation from optimal capital structure and the gradual target adjustment process[11].

Fischer *et al.* (1989) and Goldstein *et al.* (2001), among others, argue that, the option to increase leverage in the following period has a value, which in turn would cause value maximising firms to operate at a lower than the optimal leverage ratio in the current period. That is, firms that are operating at a lower than optimal leverage ratio in the current period have an unexploited borrowing power or debt capacity which gives them the option to increase leverage in the next period, if needed. The multi-period framework of the dynamic trade-off theory allows investigating the unexploited

[10] Although Kane *et al.* (1984) and Brennan and Schwartz (1984) developed the first dynamic models to consider the tax advantage of debt versus the bankruptcy costs of debt, they assumed away transaction costs and hence failed to address the target adjustment behaviour of firms over time. Fischer *et al.* (1989) was the first attempt to introduce transaction costs into the analysis of dynamic capital structure and relax the unrealistic assumption of rapid rebalancing of leverage ratio.

[11] Many studies have investigated the factors affecting the speed of adjustment (e.g. Jalilvand and Harris, 1984; Leary and Roberts, 2005; Flannery and Hankins, 2007; and Byoun, 2008). For instance, Flannery and Hankins (2007) show that, the speed of adjustment towards the target leverage ratio depends on two types of costs. First, the adjustment costs which, in turn, depend on transaction costs and the market value of equity. Second, the costs of deviating from the target leverage which are a function of the probability of bankruptcy and the present value of firm's tax shield.

borrowing power by examining the relationship between the current and the future period capital structure.

The trade-off theory has a common-sense appeal. Generally, since interest payments on debts are tax deductible, an increase in debt levels would increase firm value via a reduction in taxable income[12]. On the contrary, additional debt also increases the probability of bankruptcy and its associated costs, which in turn would lead to lower firm value.

Bankruptcy costs can be direct or indirect. Direct costs of bankruptcy may include transaction costs associated with bankruptcy procedure and reorganisations, such as filing and administration fees, legal expenses, and costs of liquidating assets. These costs are easy to identify and so they can be measured against the tax advantages of debt financing. Indirect costs of bankruptcy may arise from the conflicts of interest between debt holders and equity holders, also known as the agency costs of debt[13]. Given that equity holders are the residual claimants of the firm's assets, any reduction in the value of debt could increase the value of residual claims. Accordingly, assuming a significant risk of bankruptcy and managers acting in the interest of equity holders (i.e., maximising the stock market valuation of firm), managers could transfer value from debt holders to equity holders via two means: risk-shifting (Jensen and Meckling, 1976) and underinvestment (Myers, 1977).

The risk-shifting problem or the 'asset-substitution' problem may arise from managers' decision to undertake riskier operating strategies and investing in excessively risky assets in order to increase equity holders' wealth at the expense of debt holders (Jensen and Meckling, 1976). That is, if the risky investment succeeds, the entire gain is absorbed by equity holders as debt holders are entitled to a previously agreed fixed payment and, if the new investment fails, most of the loss is absorbed by debt holders since they have the primary claim on firm's assets. Therefore, as debt increases, equity holders and through delegation managers have stronger incentives to exploit the asymmetric share of benefit and costs of new

[12] For a comprehensive review of the impact of taxation on corporate financial policy, see Auerbach (2002) which shows that the magnitude of the tax benefit of debt to firm value depends in a complex way on the personal tax rates faced by shareholders.

[13] Agency costs of debt arising from the conflict of interest between managers and equity holders and between managers and debt holders (assuming managers acting in their own interest) will be discussed in more details in Section 2.2.3.

investments, and hence to transfer value from debt holders to equity holders by undertaking overly risky investments.

The underinvestment problem or what Myers (1977) refers to as 'debt overhang' may arise from managers' decision to cut back equity-financed capital investments. The core argument behind the debt overhang problem is essentially the reverse of the risk-shifting problem. While the equity holders incur the entire cost of a fully equity-financed investment (i.e., via using retained earnings or issuing new equity), debt holders would absorb part of the additional generated value in the form of higher value of debt. That is, the larger the capital investments of the firm, the greater are the collaterals against which debt holders could make a claim, and hence the higher would be the market value of debt. This gain in the value of debt is similar to a tax expense, in the sense that it could discourage managers to undertake value-enhancing capital investments and instead distribute cash to equity holders. Accordingly, the larger the debt component of capital structure, the larger would be the increase in the value of debt and hence the greater would be the incentive of managers to cut back on new capital investments.

However, debt holders are also aware of the possible exploitation of their wealth by equity holders and would design the debt contracts accordingly[14]. As firms obtain additional borrowing, the probability of bankruptcy would increase and thus debt holders would require higher return on their investment (i.e., higher cost of debt) to reflect the increased costs of bankruptcy. This would increase the firm's cost of capital (i.e., discount rate for valuations) which would in turn reduce firm value. Accordingly, the theory suggests that, the optimal capital structure that maximises firm value is the leverage ratio at which marginal benefit of debt financing equal marginal costs associated with debt financing.

With regard to possible determinants of capital structure, the trade-off theory suggests that firm-specific characteristics that may imply higher bankruptcy costs are expected to be negatively correlated with leverage ratio and those that suggest higher tax advantage of debt are expected to be positively correlated with leverage ratio.

[14] For instance, different debt covenants such as constraint on new debt issues or dividend payments and minimum debt coverage ratios may be imposed to restrict the firm's ability to exploit debt holders. See Smith and Warner (1979) and Barclay and Smith (1995a, b) for a detailed analysis of how debt contracts are designed to avoid indirect bankruptcy costs.

Furthermore, given that interest tax shields are associated with higher debt ratios, non-debt tax shields due to other tax deductible items such as depreciation and amortisation expenses are expected to have a negative correlation with leverage ratio.

Overall, the trade-off theory suggests that, firms choose their optimal capital structure by balancing the tax advantages of debt against the bankruptcy costs associated with debt financing. However, this implies that, no debt should ever be used in the absence of tax shields, if bankruptcy costs are positive. Nonetheless, firms have a long history of using debt in their capital structure before the introduction of tax deductibility of interest payments. Moreover, the tax advantage of debt could only explain debt levels to a certain extent, as there are limits to the amount of corporation tax deductions allowed for interest and other finance expenses (e.g., the debt cap rules introduced in Finance Act 2009 for UK firms). Thus, the trade-off theory seems to have failed to capture some important determinants of the corporate capital structure.

2.2.3. The Agency Theory

As discussed in the previous section, the trade-off theory assumes that managers hold a large proportion of firm's equity such that there is no conflict of interest between managers and outside equity holders (Kraus and Litzenberger, 1973). However, in practice, ownership and management of firms are not necessarily the same (i.e., managers often hold only a small proportion of the firm's equity), which could cause a conflict of interest between the two stakeholders. Accordingly, assuming management acting and undertaking financing decisions in line with the interest of equity holders might not be a plausible condition to hold in practice[15].

The agency theory of capital structure, originally developed by Jensen and Meckling (1976), highlights the importance of ownership structure (i.e., the relative amount of ownership claims held by managers and outside equity holders), separation of

[15] An important point to note is that, in the context of trade-off theory, the agency costs of debt component of indirect bankruptcy costs are based on the assumption that managers act in the interest of equity holders and thus have conflict of interest with debt holders. However, in the context of agency theory, managers are assumed hold a proportion of the firm's equity and act in their own interest, thus the agency costs of debt arise from managers' incentive to reallocate wealth from debt holders to themselves and not necessarily to other equity holders.

ownership and control, and firm's objectives in determination of capital structure[16]. Jensen and Meckling (1976) define agency relationship as a contractual agreement between one or more person, called principal(s), and another person, called the agent, under which an agent is delegated some authority to make decisions on behalf of the principals, usually, to increase the value of their investment. However, as they note: *"If both parties to the relationship are utility maximizers there is good reason to believe that the agent will not always act in the best interests of the principal"* (Jensen and Meckling, 1976: p. 308). Such conflicts of interest could be reduced by enforcing various monitoring and controlling mechanisms aimed to discourage managers from making suboptimal decisions in the pursuit of their own interest. Accordingly, the agency theory proposes that an optimal capital structure is determined by minimising the total costs associated with the conflict of interest between management of the firm and other stakeholder (i.e., outside equity holders and debt holders).

Generally, the sum of the monitoring expenditures by the principal, the bonding expenditure by the agent (where, it will pay the agent to incur the monitoring costs himself), and the residual loss (i.e., the dollar value of reduction in principals' welfare due to the suboptimal decisions of managers) are referred to as 'agency costs' (Jensen and Meckling, 1976). The agency costs due to the conflict of interest between equity holders and managers are referred to as the agency costs of equity and the agency costs due to the conflict of interest between managers and debt holders are referred to as the agency costs of debt.

2.2.3.1. The Agency Cost of Equity

In the existence of outside equity holders (equity holders other than managers), managers may have the incentive to act in their own interest and seek private benefits, both pecuniary and non-pecuniary (e.g., salaries, perquisites, job security, reputation, empire-building etc.), rather than maximising equity holders' welfare or increasing firm value. That is because managers would absorb the entire gain from using firm's

[16] Jensen and Meckling (1976) developed a simple model to analyse the impact of agency costs of equity and debt on the optimal capital structure of firms. However, their model is based on a number of restrictive assumptions that are very difficult to hold in practice. For instance, it ignores the dynamic aspects and the multi-period nature of the problem (i.e., static model), it assumes all taxes to be zero (i.e., no tax advantage of debt), and all outside equity shares are assumed to be non-voting (i.e., managers control the firm).

resources for personal benefits, while only bearing a fraction of the costs[17]. Similarly, managers may have insufficient incentive to maximise total equity value because they would only absorb a fraction of the gains (depending on their proportional equity holding) from making optimal investments decisions that maximises firm value, while they must bear the entire costs of curbing self-utility maximising activities. However, new investors are also aware of the divergence of interest between managers and outside equity holders and therefore have an incentive to incur some monitoring costs in order to ensure that managers' activities are aligned with their interest[18]. Since such monitoring of expenditures would reduce the value of their claims on the firm, outside equity holders would take the present value of the expected monitoring costs and other agency costs of equity into account, when determining the maximum price they are willing to pay for any given fraction of the firm's equity.

Accordingly, the agency theory suggests that, the agency cost of equity is at minimum (zero); where, a firm is wholly owned by its management, and it increases as the proportion of outside equity increases. Conversely, the increase in outside equity holding reduces managers' share of the costs associated with self-utility maximising activities and the suboptimal decisions, while holding constant their share of benefit from undertaking such decisions. This would, in turn, increase their incentive to transfer wealth from outside equity holders to themselves. On the other hand, the marginal benefit from monitoring activities increases as outside equity holding increases, which would consequently increase the optimal level of monitoring. Both of these factors would imply greater agency costs of equity, suggesting a smaller equity component in the firms' capital structure.

2.2.3.2. The Agency Cost of Debt

The agency costs of debt were previously discussed in the trade-off theory section as part of the indirect costs of bankruptcy. While under both theories the agency costs of

[17] For instance, if the management own 95% of firm's equity, they would spend firm's resources on self-utility maximising activities to the point where the marginal utility derived from a dollar's expenditure of the firm's resources on such activities equals the marginal utility of an additional 95 cents reduction in equity value, and not one dollar.

[18] Monitoring includes more than just measuring or observing the behaviour of the agent. It includes efforts on the part of the principal to 'control' the behaviour of the agent through budget restrictions, compensation policies, operating rules etc. See Ross (1973) and Jensen and Meckling (1976) for more details.

debt are expected to have a detrimental impact on firm value and a negative relation with the debt-to-equity ratio, the trade-off theory and the agency theory differ in their assumption regarding the agency relationship between managers and outside equity holders. In the trade-off theory, managers are assumed to act in the interest of equity holders and hence the agency costs of debt are due to the conflict of interest between equity holders and debt holders, whereas in the agency theory managers are assumed to have a fraction of the residual claims on the firm and act in their own interest and, thus the agency costs of debt stem from the conflict of interest between managers and debt holders rather than the outside equity holders.

The limited liability nature of equity implies that, if a firm is successful, once the *ex-ante* fixed payment to debt holders is paid, equity holders are entitled to a claim on the entire remaining of the firm's assets, and if the firm defaults or goes into bankruptcy, equity holders would only lose the amount initially invested in the firm and the majority of the costs are borne by debt holders. Thus, while the total cost borne by equity holders remains constant, their expected payoff would increase as the investment payoff increases. The reverse is true for debt holders. That is, while their maximum payoff is constant, the total cost borne by debt holders increases as the riskiness of the investment increases. Accordingly, the agency theory suggests that, with inclusion of debt component in the capital structure of firms, managers would have an incentive to substitute firms' assets with riskier assets by undertaking risky investments with high payoffs[19].

In addition to the 'asset-substitution' effect of debt, there may also exist an under-investment effect of debt or what Myers (1977) refers to as the 'debt overhang' problem. He suggests that, at substantially high leverage ratios where debt-financing is not a practical option, managers (and outside equity holders) would have strong incentives to pass on value-adding opportunities because of the unbalanced share of benefits and costs associated with fully equity-financed investments[20]. Furthermore, as discussed in Section 2.2.2, increased capital investments could decrease the probability of bankruptcy and its associated costs and, therefore, could increase the

[19] Jensen and Meckling (1976) use the analogy of poker players playing with money borrowed at a fixed interest rate with their own liability limited to some very small stake to describe the risk-shifting or the asset substitution effect of debt.

[20] That is, if the investment is successful, most of the gain would be absorbed by debt holders in the form of debt repayment, while the entire cost is borne by equity holders (including managers).

value of debt at the expense of equity holders. That is, the larger the capital investments of the firm, the greater are the collaterals against which debt holders could make a claim, and hence the higher the market value of debt. This gain in the value of debt is similar to a tax expense, in the sense that it could encourage managers to pass on value-enhancing capital investments financed by equity holders to avoid transfer of value from equity holders to debt holders.

Finally, the agency theory also acknowledges the role of direct bankruptcy costs as another factor explaining the firm's choice of capital structure, suggesting that the size of the debt component in the capital structure and consequently the firm's leverage ratio is expected to be negatively correlated with the probability of bankruptcy. As Jensen and Meckling (1976: p. 341) note:

> In practice, bankruptcy is not costless, but generally involves an adjudication process which itself consumes a fraction of the remaining value of the assets of the firm. Thus the cost of bankruptcy will be of concern to potential buyers of fixed claims in the firm since their existence will reduce the payoffs to them in the event of bankruptcy.

Similar to the outside equity holders in the previous section, debt holders are also aware of these conflicts of interest and have an incentive to incur some monitoring costs to prevent managers from undertaking decisions that would reduce value of debt[21]. These monitoring costs generally involve writing and enforcing different covenants as part of the debt agreement such as, imposing constraint on new debt issues, dividend payments and minimum debt coverage ratios that would limit managers' ability to exploit debt holders' claims.

Accordingly, the agency cost of debt is also at minimum where a firm is wholly owned by its management and increases as the amount of debt in the firm's capital structure increases. This is because as the amount of debt increases, managers would have a greater incentive to reallocate any given amount away from debt holders to themselves, as simply there is a greater amount of debt available. Thus, as debt

[21] Although the monitoring expenses component of the agency costs of debt or equity may be incurred by equity holders or debt holders, they would incorporate the present value of the expected future monitoring costs in the price they will pay for buying any fraction of equity or debt claims and hence the costs are ultimately borne by managers.

increases the optimal level of monitoring by debt holders to prevent such activities amount of debt increases too. Both of these factors would cause the agency cost of debt to increase, suggesting smaller debt components in the firms' capital structure.

2.2.3.3. The Agency Cost of Free Cash Flows

While the agency theory of Jensen and Meckling (1976) suggests that, the agency costs associated with debt (monitoring costs and bankruptcy costs) would discourage the use of debt and hence correspond to lower leverage ratios, Jensen (1986) identifies an offsetting effect of debt that would encourage larger debt components in firms' capital structure. He introduces an alternative angle to look at the conflict of interest between managers and outside equity holders, or what he refers to as the 'agency theory of free cash flows'. As discussed before, managers have a tendency towards empire building and increasing the resources under their control by undertaking suboptimal investment decisions. However, equity holders would surely prefer the distribution of firm's free cash flows in the form of dividends or share repurchases, rather than wasting them on non-value adding or negative NPV investments. Jensen (1986: p. 323) argues that: "*the problem is how to motivate managers to disgorge the cash rather than investing it below the cost of capital or wasting it on organizational inefficiencies*". Accordingly, he suggests that, since debt is a contractual agreement that obligates firms to pay out cash and the failure to do so could lead to bankruptcy of the firm, debt can be used as a disciplinary tool to reduce the agency cost of free cash flows by constraining the cash flow available for spending at the discretion of managers.

Overall, the agency theory of Jensen and Meckling (1976) proposes that the optimal capital structure of the firm is obtained at the debt-to-equity ratio that minimises total agency costs. Consequently, the firm-specific characteristics that may indicate higher agency cost of debt and/or lower agency cost of equity are expected to be negatively correlated with the firm's leverage ratio and those characteristics that suggest lower agency cost of debt and/or higher agency costs of equity are expected to be positively correlated with the firm's leverage ratio.

2.2.4. The Pecking Order Theory

Although the pecking order theory's roots can be traced back to Donaldson (1961), it was only in the early 1980s that Myers (1984) and Myers and Majluf (1984) formally introduced and developed the pecking order theory of capital structure, as an alternative to the trade-off theory. The pecking order theory of capital structure is based on a number of underlying assumptions: managers as insiders to the firm know more about the true value of the assets-in-place and the future growth opportunities than outside investors, only positive-NPV investments will be undertaken, and managers act in the interest of existing equity holders (Myers and Majluf, 1984)[22].

The theory starts with a firm with some assets-in-place and a growth opportunity that requires additional financing, where the only financing option is equity issuance. Since outside investors do not know the true value of the assets-in-place and the new investment's NPV, the announcement of an equity issue could be inferred as either good or bad news. It is good news, if it reveals positive-NPV growth opportunities, and it is bad news, if it reveals that managers perceive the firm's equity to be overvalued and thus attempt to take advantage of the current high prices. Outside investors are aware of the latter 'adverse selection' problem and would infer a decision to issue equity as signalling an over-valued firm[23]. Accordingly, they would incorporate the bad news in the price they will pay to buy equity claim, which in turn affects the financing-investing decision of the firm.

Myers and Majluf (1984) show that, when firms decide to finance new investments by equity issues, the bad news (overvalued equity) would always outweigh the good news (positive-NPV investment), and would result in an undervaluation of the firm's equity[24]. In the existence of severe information asymmetry, the undervaluation of

[22] The last assumption implies that; managers' objective is to maximise the true value of the existing equity holders' claim. Furthermore, this objective function also assumes that outside investors will discover the true value of the firm's assets-in-place *after* the decision to invest is made.

[23] Ross (1977, 1978) develops a signalling model to explain firms' choice of capital structure. He shows that, when the quality of firm (high quality or low quality) are only known to the inside managers and not to the market, debt issuance can be a signal of firm's quality. He proposes that, due to high costs to management, in the form of increased probability of bankruptcy, a low quality firm will not issue debt to signal that it is of high quality.

[24] They argue that, although equity would be, *on average*, correctly priced, the information asymmetry problem implies that a particular issue would be over- or under-priced. Outside investors are willing to pay an average price for the shares being offered by the firm as they do not know if the firm is overvalued or undervalued. Thus, the average price is favourable for overvalued firms and

equity may be so large that the value transferred to new investors from buying equity at the new low price would exceed the NPV of the new investment, resulting into a net loss to the existing equity holders. Given that managers' objective is to maximise the value of the existing equity holders' claim, managers of a good firm (i.e., equity is undervalued) would pass up new investment opportunities and not issue any new equity. Accordingly, the decision to issue new equity would be inferred as bad news, indicating an overvalued firm[25].

Myers and Majluf (1984) then introduce risk-free debt as an alternative source of finance in their model and show that, the above underinvestment problem could be avoided if the firm uses debt instead of equity to finance the new investment. That is, since debt has the prior claim on the firms' earnings and assets-in-place and no new equity claims are sold, debt issues would not have a detrimental impact on firm value[26]. Assuming risk-free debt, the trade-off theory implies that, for as long as debt is available as an external source of finance, firms would never issue equity as any attempt to do so would signal overvalued equity (Myers and Majluf, 1984). However, Myers (1984) relaxes this assumption by introducing risky debt. He shows that, if risky debt is issued, the negative impact of the information asymmetry and the consequent underinvestment problem on firm's value would be less severe than equity issue but more than the risk-free debt[27].

So far, it has been assumed that firms require external finance in order to fund the new investment opportunities. However, if a firm has sufficient financial slack (i.e., internal funds) to finance its investments, then the information asymmetry problem does not matter anymore. That is, using internal sources of finance such as retained earnings and free cash flows instead of raising new debt or equity would signal a positive-NPV investment opportunity (i.e., good news). Furthermore, since no new claims on a firm's assets-in-place are issued, financing the new positive-NPV

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unfavourable for undervalued firms. Consequently, managers are only willing to issue equity if they think the firm is overvalued.

[25] Consistent with this argument, empirical studies have documented substantial negative price reactions to equity issue announcements (Masulis and Korwar, 1986) that are less negative following credible releases of information (Korajczyk *et al.*, 1991).

[26] Consistent with this, analysing around 300 US corporate debt issues during 1980-1986, Shyam-Sunder (1991) shows that for investment-grade issues, where default risk is very small, the stock price impact of debt issue announcement becomes negligible.

[27] Eckbo (1986) and Asquith and Mullins (1986) provide event study evidence in support of the pecking order theory and show that adverse selection is more significant for equity issues than for risky debt issues.

investments by using internal funds would not have any detrimental impact on firm value.

Overall, the pecking order theory of Myers and Majluf (1984) and Myers (1984) suggests that, using internal sources of finance enables the firm to disentangle its investment decisions from possible conflicts of interest between existing equity holder and new investors. Furthermore, since the forgone opportunity cost of retained earnings and free cash flows is cheaper than issuing new debt or equity, firms would always prefer to exhaust their internal sources of finance to fund new investments before raising external finance. Besides, while issuing additional debt increases the probability of bankruptcy and its associated costs, which in turn would increase the firm's cost of capital, internal financing does not have such undesirable consequences. Finally, as Myers (2003: p. 241) notes: "*the firm prefers internal to external finance, and prefers debt to outside equity until debt becomes so risky and costly that managers turn to outside equity as a last resort*". Accordingly, it is only when internal resources are not available or are insufficient that firms raise external finance, and they would do so in accordance to the riskiness of securities (i.e., safest securities are issued first), implying the issuance of debt before equity.

To summarise, unlike the trade-off and the agency theory that are based on the existence of an optimal capital structure that maximises firm value, the pecking order theory focuses on the hierarchy of the firm's financing sources. It suggests that, due to the information asymmetries between new investors and managers about the firms' true values, firms would prefer to finance their new investment by using their internal funds rather than raising external finance. Likewise, if external financing is required, debt is always preferred to equity, because of the smaller associated adverse selection problem. Finally, equity would only be issued as a last resort, when the risk of bankruptcy due to large amounts of debt is sufficiently high. Accordingly, with regard to the possible determinants of capital structure, the pecking order theory suggests that firm-specific characteristics that may imply greater information asymmetries or smaller internal sources of finance are expected to be positively correlated with leverage ratio and those characteristics suggesting that firms have greater internal sources of finance to fund their investment activities and are therefore

less exposed to the 'adverse selection' problem, are expected to be negatively correlated with leverage ratio.

2.2.5. Summary

In sum, each of the theories proposes a different explanation for how firms make financing decisions and suggests different predictions regarding the firm-specific determinants of capital structure. For instance, firm characteristics that are associated with larger tax-benefit of debt (trade-off theory), greater agency cost of equity and free cash flows (agency theory), or severe information asymmetries and adverse selection problem (pecking order theory) are expected to be associated with larger debt component in the capital structure, and hence to have a positive relationship with the firms' leverage ratios. On the other hand, factors associated with higher bankruptcy costs, greater probability of bankruptcy and agency costs of debt, or smaller information asymmetries are expected to have a negative relation with the debt-to-equity ratio.

However, these theoretical predications may not exactly correspond to the financing behaviour of firms in practice, as they are based on simplified models that work best in theory and assume away many of the real life complications such as transaction costs, market conditions, firm's financial health, risk attitude of investors, and the overall economic conditions in which firms operate. Accordingly, in order to obtain a better understanding of the firms' financing decisions and identify the determinants of capital structure in practice, we must look at the findings of the empirical studies of capital structure. This will be the focus of the next section.

2.3. Empirical Findings

There have been many attempts to investigate empirically the predictions of capital structure theories by using a set of firm-specific variables that represent tax benefits of debt, bankruptcy costs of debt, agency costs of equity and debt, and information asymmetries associated with issuing debt and equity. These studies vary in purpose, sample, choice of variables and estimation techniques. Focusing on the most important and frequently cited empirical studies, we will identify the most commonly used and significant firm-specific determinants of capital structure, review the theoretical predictions and empirical findings regarding their impact on firms' leverage ratios, and identify the proxy variables to measure them. After that, we will provide a critical review of the empirical studies focusing on the impact of the recent GFC on firms' capital structure and their findings. Finally, in order to introduce the concept of zombie firms and put it into context, we will provide a brief summary of corporate insolvency in the UK after the recent GFC and the consequent recession, and how it may have led to the emergence of zombies.

2.3.1. Measure of Capital Structure

In order to conduct an empirical investigation about the possible determinants of capital structure, one must first define the measure of capital structure that will be used in the analysis. However, apart from the many competing theories of capital structure, there have also been significant variations in the choice of capital structure measure used by the empirical studies of capital structure. While most studies use some form of a debt to equity ratio as their measure of capital structure, they differ in their choice components, depending on the objective of the analysis (Myers, 2003).

Generally, measures of capital structure may vary on three main accounts: whether debt is defined as total financial obligations or only interest-bearing obligations; whether total debt or long-term/short-term debt components are used; and whether leverage ratios are calculated using book values or market values.

With regards, to the definition of debt, while some studies have used total liabilities as the debt component of capital structure (e.g., Bevan and Danbolt, 2004 and González

et al., 2013), the majority others only include the interest-bearing debt in their measure of capital structure (e.g., Ozkan, 2001; Deesomsak *et al.*, 2004; Wanzenried, 2006; De Jong *et al.*, 2008; and Fosberg, 2012)[28]. The advocates of the interest-bearing debt argue that, since total liabilities include non-financing items such as accounts payable and receivables, they are likely to overestimate and fail to capture the true default risk of the firm (Drobetz and Wanzenried, 2006). On the hand, the measure of total interest-bearing interest excludes non-financing items that are used for transaction purposes rather financing purposes and, thus does not suffer from an overestimation bias (Rajan and Zingales, 1995).

Furthermore, leverage ratios may also vary depending on whether they are computed using short-term/long-term or aggregate debt components. While the choice of type of debt is determined by the objective of the analysis, studies that do not use the aggregate measure of debt argue that some of the theories of capital structure have different implications for the different types of debt and thus the predicted impact of the determinants of capital structure may differ according to whether long-term, short-term or total debt is used in the leverage ratio (see, Titman and Wessles, 1988; Bevan and Danbolt, 2004; and Frank and Goyal, 2009). However, this is only relevant when the objective is to evaluate the performance of different theories, rather than merely identifying the determinants of the overall capital structure of the firm, irrespective of its debt structure. In fact, if the objective is to merely identifying the determinants of the overall capital structure of the firm, irrespective of its debt structure, using only long-term or short-term debt can lead to substantial underestimation of the degree of indebtedness and fail to capture the true financial structure of the firm.

The final issue is whether leverage should be computed using the book or the market values. Although there is no consensus, most of the empirical studies of capital structure have focused on one main leverage measure and report the results based on alternative measures only as a robustness check (Titman and Wessels, 1988; Lasfer, 1995; Rajan and Zingales, 1995; Bevan and Danbolt, 2002 & 2004; Frank and Goyal, 2009; Kashefi-Pour, 2011; Fosberg, 2012). However, the arguments in favour of

[28] Many other leverage definitions have also been used in the literature. For instance, some studies treat cash holdings as negative debt and hence subtract cash from the debt measure to obtain a net debt measure. Similarly, corrections can also be made for a range of other assets and liabilities such as deferred taxes, pension liabilities, and others

using book value have been relatively stronger than those for using the market value. For instance, one caveat to using market value is that, given that market value of equity is affected by a number of external factors which are out of the control of the firms, using market value may not necessarily reflect the underlying financing decisions of the firm (Thies and Klock, 1992). In addition, book leverage is believed to be more reliable basis for financing decisions than market leverage as they are less affected by the fluctuations financial markets (Frank and Goyal, 2009). Consistent with this argument, the results of the CFOs survey study by Graham and Harvey (2001) indicate that, managers, in fact, do not consider changes in market value of their equity as an important factor affecting their debt policy. Furthermore, as noted by Fama and French (2002), most of the theoretical predictions regarding the determinants of capital structure are directly related to book leverage. On the other hand, there have been some arguments against the use of book leverage as a relevant measure of capital structure. For instance, Welch (2004) argues that, book value of equity is merely a 'plug number' to balance the left-hand side and the right-hand of the balance sheets rather than a managerially relevant number. However, given the documented high cross-sectional correlation between the book value and market value of debt correlations between the book and market values of leverage (e.g., Bowman, 1980; Titman and Wessels, 1988; Rajan and Zingales, 1995; Colombo, 2001; and Drobetz and Wanzenried, 2006), one should not expect to find significant differences in the estimation results based on the two measures[29]. Finally, market values of debt are often not readily available.

Accordingly, we use debt-to-capital leverage ratio (book leverage ratio hereafter), computed as: $\frac{Total\ Debt}{Total\ Debt+Total\ Shareholders'Equity}$, as our measure of capital structure. Where, *Total Debt* is calculated as the sum of firm's short-term and long-term interest-bearing obligations, and *Total Shareholders' Equity* is computed as the sum of common equity, minority interest and preferred equity. Previous studies of capital structure using this leverage ratio as their dependent variable include: Bradley *et al.* (1984); Rajan and Zingales (1995); Jordan *et al.* (1998); Bevan and Danbolt (2002);

[29] In a contrary argument, Barclay *et al.* (2006) and Frank and Goyal (2009) argue that, since the book and market ratios are conceptually different, the former being backward looking while the latter is of a forward looking nature, there is no reason why the two ratios should lead to the same results. They further note that, in fact, obtaining similar results based on significantly different measures could indicate potential problems with the analysis.

Drobetz and Wanzenried (2006); Kashefi-Pour (2011); and Iqbal and Kume (2014). We choose to use the book debt-to-capital leverage ratio as our measure of capital structure, having considered the followings:

Firstly, total interest-bearing obligations is chosen as the numerator, as unlike total liabilities, it excludes all non-financing items such as accounts payable and receivables that are used for transaction purposes rather financing purposes and, thus does not suffer from an overestimation bias of the financial position and default risk (Rajan and Zingales, 1995).

In addition, total debt is chosen as the numerator to capture both long-term and short-term debt obligations of firms and hence provide a better reflection of the firms' degree of indebtedness. Furthermore, since most of the firms in our sample use banks rather than capital markets as their main source of borrowing and most types of business borrowing such as lines of credit and loans to finance non-investment activities and short-term assets are typically of short-term nature, excluding them from the debt component may lead to substantial understatements of the leverage ratios. Moreover, the choice of using total vs. long-term debt does not affect the choice of explanatory variable, as all the studies that looked at long-term debt (e.g., Bradley *et al.*, 1984; Titman and Wessels, 1988; Kim and Sorensen, 1986; Lasfer, 1995; Booth *et al.*, 2001; De Jong *et al.*, 2008; and Fosberg, 2012) and total debt (e.g., Rajan and Zingales, 1995; Bevan and Danbolt, 2002; Frank and Goyal, 2003; Deesomsak *et al.*, 2004; Hovakimian, 2006; and Kashefi-Pour, 2011) separately, have used the same explanatory variables in their estimation models and only change the dependent variable.

Finally, given the sensitivity of the market value of equity to the fluctuations in the financial markets, and in order to better capture the underlying financing decisions of the firm, book value of equity is used in the denominator (see, Thies and Klock, 1992 and Frank and Goyal, 2009). However, while book leverage ratio is used as the measure of capital structure for the main analysis, we use the market leverage ratio, computed as $\frac{Total\ Debt}{Total\ Debt+Market\ Value\ of\ Equity}$, as an alternative measure of capital structure to conduct the robustness analysis (see, Section 4.3.5).

2.3.2. Dynamic Capital Structure

Recalling the discussion on the theories of capital structure in Section 2.2, unlike the trade-off and the agency theory that are based on the existence of an optimal capital structure that maximises firm value, the pecking order theory does not assume the existence of an optimal capital structure and instead focuses on the hierarchy of the firm's financing sources.

While, the argument for the existence of an optimal capital structure implies that, in a frictionless environment with no transaction costs and other adjustment costs, firms can adjust their capital structure completely and instantly towards the target level, Fischer *et al.* (1989) developed a dynamic model of capital structure, in which they allow for temporary deviations from target ratio by introducing transaction costs. Accordingly, they propose that, due to the existence of transaction costs and other associated adjustment costs, firms would adjust their capital structure towards their optimal level gradually rather than instantly.

Accordingly, a large body of empirical studies have attempted to test the two alternative views of capital structure by examining whether and how fast firms move towards target leverage. Reviewing the empirical literature suggests that, previous empirical studies of capital structure generally support the existence of target leverage and find evidence consistent with the gradual adjustment towards a target level (e.g., Marsh, 1982; Jalilvand and Harris, 1984; Hovakimian *et al.*, 2001; Ozkan, 2001; Fama and French, 2002; Maghyreh, 2004; Leary and Roberts, 2005; Flannery and Rangan, 2006; Lemmon *et al.*, 2008; Antoniou *et al.*, 2008; and Getzmann *et al.*, 2014). For instance, examining international data in the G-5 countries, Antoniou *et al.*, (2008) find supporting evidence for the dynamic nature of capital structure decisions, in the sense that firms tend to adjust their leverage ratios in order to achieve their target. They further find that, firms in different countries seem to adjust their capital structure at different speeds. That is, while firms in the US, UK, and France tend to have reasonably fast adjustment speeds (32%, 32%, and 39%, respectively), the German and the Japanese firms adjust their leverage ratios at a much slower pace (24% and 11%, respectively). Furthermore, using 1,239 large firms listed on 11 Asian stock exchanges, Getzmann *et al.* (2014) find significant evidence in support of the

existence of target leverage and active target adjustment behaviour of firms. In particular, they find that the annual speeds of adjustment range from 24% to 45%, depending on the specific industry effects.

While, the empirical studies of capital structure that are based on the existence of target capital structures estimate a standard dynamic model with no reference to the target leverage, it is important to know how the model has been constructed.

Assuming that the optimal leverage, (y_{it}^{*}), is a function of firm-specific characteristics, the following can be specified for the target leverage of firm i at time :

$$y_{it}^{*} = \emptyset_0 + \sum_{k=1}^{K} \gamma_k X'_{k,it} + \alpha_i + \alpha_t + u_{it}. \quad (2.1)$$

Where, X_{it} represents the vector of k possible determinants of leverage; α_i represents time-invariant unobservable firm-specific effects; α_t represents firm-invariant unobservable time-specific effects which are common to all firms and can change through time; u_{it} is the idiosyncratic disturbance term (i.e., error term) which varies across both time and individuals and is assumed to be serially uncorrelated with mean zero and constant variance: $u_{it} \sim i.i.d.N(0, \sigma^2)$; $\emptyset$ is the constant; and γ_k, is the unknown parameters to be estimated.

Accordingly, in the absence of transaction costs and other associated adjustment costs, firm is always operating at the optimal leverage, and hence the observed leverage ratio, y_{it}, is equal to the optimal leverage: $y_{it}^{*} = y_{it}$. This, in turn, implies that, the change in leverage from the previous period to the current period must be the same as the change required to return to the optimal leverage at time t:

$$y_{it} - y_{i,t-1} = y_{it}^{*} - y_{i,t-1}. \quad (2.2)$$

However, in practice, the existence of transaction and other adjustment costs make the adjustment process costly, and hence firms may not fully adjust their current leverage ratios to their optimal level from one period to the other. Accordingly, the incomplete adjustment toward the target leverage ratio can be specified by the following partial adjustment model:

$$y_{it} - y_{i,t-1} = \delta_{it}(y_{it}^{*} - y_{i,t-1}). \quad (2.3)$$

Where, δ_{it} is denotes the speed of adjustment. Moving $y_{i,t-1}$ to the other side, Eq. (2.3) can be written as follows:

$$y_{it} = (1 - \delta_{it})y_{i,t-1} + \delta_{it}y_{it}^{*}. \quad (2.4)$$

Substituting Eq. (2.1) into Eq. (2.4) to remove the unobservable optimal leverage (y_{it}^{*}) will yield:

$$y_{it} = (1 - \delta_{it})y_{i,t-1} + \delta_{it}\left(\emptyset_0 + \sum_{k=1}^{K}\gamma_k X'_{k,it} + \alpha_i + \alpha_t + u_{it}\right). \quad (2.5)$$

Simplifying Eq. (2.5) will yield the following:

$$y_{it} = \alpha_0 + \beta_1 y_{i,t-1} + \sum_{k=1}^{K}\beta_k X'_{k,it} + \mu_i + \lambda_t + \varepsilon_{it}. \quad (2.6)$$

Where, $\alpha_0 = \delta_{it}\emptyset_0$, $\beta_1 = 1 - \delta_{it}$, $\beta_k = \delta_{it}\gamma_k$, $\mu_i = \delta_{it}\alpha_i$, $\lambda_t = \delta_{it}\alpha_t$, and $\varepsilon_{it} = \delta_{it}u_{it}$.

Where, the estimate on the speed of adjustment is computed as (*1- the coefficient on the lagged leverag*e).

Accordingly, given the strong empirical support for the significant coefficient on the 1-period lagged capital structure, and in order to account for the dynamic nature of the capital structure decision, we include the 1-period lagged book leverage ratio as an additional determinant of the observed capital structure and hence estimate a dynamic model to investigate the determinants of capital structure.

2.3.3. Determinants of Capital Structure

Conducting an extensive review of literature on the determinants of capital structure, Harris and Raviv (1991) identify the following firm characteristics as the most generally agreed determinants of leverage: tangibility, non-debt tax shields, growth opportunities, size, volatility, advertising expenditure, research and development expenditure, bankruptcy probability, profitability and uniqueness of the product. We focus on growth opportunities, size, tangibility, profitability, non-debt tax shields and business risk as possible determinants of capital structure. We focus on these 6 firm-specific determinants for two reasons. First, these factors have consistently shown up among the significant determinants of capital structure in the literature, including the subsequent survey studies after Harris and Raviv (e.g., Chaplinsky and Niehaus, 1993; Lasfer, 1995; Rajan and Zingales, 1995; Michaelas *et al.*, 1999; Booth *et al.*, 2001; Hovakimian *et al.*, 2001; Ozkan, 2001; Fama and French , 2002; Korajczyk and Levy, 2003; Bevan and Danbolt, 2004; Deesomsak *et al.*, 2004; Leary and Roberts, 2005; Drobetz and Wanzenried, 2006; Flannery and Rangan, 2006; De Jong *et al.*, 2008; Frank and Goyal, 2009; Kashefi-Pour, 2011; Fan *et al*., 2012; Harrison and Widjaja; and Iqbal and Kume, 2014)[30]. Second, availability of data limits our ability to consider the impact of research and development expenditure, advertising expenditures, and the uniqueness of product on leverage ratio.

2.3.3.1. Growth Opportunities

High growth firms have most of their value from future investment opportunities rather than the assets-in-place that can be used as collaterals. Consequently, debt holders of such firms would have more to lose than debt holders of mature firms with greater assets-in-place, in the event of bankruptcy (Kraus and Litzenberger, 1973). This would imply that, high growth firms with small assets-in-place should face higher bankruptcy costs. As a result, the trade-off theory predicts a negative relationship between growth opportunities and firm's leverage ratio.

[30] Other less commonly used determinants of capital structure that might worth mentioning include management ownership (Lasfer, 1995), liquidity (Ozkan, 2001), and shareholder protection (Fan *et al.*, 2012). However, since these variables have not commonly appeared in the literature and also in the case of shareholder protection it is not applicable to our analysis sample, as all firms in our sample are subject to the same legal framework and protection schemes, we will not devote space to discuss them in our review of literature.

Similarly, the agency theory predicts that, high growth firms are likely to have greater agency costs of debt but less severe agency costs of equity than low growth firms (Jensen and Meckling, 1976). That is, if most of the firm's value stems from the promise of undertaking future investments, managers (and equity holders) of such firms would have more incentives to pass on positive NPV investment opportunities (i.e., the debt overhang problem) and for their own benefits. Given their heavy reliance on future investment opportunities, it would be quite difficult for the debt holders of high growth firms to detect changes in the risk-profile of the firm's investments, which may have been caused by managers' decision to undertake riskier investments (i.e., the asset substitution problem). Furthermore, the disciplinary role of debt in mitigating the free cash flow problem is less valuable for firms with higher investment opportunities as managers of such firms would have less resources to spend at their discretion (Jensen, 1986). Accordingly, both the trade-off and the agency theories suggest that, debt is more costly for firms with greater growth opportunities and predict a negative relationship between firm's growth opportunities and its leverage ratio.

In contrast, the pecking order theory predicts a positive relationship between firm's growth opportunities and its leverage ratio. Under the pecking order theory, debt will only be issued when firm's internal funds (i.e., retained earnings and cash) are not sufficient to finance its investments. Consequently, holding profitability constant, firms with greater growth opportunities would require more external finance. In addition, as high growth firms have most of their value from future investments and hence smaller assets-in-place, they are expected to suffer more from information asymmetries associated with equity issues (Myers and Majluf, 1984). Thus, the pecking order theory implies that high growth firms are expected to have larger debt components in their capital structure. However, the importance of financial slack and assuring that financing will be available when needed might lead to a violation of the strict pecking order theory, especially for high growth firms with valuable future investment opportunities. As Myers (2003: p. 239) notes: *"if there is a window of opportunity when information asymmetries are small, it can make sense to issue shares immediately, violating the strict pecking order, in order to build financial slack for the future"*. Accordingly, while the standard pecking order theory predicts a positive relationship between growth opportunities and leverage, it also acknowledges

that under certain conditions, high growth firms might have a tendency towards reducing their leverage ratio by raising external finance in the form of issuing new equity[31].

The majority of empirical literature have found a negative relationship between growth opportunities and leverage (e.g., Lasfer, 1995; Barclay *et al.*, 2001; Bevan and Danbolt, 2004; De Jong *et al.*, 2008; and Kashefi-Pour, 2011). For instance, using random effect regression analysis to examine the determinants of capital structure of 88 industrial and commercial UK firms over the time period from 1972 to 1983, Lasfer (1995) finds that, high growth firms consistently use less debt in their capital structure than low growth firms. His finding is consistent with the trade-off and agency theory predictions that debt is more costly for firms with high growth opportunities and small assets-in-place due to more severe agency costs of debt and greater expected bankruptcy costs.

The positive relationship between growth opportunities and leverage has also received some empirical supports (e.g., Chittenden *et al.*, 1996; Jordan *et al.*, 1998; Michaelas *et al.* 1999; Bevan and Danbolt, 2002; and Iqbal and Kume, 2014). For instance, consistent with prediction of the pecking order theory, Jordan *et al.* (1998) and Michaelas *et al.* (1999) find that, the investment needs of high-growth firms often exceeds their internal sources of finance such as retained earnings, and hence they tend to frequently raise external finance via issuing debt and will end up with high debt ratios.

The market-to-book asset ratio, suggested by Myers (1977), is the most commonly used proxy for growth opportunities in the literature (e.g., Ozkan, 2001; Korjaczyk and Levy, 2003; Hovakimian *et al.*, 2004; Frank and Goyal, 2009; and Kashefi-Pour, 2011), where the numerator is a proxy for market value of assets (both assets-in-place and future investment opportunities) and the denominator is a proxy for firm's assets-in-place[32]. Other alternative proxy measures include market-to-book equity ratio (e.g.,

[31] Consistent with this argument, Minton and Wruck (2001) and Lemmon and Zender (2010) show that the most conservatively financed firms do appear to be stockpiling financial slack.

[32] Although there are different formulas to calculate the market-to-book asset ratio such as $\frac{market\ value\ of\ firm}{book\ value\ of\ assets}$ and $\frac{market\ value\ of\ firm}{replace\ value\ of\ assets}$ (i.e., Tobin's q), in order to avoid computation of market value of debt and replacement cost of assets, the common practice is to calculate the market value of

Lewellen *et al.*, 1987; Collins and Kothari, 1989; Chung and Charoenwong, 1991; and Graham and Rogers, 2002) and the ratio of capital expenditure to total assets (e.g., Titman and Wessels, 1988; Shyam-Sunder and Myers, 1999; and Frank and Goyal, 2009). However, using real options approach, Adam and Goyal (2008) show that the market-to-book asset ratio is the most reliable proxy for growth opportunities, as it has the highest information content with respect to a firm's actual investment opportunities and is least affected by confounding factors. Thus, we will use the market-to-book asset ratio calculated as $\frac{Book\ Value\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Assets}$ as our measure of growth opportunities.

2.3.3.2. Size

Large firms are typically diversified firms with stable earnings and large assets-in-place which implies that, they would be less prone to bankruptcy, face lower agency costs of debt, and hence would have lower expected costs of bankruptcy than smaller firms[33]. Accordingly, the trade-off theory predicts a positive relationship between firm's size and its leverage ratio.

To the extent that larger firms have more stable earnings and cash flows, the agency theory also predicts a positive relationship between size and leverage, due to the higher disciplinary value of debt to mitigate the agency costs of free cash flows.

On the other hand, size could be also regarded as a proxy for information asymmetries between firm's insiders and the capital markets (i.e., new debt or equity investors). Generally, larger firms have greater assets-in-place and are more closely observed by the market, which would imply that they should suffer less from the information asymmetries associated with issuing information-sensitive securities such as equity. Thus, *ceteris paribus*, larger firms would be able to issue more equity capital. Accordingly, the pecking order theory predicts a negative relationship between firm size and the debt component of the capital structure.

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assets as the sum of book value of assets and the difference between market value and book value of equity.

[33] Consistent with this argument, Gruber and Warner (1977), Ang *et al.* (1982) and White (1996) among others have documented the significantly higher bankruptcy cost of smaller firms relative to larger firms.

Empirical studies of capital structure have found the relationship between firm size and leverage to be robustly positive, supporting the trade-off and the agency theory prediction (e.g., Fama and French, 2002; Panno, 2003; Deesomsak *et al.*, 2004; Antoniou *et al.*, 2008; and Iqbal and Kume, 2014)[34]. For example, using logistic regression analysis to investigate the determinant of the decision to issue debt versus equity of constituents of the FTSE All Share index, Panno (2003) finds that larger firms tend to issue more debt and tend to have higher leverage ratios. Frank and Goyal (2009) have found similar results in their attempt to identify the most reliable factors for explaining the capital structure decisions of US firms from 1950 to 2003. They find that, the estimated coefficient of firm's size from regression on leverage measure is consistently positive and significant during their analysis period, suggesting that larger firms are less prone to bankruptcy and hence tend to have higher leverage ratios.

There have also been very limited empirical supports for the negative relation between size and leverage. For instance, using a large dataset on US firms from 1974 to 1982, Titman and Wessels (1988) find that smaller firms tend to have greater debt components in their capital structure. Consistent with the prediction of the pecking order theory, they attribute their finding to the greater exposure of small firms to the adverse selection costs associated with issuing new equity.

The two commonly used variables to proxy firm's size are the natural logarithm of total assets, $\ln(Total\ Assets)$ and the natural logarithm of sales, $\ln(Sales)$ (e.g., Titman and Wessels, 1988; Rajan and Zingales, 1995; Bevan and Danbolt, 2002; Frank and Goyal, 2003; De Jong *et al.*, 2008). However, $\ln(Sales)$ may be too volatile to be used as a reliable measure to proxy firm size as the sales figure can change dramatically due to fluctuations and temporary shocks in the product market which might not have an impact on firm's size and assets used for operations, Thus, we use $\ln(Total\ Assets)$ as our proxy variable to measure firm's size. Following the literature, the logarithmic transformation is used to account for the conjecture that smaller firms are particularly affected by a size effect.

[34] Marsh measures the probability of issuing equity conditional on issuing securities and on firm characteristics. The negative relationship found in his study indicates that the negative impact of change in size on the probability of firms issuing equity instead of debt, hence suggesting a positive relation between firm size and issuing additional debt.

2.3.3.3. Tangibility

Firms typically use their tangible assets as collaterals for their borrowings because they are easier for outsiders to value than intangible assets such as goodwill, patents, copyrights or brand recognition and would suffer a smaller loss of value in the event of bankruptcy. Therefore, firms with greater tangibility in their assets structure are perceived as less risky borrowers and are expected to have lower bankruptcy costs, as the lenders have the right to seize and sell the assets, should the borrower default on his agreement. Thus, based on the trade-off theory, the larger proportion of collateralizable assets and the lower bankruptcy costs of firms with high tangible assets would suggest a higher debt component in their capital structure.

Furthermore, firms with more tangible assets are also expected to have lower agency costs of debt because in addition to providing a form of guarantee of repayment (i.e., seize of the assets), the high proportion of tangible assets makes it more difficult for equity holders and managers to undertake excessively risky investments and substitute the low-risk assets with high-risk ones. Accordingly, both the trade-off and the agency theory predict a positive relationship between tangibility and firm's leverage ratio.

Tangible assets such as property, plant and equipment are easy to value and the information asymmetry between managers and outside investors about their true value is not substantial. Consequently, firm may find it advantageous to issue secure debt by using their tangible assets with known values as collaterals and avoid the costs associated with information asymmetries and the adverse selection problem. Furthermore, firms with greater tangibility are also expected to face lower cost of equity financing and suffer less from the negative shocks associated with new equity issuance. However, since under the premise of the pecking order debt is always preferred to equity, it also implies a positive relationship between tangibility and firms' leverage ratio.

The empirical capital structure literature has consistently found a positive relationship between the firms' degree of asset tangibility and their leverage ratio (e.g., Rajan and Zingales, 1995; Michaelas *et al.*, 1999; Drobetz and Wanzenried, 2006; Frank and

Goyal, 2009; and Harrison and Widjaja, 2014)[35]. For instance, Rajan and Zingales' (1995) cross-sectional analysis examining the determinants of capital structure among the G7 countries using data on firm's leverage ratios in 1991 provide evidence to suggest a significant positive relationship between tangibility and leverage. Consistent with the prediction of the agency and the trade-off theory, they suggest that this positive relation between tangibility and leverage may reflect the fact that debt may be more readily available to firms with higher proportion of tangible assets as their greater buffer of collateralizable assets would reduce the bankruptcy and agency costs associated with debt.

The appropriate measure of tangibility must capture the proportion of a firm's total assets that could be used as collaterals, reducing the agency costs of debt and the information asymmetries associated with equity issues. Following the consensus in the literature, we will use the ratio of Net Fixed Assets (i.e., net property, plant, and equipment) to Total Assets, $\frac{Net\ Fixed\ Assets}{Total\ Assets}$, as a proxy for firm's degree of asset tangibility (e.g., Rajan and Zingales, 1995; Deesomsak *et al.*, 2004; Flannery and Rangan, 2006; Frank and Goyal, 2009; and Kashefi-Pour, 2011). An advantage of using net fixed assets over book value of fixed assets is that it better reflects the true value of collateralizable assets as it takes into account the accumulated depreciation of using them over time[36]. Although the commonly used measure of tangibility is net fixed assets divided by total assets, there have been a few studies using different versions of the same ratio to control for firm's asset structure. For instance, Titman and Wessels (1988) use a reverse proxy for tangibility, $\frac{Intangible\ Assets}{Total\ Assets}$, and Korajczyk and Levy (2003) use $\frac{Intangible\ Assets}{Fixed\ Assets}$ to measure tangibility. However, both studies have found similar results as for the conventional measure of tangibility used in the literature.

[35] Marsh (1982) and Walsh and Ryan (1997) find that, the probability of debt issues is positively related to the firms' fixed asset ratio.

[36] Fixed assets lose value as they age and, thus are subject to periodic depreciations. Therefore, the current market value of fixed tangible assets may well be below their book value, and hence using Fixed Assets at their book value instead of the Net Fixed Assets would overstate the ability of the firm to provide collaterals against its borrowing.

2.3.3.4. Profitability

The trade-off theory suggests that, *ceteris paribus*, the tax advantage of debt due to deductibility of interest payments should be more valuable for profitable firms as they have greater income to shield from tax expenses than less profitable firms. Thus, profitable firms would have the incentive to carry large debt components in their capital structure. In addition, their strong income-generating ability implies that, highly profitable firms should have lower bankruptcy probability as they are able to service more debt without risking financial distress. This, in turn, would allow them to operate at a higher financial leverage. Accordingly, given the higher tax advantage of debt and the lower risk of bankruptcy of profitable firms, the trade-off theory would predict a positive relationship between profitability and leverage.

Furthermore, the agency theory suggests that, profitability is positively correlated with the agency costs of equity (Jensen, 1986). That is, the more profitable the firm, the greater would be the amount of free cash flows available for managers' discretional spending and, thus the more severe would be the agency costs of equity. Consequently, the disciplinary role of debt to mitigate the agency costs associated with free cash flows would be more valuable for profitable firms, and hence they would be more likely to have large debt components in their capital structure. Accordingly, the agency theory would predict a positive relationship between firms' profitability and their leverage ratio.

In contrast, under the pecking order theory, profitability is expected to have a negative relationship with leverage (Myers and Majluf, 1984). The theory implies that, holding investments constant, profitable firms with high levels of retained earnings and free cash flows are less likely to require external funds to finance their investments and thus would be more likely to have lower amounts of debt in their capital structure.

While there are major disagreements in the theoretical predictions, there has been a strong agreement about the impact of profitability on firm's leverage among empirical studies investigating determinants of capital structure. The absolute majority of the empirical literature have confirmed the negative relationship between profitability and leverage as predicted by the pecking order theory (e.g., Titman and Wessels, 1988; Bevan and Danbolt, 2004; Flannery and Rangan, 2006; De Jong *et al.*, 2008; and Fan

et al., 2012). For instance, using an unbalanced sample of all listed non-financial UK firms over the time period from 1991 to 1997, Bevan and Danbolt (2004) find a significant negative relation between firm's profitability and its leverage ratio. The negative coefficient has shown to be robust across a series of leverage measures (obtained by decomposition of debt into different long- and short-term elements). Furthermore, Fan *et al.* (2012) examine capital structure and debt maturity choices in 39 developed and developing counties and find that, positive shocks to profitability lead to an increase in the value of equity and a decrease in debt value. They also note that, as firms do not adjust capital structures immediately after shocks due to transaction costs, their results also support the negative correlation between profitability and leverage.

The appropriate profitability measure must capture the operating performance of the firm and the amount of earnings available to be retained so that it could be used as a proxy for the availability of internal funds and an indication of the firm's ability to finance its investments without the need to raise external finance. The most commonly used variable to proxy profitability is the Return on Assets (ROA) ratio, which is computed as $\frac{Operating\ Income\ before\ Depreciation\ Expenses}{Total\ Assets}$ (e.g., Rajan and Zingales, 1995; Ozkan, 2001; Bevan and Danbolt, 2004; Deesomsak *et al.*, 2004; Frank and Goyal, 2009). However, a number of studies have used $\frac{Operating\ Income}{Total\ Assets}$ as an alternative proxy for firm's profitability (e.g., Titman and Wessels, 1988; Frank and Goyal, 2003; and De Jong *et al.*, 2008). While both measures have indicated similar results regarding the relationship between profitability and leverage, the former measure is deemed to be a more appropriate as, unlike the latter measure, it is not distorted by non-operating and non-cash expenses such as depreciation and amortization. Thus, following the common practice in the literature, we also use $\frac{EBITDA}{Total\ Assets}$ as the proxy variable for profitability in our model[37].

2.3.3.5. Non-Debt Tax Shields

The trade-off theory proposes that, the larger the tax advantage of debt due to the tax deductibility of interest expenses, the greater would be the incentive of firms to

[37] Operating income before depreciation expenses is equivalent to the Earnings Before Interest, Taxes and Depreciation and Amortisation expenses (EBITDA) available from Bloomberg.

increase their leverage ratios (Kraus and Litzenberger, 1973). Thus, firms are expected to issue more debt when tax rates are higher. However, if all the firms in the sample are subject to the same tax system and statutory tax rates, a general tax measure may fail to capture the tax advantage of debt and explain the cross-sectional differences in leverage ratios[38]. Nevertheless, a limited number of studies such as Lasfer (1995) and Kashefi-Pour (2011) use the 'effective corporation tax rate' as an alternative proxy for the impact of taxes on firm's capital structure[39]. Having said that, DeAngelo and Masulis (1980) show that non-debt tax shields, which denote the reduction in tax expenses due to non-debt related items such as depreciation and amortizations expenses and investment tax credits, can be used as a substitute for the tax benefits of debt financing. Furthermore, the non-debt tax shields measure is appropriate to use even if all firms are subject to the same tax standards. Accordingly, given the prediction of a positive relationship between the tax advantage of debt due to interest tax shields and the debt component of capital structure, the trade-off theory would imply that non-debt tax shields due to other tax deductible items have a negative relationship with leverage ratios.

However, a positive coefficient on the measure non-debt tax shields is predicted based on the general premises of the pecking order theory. The theory states that, in the event of insufficient internal sources of finance, firms opt for external financing, and given the more severe information asymmetries associated with equity issues, firms have a preference to issue additional debt and exhaust this option before raising funds via equity issuance. This in turn implies that, *ceteris paribus*, an increase in the income statement items (expenses) that reduce firms' retained earnings (i.e., the main source of internal funds), effectively increases the need for external financing, and hence may lead to larger debt component of the capital structure. Accordingly, to the

[38] All the firms in our sample (UK based constituents of the FTSE250 index) are subject to the same tax systems and majority of them are in the same tax bracket, hence a general tax measure would not be able explain the cross-sectional differences in leverage ratios. Using simple tax measures are more appropriate when investigating determinants of leverage in a cross-country context with different tax rates and tax systems. For instance, Rajan and Zingales (1995), Booth *et al.* (2001), De Jong *et al.* (2008), and Antoniou *et al.* (2008) use the effective tax rates to capture the impact of tax rates on firms' capital structure in different countries.

[39] They compute the effective corporation tax rate as the ratio of the tax expenses as reported in firm's profit and loss account over the Earnings Before Interest and Taxes (EBIT). Consistent with the prediction of the trade-off theory, both studies have found a positive correlation between effective tax rates and leverage ratio.

extent that non-debt tax shields lead to a reduction in the available sources of internal financing, they are expected to have a positive impact on leverage ratios.

It should be noted, as the agency theory does not incorporate income taxes or internal sources of finance in determining the optimal capital structure, no clear prediction is proposed by this theory regarding the relationship between non-debt tax shields and leverage.

The negative relationship between non-debt tax shields and leverage ratios have been also confirmed by the empirical studies of capital structure (e.g., DeAngelo and Masulis, 1980; Ozkan, 2001; Hovakimian *et al.*, 2004; Ariff *et al.*, 2008; and Getzmann *et al.*, 2014). For instance, using a dynamic model to investigate the determinants capital structure of 390 UK firms during the period 1984-1996, Ozkan (2001) identifies a negative and significant coefficient of the non-debt tax shields. Consistent with prediction of the trade-off theory, he finds that the tax deductibility of non-debt items such as depreciation expenses reduces the potential tax benefits of debt and thus leads into smaller debt components in firms' capital structure.

On the other hand, a number of studies such as Boquist and Moore (1984), Bradley *et al.* (1984), MacKie-Mason (1990), Chaplinsky and Niehaus (1993), Homaifar *et al.* (1994) and more recently, Antoniou *et al.* (2008) have found a positive relationship between non-debt tax shields and leverage. While these studies acknowledge that their results are not in line with the consensus in the literature, they argue that the positive relation between leverage and non-debt tax shields may exist because their measure of non-debt tax shields is also a proxy for other firm characteristics such as the degree of tangibility (which is positively correlated with leverage)[40]. While the documented positive relationship may actually be due to the impact of tangibility on leverage captured by a measure of non-debt tax shields, none of the studies have attempted to control for firm's tangibility in their models and then compare the coefficients on non-debt tax shields. This is also consistent with the negative and significant relation between non-debt tax shields and leverage found by studies such as Deesomsak *et al.* (2004), Hovakimian *et al.* (2004) and Huang and Song (2006), in

[40] Consistent with this argument, Graham (2003) also points out, if a firm invests heavily and borrows to invest, a positive relation between proxies for non-debt tax shield and debt may result.

which they simultaneously control for the impact of tangibility and non-debt tax shields on the firm's leverage in their model.

DeAngelo and Masulis (1980) have introduced a multi-component variable to capture the full extent of a firm's non-debt tax shields: the sum of depreciation expenses, depletion allowances (e.g., net operating loss carried forward), and investment tax credits. To the best of our knowledge, except for Titman and Wessels (1988) that uses the exact variable suggested by DeAngelo and Masulis (1980), the great majority of studies have focused only on one or two components of the original measure due data availability issues. Unfortunately, there are too many missing observations for investment tax credits and operating loss carried forward tax in our dataset, such that it prevents us from using the comprehensive measure as suggested by DeAngelo and Masulis (1980). Thus, following the common practice in the literature, we also use $\frac{Depreciation\ and\ Amortization\ Expenses}{Total\ Assets}$ as the proxy variable to measure non-debt tax shields[41].

2.3.3.6. Business Risk

As discussed in Section 2.2.3, the agency theory suggests that firms with high risk of bankruptcy tend face higher agency costs of debt, as managers and equity holders of such firms would have stronger incentive to pass on valuable investment opportunities. Similarly, the trade-off theory implies that, the greater the earnings volatility of the firm, the greater is the risk of bankruptcy, since firms with high volatility carry a higher risk of their earnings falling short of their debt obligations. Accordingly, under both theories, risky firms with highly volatile earnings are expected to have smaller amount of debt in their capital structure, hence both the trade-off and the agency theory of capital structure predict a negative relationship between risk and leverage.

[41] The alternative is to scale depreciation expense by operating income. However, Titman and Wessels (1988) show that, this measure is substantially biased due to the spurious correlation. They (p. 17) further note that: "*one should be cautious when interpreting variables scaled by operating (OI) that are positively correlated with debt ratios*". They argue that the correlation between debt and non-debt tax shields is very sensitive to its scaling. In particular, they show that because of the negative correlation between *Depreciation Expense/OI* (a measure of non-debt tax shields) and *OI/TA* (measure of profitability), and the negative correlation between *OI/TA* and leverage, *Depreciation Expense/OI* is positively correlated with leverage, whereas, if non-debt tax shields is measure by *Depreciation Expense/TA*, the corresponding correlation with leverage will be negative.

However, to the extent that business risk and earnings' volatility is expected to increase the outside investors' uncertainty about the true value of the firm, the increased costs of information asymmetries associated with equity issues would imply that riskier firms with greater earnings volatility are expected to have larger debt components in their capital structure. Furthermore, firms with volatile earnings (i.e., as the main source of internal financing) are more likely to need periodically access the external funds in order to finance their investments. Accordingly, the pecking order theory would predict a positive relationship between leverage and volatility.

While the risk factor has been included as an explanatory variable in numerous empirical investigations of capital structure, there have been major disagreements in their findings regarding its impact on firms' leverage ratio. The majority of the papers in the literature have found a negative relationship between the two, supporting the theoretical prediction that volatile firms are more prone to bankruptcy and have higher agency costs of debt (e.g., Bradley *et al.*, 1984; Friend and Lang, 1988; Jensen *et al.*, 1992; Booth *et al.*, 2001; and Kashefi-Pour, 2011). However, a number of other studies such as Titman and Wessels (1988) and more recently Deesomsak *et al.* (2004) and De Jong, *et al.* (2008) have found evidence to reject the hypothesis that volatility has a negative effect on firm's leverage. For instance, Deesomsak *et al.* (2004) suggest that, if leverage ratio is well below the firms' debt servicing capacity (i.e., ability to meet their financial obligations), they may find the risk of bankruptcy and its associated costs too small to consider in determining their capitals structure.

Moreover, there has also been some support for a positive relationship between volatility and leverage, most of which relate to the 1980s and the 1990s (e.g., Castanias, 1983; Long and Malitz, 1985; Kim and Sorensen, 1986; Jordan *et al.*, 1998; and Michaelas *et al.*, 1999). For instance, in an attempt to investigate the determinants of capital structure using data on 3500 small firms over the period 1986-1995, Michaelas *et al.* (1999) find a significant and positive relationship between earnings volatility and measure of leverage. However, interestingly, they propose that their finding of positive relation between business risk and leverage may be due to the lower agency costs of debt faced by their analysis sample, and note that: "*bankruptcy costs are not significant enough to ensure a negative relationship between risk and gearing*" (p. 121). The same argument is made by Castanias (1983); they argue that, it

is only when earnings are normally distributed and default costs are sufficiently high that business risk (measured by earnings' volatility) is inversely related to leverage ratio.

Titman and Wessels (1988) suggest that the standard deviation of the percentage change in firm's earnings is the only indicator of business risk that is not directly affected by the firm's debt level, hence avoiding the spurious correlation problem. Other possible indicators, such as beta or total volatility are partially determined by the firm's leverage ratio and could lead to biased estimates. Alternatively, 'unlevered beta' or 'unlevered volatilities' may be used, however, they require accurate measurements of the market value of the tax gain to leverage and the firm's debt value as it evolves over time, which are neither readily available nor easy to compute. In addition, as noted by Titman and Wessels (1988), the potential for spurious correlation arises if the impact of leverage and taxes is not completely purged from these volatility estimates. Thus, given the data limitation and in order to avoid possible spurious correlations with the dependent variable, we will also use earnings volatility as our proxy for business risk[42].

The commonly used measure of earnings volatility in the literature is the standard deviation of Earnings Before Interest and Taxes (EBIT) over the sample period (e.g., Kim and Sorensen, 1986; Michaelas *et al.*, 1999; Booth *et al.*, 2001; De Jong *et al.*, 2008; and Kashefi-Pour, 2011). However, the major drawback of this measure is that it is estimated as a single value for all years and thus acts as a dummy variable in the time series estimates. In order to overcome such problems, following Deesomsak *et al.* (2004), we compute earning's volatility as the absolute difference between the annual percentage change in EBIT and the average of this change over the sample period, (ratio of annual percentage change in EBIT to the average of this change over the sample period, $\frac{EBIT_{i,t}-EBIT_{i,t-1}}{Average\ Change\ in\ EBIT_i}$. Accordingly, *ceteris paribus*, firm with severe earning's volatility would be at a greater risk of bankruptcy as their earnings are more likely to fall short of their financial obligations.

[42] Although Frank and Goyal (2009) use the annual variance of asset returns, computed by unleveraging the variance of equity returns and assuming other asset values to be equal to their book values, they find similar results when using earning's volatility as their measure of business risk.

2.3.3.7. Summary

Overall, the empirical literature suggests that the economic factors that drive the theories of capital structure such as taxes, costs and probability of bankruptcy, conflicts of interest between different stakeholders, and information asymmetries seem to affect firms' financing decisions. However, the predicted impact of different firm characteristics on leverage ratios seems to vary depending on the theory and its assumption[43]. Table 2.1 summarises the theoretical predictions regarding the most commonly used firm-specific determinants of capital structure together with their actual impact on leverage ratios as suggested by empirical literature.

As illustrated in Table 2.1, the empirical literature does not show a clear picture about which of the theories of capital structure is best able to explain firm's financing decisions in practice. It appears that all three theories are at work to some extent, yet each fails to explain the financing decisions of certain classes of firms. However, it is important to note that our objective is not to test different theories of capital structure, but rather to use their prediction regarding factors affecting firms' financing decisions and identify the most significant firm-specific determinants of capital structure.

Table 2.1 Expected Theoretical and Empirical

Variable	*Theoretical Prediction*			*Mostly Reported in the Empirical Literature*
	Trade-off theory	*Agency theory*	*Pecking order theory*	
Growth Opportunities	-	-	+	-
Size	+	+	-	+
Tangibility	+	+	+	+
Profitability	+	+	-	-
Non-debt Tax Shields	-	n/a	+	-
Business Risk	-	-	+	-

[43] Although in some cases different theories may suggest a similar prediction with regards to the impact of a given determinant of the firm's capital structure, they may vary in the core arguments behind the predicted relationships. For instance, both the trade-off theory and the pecking order theory suggest that profitable firms are expected to borrow less, however, the former states that more profitable firms typically have greater income to shield against tax expenses and consequently would be able to gain more by operating at a high leverage ratios than less profitable firms, while the latter suggests that as profitable firms have more internal financing available, they would require less external financing and consequently would accumulate less debt than less profitable firms.

Having identified the possible firm-specific determinants of capital structure and their impact on firms' leverage, we proceed with reviewing the theoretical prediction and the empirical findings concerning the impact of the recent Global Financial Crisis (GFC) on firms' choice of capital structure.

2.3.4. Capital Structure and the Recent Global Financial Crisis

2.3.4.1. Theoretical Predictions

Although none of the capital structure theories have suggested any specific prediction regarding the overall economic conditions, using their predictions for the firm-specific determinants of capital structure we are able infer some generic expectations concerning the impact of macroeconomic conditions on leverage. For instance, the trade-off theory proposes that firms choose their capital structure by balancing the tax benefit of debt against the bankruptcy costs associated with debt. Accordingly, the size of the debt tax shield depends on the taxable income and cash flow of the firm, which in turn are affected by the overall conditions of the economy. Similarly, the probability of default and failure to meet financial obligations is affected by the current state of the economy (i.e., interest rates, inflation etc.), and so would be the expected bankruptcy costs of debt. Thus, based on the trade-off theory, we could infer that firms are expected to operate at higher leverage ratios during economic expansions where tax benefits of debt are expected to be higher while bankruptcy costs associated with debt are expected to be lower.

As discussed in the Section 2.2.3, firm value and the value of its collaterals are important determinants of agency costs. Accordingly, the agency costs of debt, the agency costs of equity, and hence the optimal capital structure are expected to change in response to an increase/decrease in the value of collaterals and other asset classes caused by the changes in the overall economic conditions. Furthermore, the agency theory suggests that a decrease in the equity value would reduce wealth of managers relative to outside equity holders, which would imply that firms must issue more debt in economic downturns in order to realign the interest of managers with those of outside equity holders[44]. In addition, the higher equity prices during economic booms would technically imply lower leverage ratios. Accordingly, debt issues are expected to increase in downturns while equity issues are expected to increase during benign

[44] Jensen and Meckling (1976) assume that managers hold a proportion of the firm's equity and that there exists an optimal proportional holding by managers at which the agency costs of equity are minimised. Thus, this optimal relative proportion of equity holding by managers must always hold in order to avoid agency conflicts and align the interest of managers and outside equity holders.

economic conditions, and hence we could infer a counter-cyclical pattern for firms' capital structure based on the agency theory.

Finally, the increase in firms' earnings during economic expansions is expected to improve their ability to finance investments internally. Accordingly, under the premise of the pecking order theory and the preference of debt over equity, we could infer that firms would require less external financing during economic expansions and thus are expected to have a lower leverage ratio. Overall, based on the predictions of the theories of capital structure, variations in overall economic conditions are expected to induce variations in firms' capital structure.

2.3.4.2. Empirical Evidence

Similar to the theoretical literature, the extant empirical literature on capital structure also mainly focuses on identifying the firm-specific variables that determine leverage ratio, while overlooking the possible impact of the overall economic conditions on firms' choice of capital structure (Antoniou *et al.*, 2008). The 2007 Global Financial Crisis (GFC) and the consequent economic recession provide an opportunity to investigate the impact of the overall economic conditions on firm's capital structure. Furthermore, investigating the impact of the GFC on the determination of capital structure would allow us to examine whether the prediction of the main theories regarding the firm-specific determinants of capital structure remain valid in a post-crisis environment.

There have been a limited number of studies that incorporate the GFC into their models of explaining firms' financing decisions. For instance, Fosberg (2012) attempts to identify the impact of the recent GFC on firms' capital structure by utilising a large sample of nearly 5000 US firms over the period 2001 to 2010. The core of Fosberg's analysis is to separate the capital structure effect that is attributable to the GFC from the effect caused by the consequent recession after the GFC. Following Frank and Goyal (2009), Fosberg also uses 6 firm characteristics that have been suggested by the literature as potential determinants of capital structure (i.e., size, profitability, tangibility, non-debt tax shields, growth opportunity, and product

uniqueness) to capture and control for the effect of the recession on firms' leverage[45]. In addition, a set of annual time dummy variables are used to capture the capital structure effect attributable to the GFC that is not accounted for by the firm-specific control variables. As such, significant positive (negative) coefficients on year dummies would indicate firms to have higher (lower) than the predicted leverage ratios as suggested by the control variables. Using a simple pooled regression analysis, Fosberg (2012) documents a significant change in firms' capital structure due to the recent GFC. In particular, the statistically significant difference of 5.1% between the coefficients on year dummies for 2006 and 2008 suggests that, the GFC, on average, caused firms to have 5.1% more debt in their capital structures in 2008 than they would have had otherwise. Comparing the additional 5.1% debt to the 5.5% increase in mean leverage ratios of sample firms over the same time period indicates that, the GFC caused almost all the debt accumulation observed between 2006 and 2008. Furthermore, the negative and significant coefficients on year dummies for 2009 and 2010 (-3% and -4% respectively) indicates that, the GFC impact on firms' capital structure is faded away by the end of 2010 as almost 70% of the debt accumulation occurred in 2007 and 2008 is reversed by the end of 2010[46]. Consistent with this finding, Fosberg (2012) also documents a change in the financing mix of securities after the GFC. The ratio of new debt issuance to new equity issuance (i.e., the dollar value of new debt for every dollar of new equity issues) increases from 7.57 in 2007 to 9.01 in 2008, it then falls significantly to 6.77 in 2009 and remains the same in 2010.

Another study that uses dummy variables to identify the impact of the GFC on firms' capital structure is Akbar *et al.* (2013). However, instead of annual time dummies for each year, they use a time-range dummy variable to distinguish between the crisis and the pre-crisis period. In addition to the two firm-specific determinants of capital

[45] Consistent with the prediction of the existing empirical literature, the coefficients on size ($\ln Total\ Assets$) and Tangibility ($\frac{Fixed\ Assets}{Total\ Assets}$) were found to be positive and significant, while the coefficients on profitability ($\frac{EBIT}{Total\ Assets}$), product uniqueness ($\frac{R\ \&\ D\ Expense}{Total\ Assets}$) were found to be negative and significant. Although the coefficient on non-debt-tax shield ($\frac{Depreciation\ \&\ Amortisation\ Expense}{Total\ Assets}$) was negative as expected, it was insignificant at 5% significance level. The coefficient on growth opportunities ($\frac{Market\ Value}{Book\ Value}$) was also found to be insignificant.

[46] Consistent with Fosberg's (2012) finding, Pattani *et al.* (2011) show that aggregate debt issues of UK firms continue to increase during the period 2008-2009 and then fall sharply to almost the pre-crisis level in 2010. They also report a similar pattern for equity issues. Aggregate new equity issues of UK firms increase significantly during the crisis and reach its peak in 2009 and then decrease again in 2010.

structure, their model include a dummy variable that takes a value of 1 for years 2007-2009 (crisis period) and 0 for years 2004-2006 (pre-crisis period) to capture the effect of the GFC on leverage ratios[47]. Using a sample of nearly 5,000 private firms over the period 2004-2009 and estimating a fixed effect regression model, Akbar *et al.* (2013) find that the GFC has a negative impact on the leverage ratios of UK firms. In particular, they document a negative and statistically significant coefficient (-0.059) on the crisis dummy variable, indicating the GFC has adversely affected firms' capital structures (i.e., firms tend to have 0.059% less leverage in the period 2007-2009 as opposed to the leverage ratio in the period 2004-2006)[48]. However, it is worth mentioning that the end of their sample period coincides with the end of their defined crisis period, thus they fail to accommodate and control for any changes in leverage ratios in the post-crisis period.

Similar to Fosberg (2012), Kahle and Stulz (2013) also find evidence in support of the positive impact of the recent GFC on firm's leverage ratios[49]. They use quarterly data of US firms for the period 2006-2010 and break down their analysis period as follows: 3rd quarter 2006 to 2nd quarter 2007 as the pre-crisis period, 3rd quarter 2007 to 2nd quarter 2008 as the first year of the crisis, 4th quarter 2008 to 1st quarter 2009 as the post-Lehman period (these two quarters are considered separately to allow for the impact of the financial panic that followed the bankruptcy of Lehman Brother) and 2nd quarter 2009 to 1st quarter 2010 (end point of their sample period) as the last year of the crisis.

[47] They include measures of profitability (proxied by the ROA ratio) and size (measured by sales growth) as well as their interactions with the crisis dummy as the potential firm-specific determinants of capital structure. Consistent with the evidence in the empirical literature, they find a significant and negative coefficient on profitability and a significant and positive coefficient on firm size.

[48] Consistent with this finding, Graham *et al.* (2015) show that during periods of economic downturns and increased uncertainty, valuable investment opportunities are rare to find and argue that the limited investment opportunities would lead to weaker product demand and thus weaker need for external finance, which in turn could result in a reduction in firms' leverage ratios.

[49] It should be noted that, Kahle and Stulz (2013) are actually interested in identifying the implications of the financing and investing behaviour of firms on the theories of impaired access to capital (i.e., the bank lending supply shock, the credit supply shock, the demand shock, and the balance sheet multiplier effect) rather than the impact of the GFC on firms' capital structure. They use regression analysis and matching approach of Almeida *et al.* (2012) to test whether the financing and investment decisions of firms during the recent GFC are consistent with the prediction of the theories of impaired access to capital. Accordingly, since we are interested in the impact of the recent GFC on the financing decisions of the firms, we will only focus on their descriptive findings regarding the financing policies of firms during different phases of the crisis.

They find that, the average net debt issuance as a percentage of assets increases by 6.25% in the first year of the crisis as opposed to the pre-crisis period. However, as expected, firms with already high leverage ratios in the pre-crisis period experience a significant decrease of approximately 22.6% in new debt issuance during the first year of the crisis. Furthermore, their results indicate negative net debt issuances through the last two phases of the crisis, suggesting net repayment of debts. Thus, while the average firm continue to be a net debt-issuer in the first year of the crisis, the greater amount of debt repayments than new debt issues in the last two phases of the crisis turns it into net debt-repayers, which is consistent with the sharp fall in the average debt obligation identified in their sample. They find that, the average net debt issuance as a percentage of assets experiences a significant reduction from 0.80% in the pre-crisis period to -0.37% in the last year of the crisis, an overall decrease of roughly 146%. Furthermore, as expected, the overall decrease in net debt issuance of firms with already high leverage ratios in the pre-crisis period found to be even more significant, approximately 171%.

Kahle and Stulz (2013) also note that, the average net equity issuance plummets through the first two phases of the crisis, but recovers again in the last year of the crisis. In particular, the average net equity issuance as a percentage of assets in the first year of the crisis and the post-Lehman period are substantially lower (53% and 85% respectively) than the pre-crisis period. However, it bounces back and increases considerably in the last year of the crisis such that it comes to be almost 12% greater than the pre-crisis value.

Overall, the findings of Kahle and Stulz (2013) suggest that the recent GFC had an overall positive impact on firms' leverage ratios positively through a significantly smaller decrease in new debt issuance than the decrease in new equity issuance over the crisis period. As they (2013, p. 294) note:

> Compared with the last year of the credit boom, the cumulative decrease in net equity issuance until the end of the first quarter of 2009 (defined as the sum of net equity issuance to assets over that period) is more than twice the cumulative decrease in net debt issuance (3.96% versus 1.82%).

That is, the reduction in the new debt issues had been significantly smaller than the decrease in new equity issuance, suggesting a greater increase in the numerator (debt component) than the denominator (equity component) of firms' capital structures, and therefore an overall increase in leverage ratios over the crisis period 3rd quarter 2007 to 1st quarter 2009.

In a more recent study, Harrison and Widjaja (2014) use data on the non-financial constituents of the Standard & Poor 500 Index over the period 2004 to 2011 and divide their overall sample period into a pre-crisis period (2004-2007) and a post-crisis period (2008-2011). They use a random effect regression model and infer the differences in the sign and magnitude of the pre-crisis and post-crisis coefficients on a set of 5 potential firm-specific determinants of capital structure as the impact of the GFC on firm's leverage ratios[50].

While Harrison and Widjaja (2014) do not find any significant changes in the signs of the coefficients on firm-specific determinants of leverage, they do identify significant changes in the magnitude of some of the coefficients. In particular, they find that the impact of the market-to-book ratio on firm's leverage is much stronger in the post-crisis than the pre-crisis period as its coefficient almost doubles in magnitude (i.e., absolute value) from -0.055 to -0.108. They suggest that, given the negative relationship between market-to-book ratios and firm's capital structure, the lower market valuations caused by the increased riskiness of firms (i.e., higher probability of bankruptcy, agency costs, and information asymmetries) could have caused leverage ratios to increase at an accelerated rate compared to the pre-crisis period, hence the greater negative impact of market-to-book ratio on firm's leverage.

Furthermore, they document a significant increase of almost 40% in the coefficient of tangibility for the post-crisis period (0.28) as opposed to the pre-crisis period (0.175), indicating the increased concern of lenders regarding the asymmetric information problem. The authors claim that, the greater impact of tangibility on leverage in the post-crisis period as opposed to the pre-crisis period could be attributed to greater adverse selection problem. That is, given the increased in the severity of the adverse

[50] They use the following measures as their explanatory variables: tangibility ($\frac{Fixed\ Assets}{Total\ Assets}$), profitability is measured as ($\frac{EBIT}{Total\ Assets}$), size is measured by ($\ln Total\ Assets$), growth opportunities ($\frac{Market\ Value}{Book\ Value}$), and liquidity ($\frac{Current\ Assets}{Current\ Liabilities}$).

selection problem faced by lenders during the GFC, they would have a tendency towards firms with greater tangible assets that are able to provide greater collaterals against their borrowings.

While the coefficient on the proxy variable for firm size is positive and insignificant in the pre-crisis, it changes sign and yet remains insignificant in the post-crisis period. The authors only briefly address this unconventional finding and attribute it to the *'disparities in data samples and statistical procedure*s' (Harrison and Widjaja, 2014: 74). The coefficient on liquidity (-0.006) does not change in either sign or absolute value and remains insignificant in both the pre-crisis and the post-crisis period. Finally, consistent with the expectation of reduced profitability during financial crises, the coefficient on profitability in the post-crisis period is found to be significantly smaller than its pre-crisis level (reduced from -0.587 to -0.470). The authors suggest that, the decreased impact of profitability on leverage might be attributed to the weaker internal financing capacity of firms to finance their operations and investment during the crisis. That is, *ceteris paribus*, firms might have an increased tendency towards external financing if their internal sources of finance are negatively affected by the crisis, and hence the lower coefficient on profitability.

Finally, Iqbal and Kume (2014) conduct a comparative study to examine the impact of the recent GFC on capital structure decisions of listed non-financial firms in the UK, France and Germany. In doing so, they divide their overall sample of 2006-2011 into the pre-crisis (2006-2007), the crisis (2008-2009) and the post-crisis period (2010-2011). Adopting a similar approach to Akbar *et al.* (2013), Iqbal and Kume (2014) also use time dummies to identify the crisis periods and infer the coefficient on the crisis dummy variable as the impact of the GFC on firms' capital structure[51]. They use a fixed-effect regression model and include 2 time dummy variables: a crisis dummy (takes the value of 1 for years 2008 and 2009 and zero for all the other years in the sample period) and a post-crisis dummy (takes the value of 1 for years 2010 and 2011 and zero the other years in the sample period). However, in contrast to Akbar *et*

[51] Although the main variable of interest in their analysis is the crisis dummy variable, they include the following variables to control for the firm-specific factors that may have an impact on leverage ratios: the ratio of fixed assets to total assets, natural logarithm of firm's total assets, the market-to-book ratio, change in total assets, the R & D expense to total assets, the variation in sales, the ratio of property, plant and equipment to total assets, and the ratio of net income before preferred dividends to total assets.

al. (2013) but consistent with Fosberg (2012), Iqbal and Kume (2014) find the coefficient on the crisis dummy variable to be positive and significant for UK (0.024) and Germany (0.029) and positive but insignificant for France (0.006). Furthermore, their results indicate that the coefficient on the post-crisis dummy for all three countries is statistically insignificant. Consistent with this, they show that the mean values of leverage ratios for all three countries increase in the crisis period and decrease in the post-crisis period. However, it is only in the case of UK and Germany that the differences are statistically significant. The authors also find that the difference in average leverage ratios between pre-crisis and post-crisis are statistically insignificant for all three countries. This indicates that, on average, leverage ratios of UK and German firms increase in the crisis period from their pre-crisis value, then decrease in the post-crisis such that, there are no significant differences in mean values of leverage between the pre-crisis and the post-crisis periods[52].

Overall, irrespective of direction of the impact, the recent GFC seems to exert a significant effect on firms' capital structure. Accordingly, failure to control for such effects may well lead to distorted and unreliable inferences regarding the determinants of capital structure.

However, there are some issues to consider when choosing the approach to control for such effects in our analysis. First, dividing the overall sample period into pre-crisis and post-crisis and comparing the size of coefficients on different firm-characteristics between the sub-samples may lead into ambiguous or even misleading inferences about the determinants of capital structure and the impact of crisis on firm's financing decisions. That is, it seems too simplistic and unjustified to infer an increase/decrease in the absolute value of a coefficient as the overall impact of the corresponding variable on firms' capital structure, *assuming all other things stay the same.* For instance, the larger/smaller coefficient may have been caused by the changes in the

[52] Their results become more pronounced, in particular for the UK, even after controlling for time-varying effects of determinants of capital structure by including interactions of all the firm-specific determinants of capital structure with both the crisis and post-crisis dummy variables. The coefficients on the crisis dummy become 0.046 and 0.030 for the UK and Germany, respectively. Furthermore, using t-test to examine the whether there are any significant changes in the levels of debt or equity across the three sub-periods, they find that the increase in leverage ratios for UK firms during the crisis is mainly due to an increase in debt issues while the decrease in the leverage ratio and reversion to the pre-crisis level is mainly due the new equity issues.

relationship between firm-specific variables rather than the changes in the overall economic conditions between the two subsample periods.

Second, it is difficult to objectively define a definitive end-point for the recent GFC and even more difficult to distinguish between the crisis and the post-crisis period[53]. There are major inconsistencies in the way in which different phases of the crisis (i.e., pre-crisis, crisis, and post-crisis) are defined among empirical studies, and they seem to do so such that it supports their findings the best. For instance, while Iqbal and Kume (2014) refer to the period 2008-2009 and 2010-2011 as the crisis and the post-crisis period respectively, 2009 is included in the post-crisis period defined by Fosberg (2012) and Kahle and Stulz (2013). There are similar inconsistencies about the pre-crisis period too. For instance, 2007 is included in the pre-crisis defined in Harrison and Widjaja (2014) and Iqbal and Kume (2014), while Akbar *et al.* (2013) define pre-crisis as the period 2004-2006 and include 2007 in the crisis-period.

Finally, the third and perhaps the most important issue confounding the analysis of the recent GFC is the fact that the financial crisis was accompanied by a severe economic recession which itself would be expected to affect firm capital structure. Separating the impact of economic recession (e.g., reduced firm's profitability) from the impact of financial crisis (e.g., credit crunch) is quite difficult, as the two are significantly interrelated and intertwined (Fosberg, 2012). Furthermore, the consequent global economic recession also makes it more difficult to define a definitive time period for the GFC.

In order to address the above issues, we follow the approach undertaken by Fosberg (2012) and include a set of annual time dummies for our entire sample period to identify the impact of the GFC on firms' capital structure. Since the set of commonly used firm-specific determinants of capital structure are included to control for the effects of the economic recessions on firm capital structure, the coefficients of the firm-invariant annual dummies can be inferred as the aggregate impact of the financial crisis on firms' leverage ratios. Furthermore, this way we avoid the complication of

[53] We define post-crisis period as the period since the start of the financial crisis (as reflected in companies' financial statements) until the time when consequences of the crisis on the economy are still present.

defining and imposing definitive cut-off points for different phases of the recent GFC and the possible misinterpretation of its impact on firms' capital structure.

Another advantage of the annual time dummy approach is that it acts as an aggregate proxy for the overall economic conditions. This is particularly helpful because there has not been an agreement on the choice of macroeconomic variables among empirical studies of capital structure and we cannot possibly identify all macroeconomic variables affecting the capital structure. We aim to control for the possible implications of such factors on firms' financing decisions by including a year dummy variable that acts as an aggregate macroeconomic measure, capturing all the firm-invariant factors in a particular time period such as changes in economic growth, inflation, interest rate, exchange rate etc.

Finally, the coefficients on the annual dummies indicate the net effect rather than focusing on individual effects which might cancel out each other. For instance, while fall in interest rates in 2008-2009 could have a positive impact on leverage, the inflationary environment might have deteriorated firms' profitability and impaired their ability to pay their financial obligations, hence negatively affect their leverage ratios.

2.3.4.3. Implication for Our Study

Overall, prior literature offers inconsistent results regarding the exact impact of the recent GFC on firms' capital structure, depending on the analysis sample (i.e., country, time period, and types of firms) and the approach to investigate the impact of GFC on firms' leverage ratios (i.e., controlling for crisis and defining different phases of crisis). However, whether considering the significant positive/negative coefficients on time dummy variables (annual or time-range) used as proxy for the crisis period, or focusing on the significant differences in the coefficients on firm-specific determinants of leverage before and after the crisis, the recent GFC seems to have a significant impact on the firms' capital structure. Accordingly, we will include a set of annual time dummies for the entire sample period in our estimation model to control for the impact of the recent GFC on firms' capital structure.

2.3.5. The Issue of Zombies

In order to introduce the concept of zombie firms and put it into context, we first provide a brief summary of corporate insolvency in the UK after the recent Global Financial Crisis (GFC) the consequent recession, and how it may have led to the emergence of zombies.

2.3.5.1. Corporate Insolvency After the 2008/9 Recession

Firms may become insolvent at any point in time for an extensive number of reasons, however, the corporate insolvency literature has suggested a correlation between aggregate insolvency of the firms and overall economic conditions[54]. That is, aggregate insolvency tends to increase when in recessionary environments and decrease when the economy is growing (Desai and Montes, 1982; Goudie and Meeks, 1991; Liu 2004; Bonfim, 2009). Plotting the changes in the UK aggregate corporate insolvency and the measure of economic growth over the last three economic downturns indicates a historical trend; that is, economic recessions are associated with an increase in aggregate insolvency[55]. Figure 2.1 illustrates the growth rates in real Gross Domestic Product (GDP) and aggregate corporate insolvency in the UK over the period 1978-2012. As can be seen from Figure 2.1, there have been three economic recessions (i.e., instances of 2 consecutive quarterly downturns in GDP) in the UK over the last three decades: the 1980s recession (1980/81), the 1990s recession (1991/1992) and the 2008/9 recession.

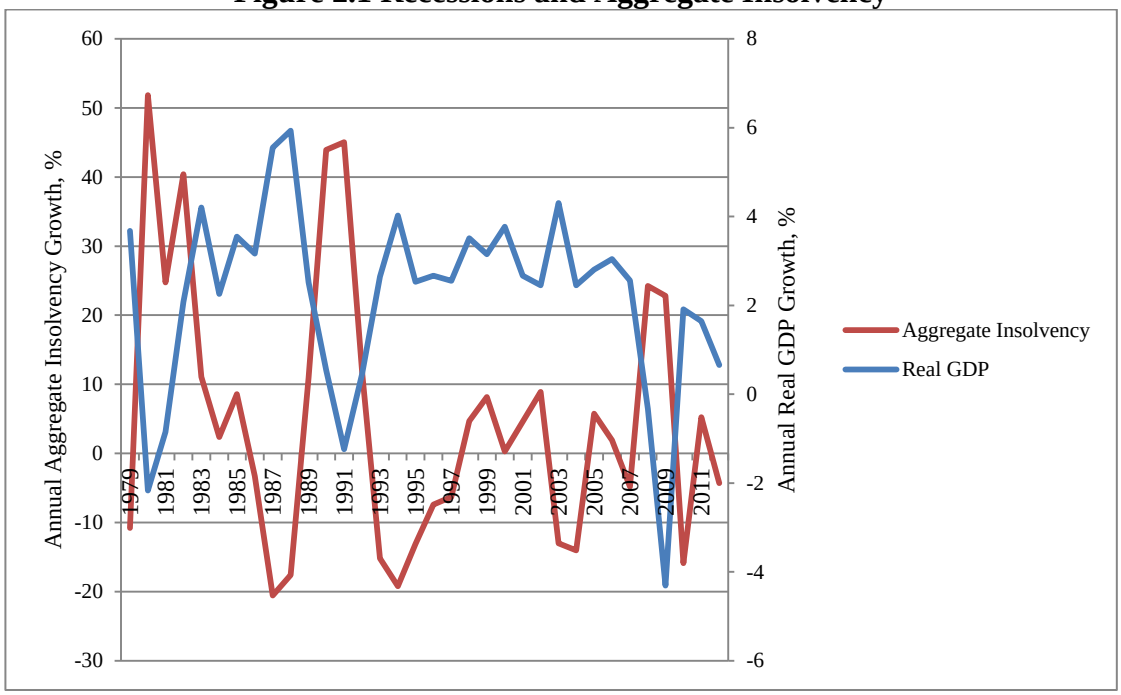
As for the 1980s recession, the annual real GDP contractions of 2.2% and 0.8% were accompanied with a 51.9% and 24.8% increases in aggregate insolvency in 1980 and 1981, respectively. Similarly, the negative GDP growth rate of 1.2% in 1991 was accompanied with a 45% increase in aggregate corporate insolvency level. However, aggregate corporate insolvency has only risen modestly during the 2008/9 recession,

[54] The Insolvency Service (2016: p. 4) defines corporate insolvency as: "being unable to pay creditors the money they are owed". Furthermore, the term "bankruptcy" is the US equivalent term for insolvency in the UK. The term is also used to refer to the five possible formal procedures that can apply to insolvent companies: administration, company voluntary arrangements, administrative receiverships, compulsory liquidations, and creditors' voluntary liquidations. We will use the term insolvency throughout this Thesis to refer to firm's ultimate failure (i.e., liquidation).

[55] Bank of England defines annual recessions as one or more years of negative calendar-year growth in GDP, and the recessions are assumed to end once GDP begins to rise (Hills *et al.*, 2010).

in comparison to the prevailing historical trend in previous recessions. That is, the annual real GDP contractions of 0.3% and 4.3% were accompanied by only 24.4% and 22.8% increases in aggregate insolvency in 2008 and 2009, respectively. In fact, while the GDP contraction in 2009 is almost twice as large as the GDP contraction in 1980, the corresponding increase in aggregate insolvency in 2009 is about half the size of the increase in aggregate insolvency in 1980. Accordingly, aggregate corporate insolvency after the recent Global Financial Crisis (GFC) and the consequent economic recession is nowhere close to where it should have been, had it followed the pattern in previous recessions. In other words, firm survival rates were unusually high during the 2008/9 recession.

Figure 2.1 Recessions and Aggregate Insolvency



Data Source: Bank of England and The Insolvency Service

The evident 'smaller-than-expected' increase in aggregate corporate insolvency levels after the recent recession has been extensively investigated by government authorities, and other professional bodies such as the Bank of England (BoE) and the Financial Services Authority (FSA). While, there may be a variety of factors that may have prevented UK firms from insolvency, Arrowsmith *et al.* (2013), BoE (2013a), Barnett *et al.* (2014b), and Nelson and Tanaka (2014) amongst others, have identified the record-low level of interest rates, various government-sponsored support schemes, and the exceptional level of bank forbearance on non-performing loans as the main causes

for the unusually high firm survivals after the recent recession. Each of these factors will be briefly discussed.

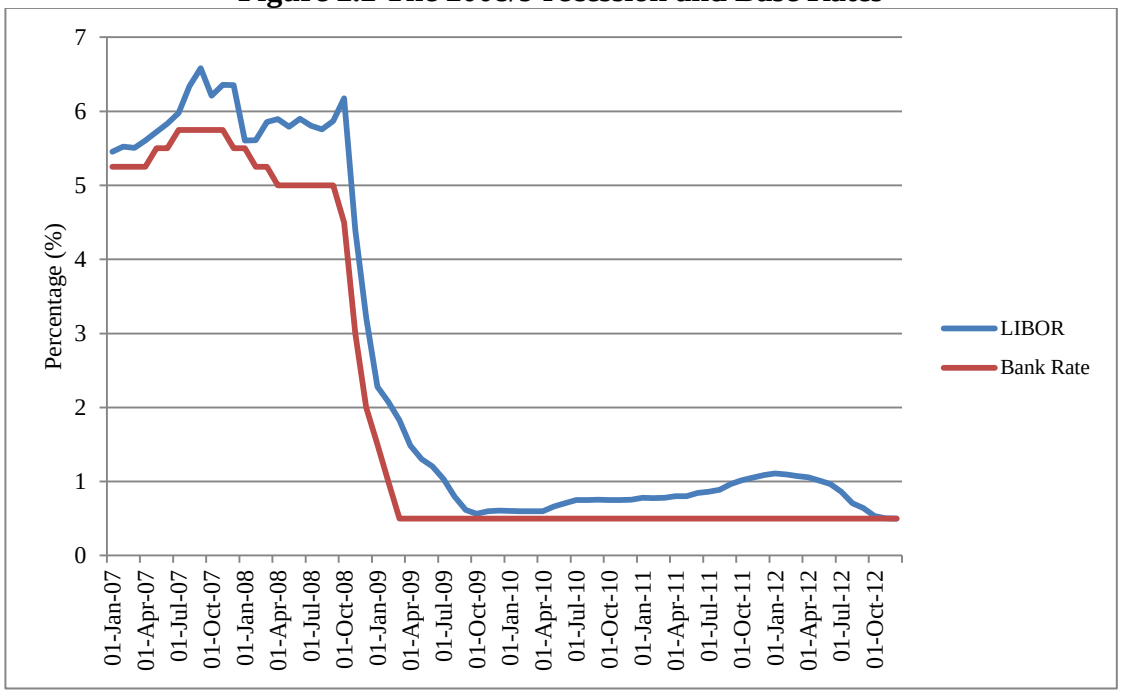
2.3.5.1.1. Low Interest Rates

The amount of debt a firm carries is the main driver of its financial obligations, and therefore, the rate of interest charged on debt is a critical factor affecting the firm's ability to meet its financial obligations. Accordingly, since insolvency occurs when a firm defaults on its financial obligations and cannot make the required payment, the rate of interest charged on borrowings can be an important determinant of the firm's probability of insolvency.

Figure 2.2 shows the changes in the UK base rates, the Bank Rate and the London Interbank Offered Rate (LIBOR), over the period 2007-2012. Where, Bank Rate is the end of month official rate paid on commercial bank reserves by the Bank of England, and LIBOR is the monthly average Sterling 3-month mean interbank lending rate. Typically loans to small firms are linked to Bank Rate and loans to the medium-sized and large firms are often linked to LIBOR (BoE, 2015). As can be seen from Figure 2.2, since the onset of the GFC in 2007 and the consequent recession, the Bank of England attempted to stimulate economic growth, by reducing base rates on multiple occasions and kept it at historical low levels since the early 2009.

Accordingly, the downward trend in the base rates after the 2008/9 recession and the historical low levels (0.5% and 0.6% for Bank Rate and LIBOR, respectively) as opposed to their pre-recession peaks (5.75% and 6.71%, respectively) and averages (4.8% and 5.1%, respectively), would imply that, *ceteris paribus*, firms are less likely to default on their financial obligations and face insolvency. This could have contributed to the smaller-than-expected increase in aggregate insolvency.

Figure 2.2 The 2008/9 recession and Base Rates



Data Source: Bank of England

2.3.5.1.2. Government-Sponsored Support Schemes

Furthermore, many firms may have been prevented from failure during the 2008/9 recession and the subsequent period of weak demand, due to the introduction of different support and rescue schemes (BoE, 2013a). The first support scheme introduced by the UK government after the GFC was the Business Payment Support Service (BPSS), which was introduced as part of the 2008 Pre-Budget Report. The BPSS aimes to provide assistance and help viable businesses facing temporary financial difficulties to pay their Income Tax, National Insurance, VAT or other payments owed to HMRC in the form of extended time to pay, or payment in instalments (DBIS, 2010)[56].

Similarly, scarcity of credit and banks' reluctance to lend money to businesses led to the introduction of the Asset Protection Scheme (APS) by the HM Treasury (early 2009), in an attempt to maintain financial stability and support lending (HM Treasury, 2010). Accordingly, under APS arrangements, the government protects banks against future losses on their riskiest assets (i.e., their loans) and in return, banks enter into legally binding agreements to increase the amount of their lending. However,

[56] In fact, as of the end of February 2010, the service had supported over 160,000 businesses, spread over £5 billion of tax with £3.9 billion already paid.

insufficient improvement in the amount of bank lending ultimately led to the introduction of a new scheme by the BoE and HM Treasury, Funding for Lending Scheme (FLS) in the 3rd quarter of 2012. The aim was to increase the amount of corporate lending[57]. The FLS was aimed directly to boost lending in the UK real economy by providing funding to Monetary Financial Institutions (MFIs) for an extended period, with both the price and quantity of funding provided linked to their lending performance (BoE, 2012a and Churm, *et al.*, 2012)[58].

Accordingly, the support schemes were introduced to help both lenders and borrowers and could have contributed to high firm survivorship after the 2008/9 recession, by either direct support with payments (i.e., BPSS) or indirectly via increasing credit availability (i.e., APS and FLS).

2.3.5.1.3. Banks' Loan Forbearance

Finally, the exceptional level of forbearance by banks on their non-performing loans, may have been another factor that could have contributed to the unusually high firm survival rate after the 2008/9 recession (BoE, 2011a; Arrowsmith *et al.*2013). The BoE defines forbearance as "*the renegotiation or relaxation of the terms of a loan in response to an actual or prospective breach of its original terms; it is an alternative to foreclosure or insolvency procedures"* (BoE 2011a: p. 21). Accordingly, banks may exercise forbearance on their existing loans in different forms, such as:

- granting waivers to the breach of pre-agreed loan covenants where for instance, the Loan-to-Value (LTV) ratio or the debt coverage ratio falls below the pre-specified minimum level;
- switching to an interest-only loan where the borrower is required to only pay the interest and the principal remains unchanged;
- offering payment holidays; and

[57] For instance, only a few months after two of the major UK lenders, the Royal Bank of Scotland and the Lloyds Banking Group, joined the scheme, in November 2009 Lloyds Banking Group paid £2.5 billion to exit the scheme and raise additional capital to comply with the new capital adequacy requirements via right issue.

[58] Given that the FLS was introduced in the 3rd quarter of 2012, the possible effect of the scheme on bank lending and firm insolvency is not reflected in the findings of this Thesis, which covers the period 2008-2012.

- offering loan restructurings such as: lowering the interest rate, extending the maturity, writing off debts where the amount of loan is reduced, and rolling over the loans[59].

The practice of rolling over loans to weak firms with a high risk of insolvency in order to avoid the accounting of credit losses is referred to as "evergreening" (see, Albertazzi and Marchetti, 2010; and Nelson and Tanaka, 2014).

While, due to the inconsistent disclosures and the survey nature of the available data, it is quite difficult to report the exact extent of forbearances exercised on UK corporate loans, the existing evidence generally suggest that it could be substantial. For example, a series of surveys from the 6 largest UK banks (i.e., Banco Santander, Barclays, HSBC, Lloyds Banking Group, Nationwide, and Royal Bank of Scotland) conducted by the Financial Services Authority (FSA) indicate that around 28% of leveraged loans by value (as at June 2011) and around 35% of Commercial Real Estate (CRE) loans by value (as at June 2012) were subject to some form of forbearance. This was where borrowers were granted waivers to breach of loan-to-value and debt-service coverage ratio covenant, payment holidays or maturity extensions (BoE, 2011b & 2012b and Benford and Burrows, 2013).

Furthermore, although the available data on corporate loan forbearance outside the CRE sector are limited, the results of the March 2013 Bank of England survey conducted in association with the FSA indicate that, around 6% of loans to the non-CRE Small and Medium-sized Enterprise (SME) borrowers by the 5 largest commercial banks in the UK (i.e., Barclays, HSBC, Lloyds Banking Group, Nationwide, and Royal Bank of Scotland) were in receipt of some form of loan forbearance, which accounted for around 14% of the loans by value to the SME sector (BoE, 2013c) [60].

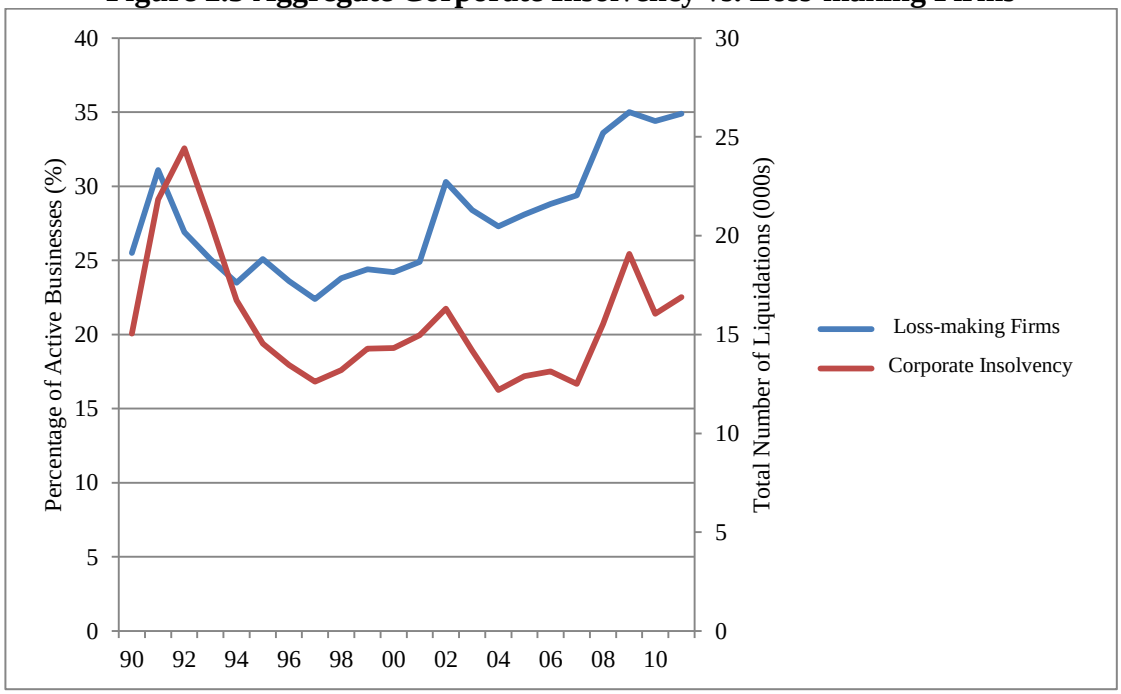
[59] While there may have been different incentives and motivations that could explain banks' decision to exercise forbearance on their loans, an in depth discussion of the causes for exercising forbearance on non-performing loans is beyond the scope of this Thesis and requires an extensive knowledge on the banking regulations. For detailed discussion of incentives and consequences of loan forbearances please see BoE (2011a); Arrowsmith *et al.* (2013); BoE (2013a & 2013c); Barnett *et al.* (2014); and Nelson and Tanaka, 2014.

[60] The main types of forbearance were term extension (around 45%) and waivers of covenant breach (around 38%), followed by payment holiday, reduced payment and transfer to interest only loans.

However, a word of caution is in order. While banks' forbearances on loans may have protected some viable firms suffering from temporary negative shocks and weak demands from insolvency, they could have also led to the survival of some unviable businesses that would have otherwise defaulted[61]. In fact, the March 2013 BoE survey on SMEs' forbearance shows that, around 30% of banks' exposure to forborne loans were judged by individual bank relationship managers to be provided to businesses without viable long-term futures (Arrowsmith *et al.*, 2013). More specifically, around 0.6% of the borrowers had a 50% or more chance of default even without a change in interest rates, and 4.7% had more than 50% chance of defaulting, if rates were to rise by 4%.

Comparing the proportion of loss-making firms with aggregate insolvency over the recent recession and the previous recession may shed more light on the possible survival of unviable firms. Figure 2.3 shows the proportion of loss-making firms versus aggregate corporate insolvency from 1990-2011[62].

Figure 2.3 Aggregate Corporate Insolvency vs. Loss-making Firms



Source: Bank of England and The Insolvency Service[63]

[61] For a discussion of the economic impact of preventing unviable businesses from default, see Ahearne and Shinada (2005); Caballero *et al.* (2008); and Nelson and Tanaka (2014).
[62] Data on loss-making firms were only available for the period 1990-2011.
[63] The proportion of loss-making firms is the number of firms that reported negative pre-tax profits in each year as a percentage of the total number of private non-financial companies in the Bureau van Dijk dataset, which reports data on pre-tax profits, with firms in the mining and quarrying, electricity and

As can be seen from Figure 2.3, the argument about the existence of unviable and weak businesses among the survivors of the 2008/9 recession seems consistent with the wider gap between the proportion of loss-making firms and the number of corporate insolvencies in the recent recession than that of the early 1990s.

That is, despite a higher proportion of loss-making firms over the 2008/9 recession than that of the 1990s recession, the increase in aggregate insolvency is much smaller both in absolute and relative values. More specifically, while the peak of corporate liquidations for the 1990s recession was 24,425 (in 1992) which corresponds to 26.9% loss-making firms, the peak of corporate liquidations after the 2008/9 recession was 19,077 (in 2009) which corresponds to 35% loss-making firms.

Overall, regardless of its causes, the unusually high firm survivorship after the 2008/9 recession is evident. Furthermore, while in previous recessions struggling businesses did not really have a chance to survive, near-zero interest rates, the introduction of different support schemes, and loan forbearances during the 2008/9 recession may have contributed to the survival of unviable and weak firms that would have otherwise defaulted.

2.3.5.2. Zombies in the UK

In line with the above argument, the Association of Business Recovery Professionals (R3) published a report in July 2012, highlighting the existence of so called "zombie businesses" (zombies hereafter) in the UK[64]. As noted by Lee Manning, R3 president: "*Essentially, a zombie business is one that is on the edge of insolvency but has been holding on, often for a prolonged period of time*" (R3, 2012). The report further notes that, the risk for such firms is that, since they have no financial flexibility, any negative change of circumstances such as rise in interest rates, increase in input prices or loss of a major customer would push them over the edge and lead to their insolvency.

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gas supply, and water supply sectors and extra-territorial organisations are excluded from the calculations.

[64] The Association of Business Recovery Professionals (known by its brand name 'R3' which stands for 'Rescue, Recovery, and Renewal'), is made up of 97% of the UK's Insolvency Practitioners and is the leading professional association for insolvency, business recovery and turnaround specialists in the UK.

To the best of our knowledge, R3's report is the first attempt to identify zombies in the UK and provide an estimate of their number using data from 502 telephone interviews with SMEs conducted by the market research agency BDRC Continental in June 2012[65]. Based on any current debt repayments the firm might have had, the owners or the financial directors were asked whether they were experiencing any of the following:

- Only able to pay the interest on debts and not the principal amount;
- Unable to repay debts if interest rates increase by a small amount (for example 2%);
- Struggling to pay debts when they fall due; and
- Having to negotiate payment terms with creditors.

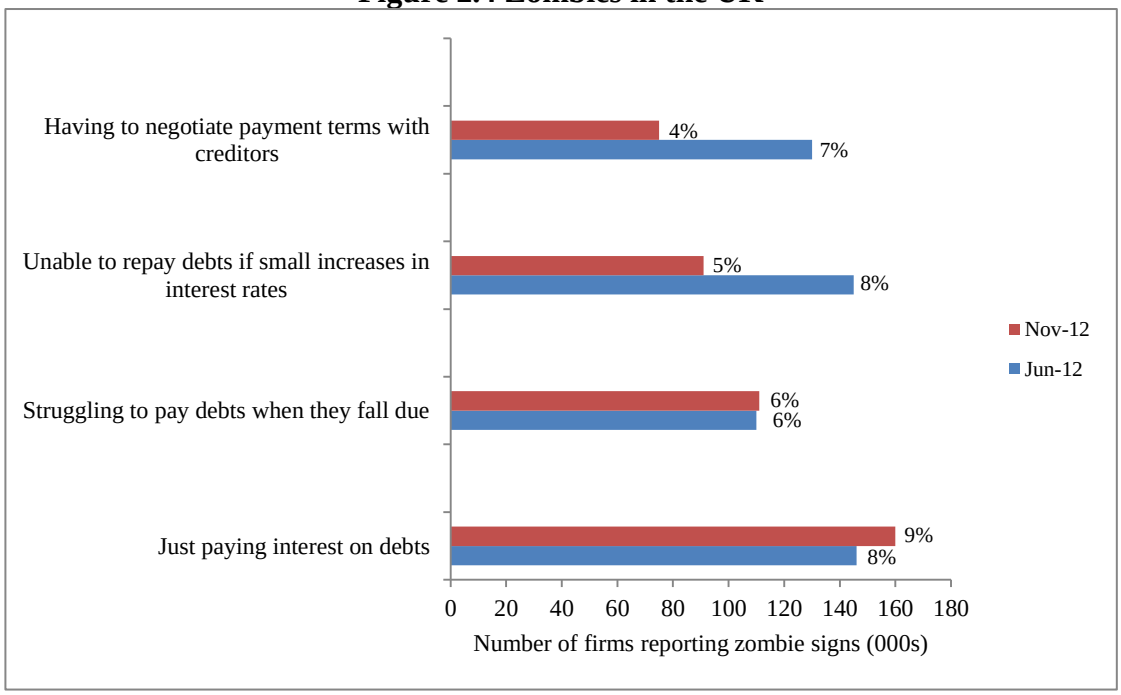
The most commonly reported answer was "*only paying the interest on debts and not the principal amount",* which was experienced by 8% of the respondents (equating to a total of 146,000 firms in the UK). Accordingly, R3 uses this as the definition of zombies[66]. The "*inability to repay debts if interest rates increase by a small amount*" was ranked second with 145,000 firms claiming they had experienced it. The very close numbers of firms experiencing the first 2 signs may have been due to the fact that, firms that generate just enough cash to service their debts and cannot pay down the principal, would be also very likely to default on their already minimal repayments in the event of a rise in interest rates. Furthermore, "*having to negotiate payment terms with creditors*" and "*struggling to pay debts when they fall due*" were the next common signs with 130,000 (7%) and 110,000 (6%) firms experiencing them, respectively. The report also indicates that, the Construction sector reports the highest number of zombies, around 37,000 (16%). However, overall, the Retail sector is identified as the most troubled sector, with around 31,000 (18%) claiming they would default on their debts in the event of a rise in interest rates; 30,000 firms (17%) struggling to pay their debts when they fall due; and 29,000 firms (16%) admitting they have had to renegotiate their payments terms with creditors.

[65] Strict quotas are set by size, region and sector, and data are weighted according to the make-up of the business population to enable them to be extrapolated and representative of the Office for National Statistics (ONS) profile of UK businesses with an annual turnover of £50,000-£20m. According to the Department for Business, Innovation, and Skills, there were around 1.7 million such businesses in the UK in 2012.

[66] It is also the commonly used definition used by other authorities and professional bodies such as the Bank of England.

In November 2012, R3 updated their results and estimated an increase of 14,000 in the number of zombies, bringing their total number to 160,000, equating to 9% of all UK firms (R3, 2013). Figure 2.4 presents the results of the two reports, indicating the number of firms experiencing each situation and their proportions as a percentage of all UK firms. In fact, the November report identifies Hotels and Catering as the most zombie-dominant sector with 47,000 (22%), followed by Construction and Retail, each with 10% of firms meeting the definition of zombies. However, Retail remained as the most troubled sector across all four propositions (R3, 2013).

Figure 2.4 Zombies in the UK



Data Source: R3

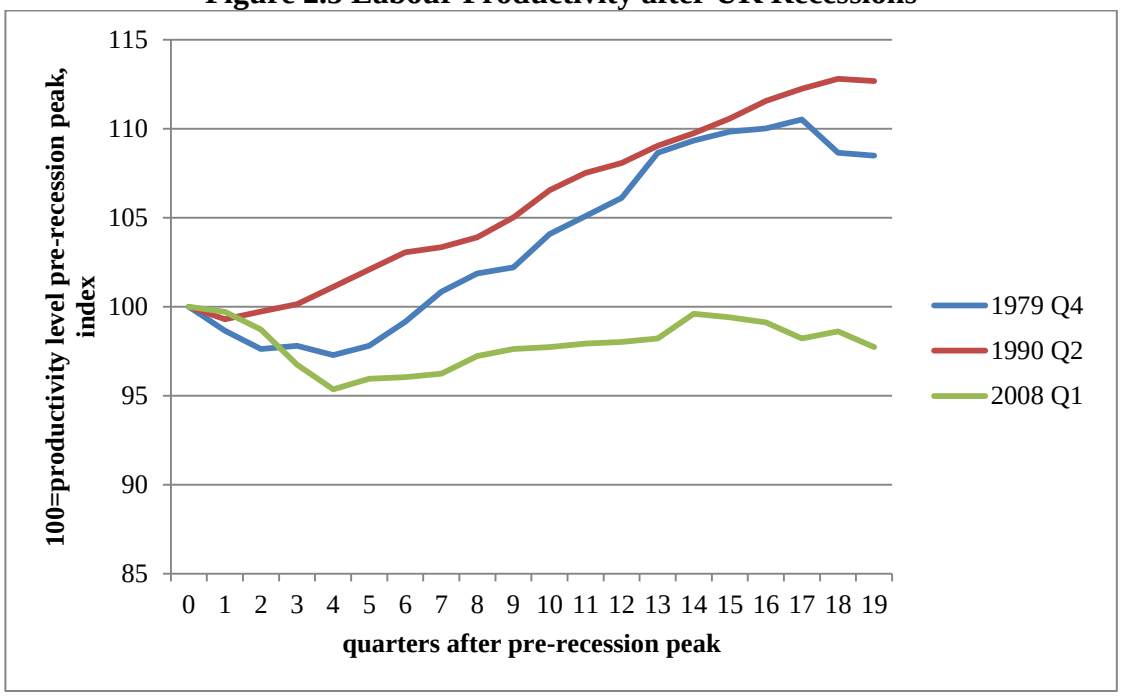
2.3.5.3. Economic Significance of Zombies

Economic growth can come from having more labour (recruiting more workers, or making existing employees work for longer hours), more capital, or from using that labour and capital more effectively, or what is referred to as Total Factor Productivity (TFP). Accordingly, given that both labour and capital are scarce resources, productivity is key to long-term growth. Labour productivity measures the quantity of output produced per unit of labour input and is commonly measured by output per worker. Macro-level data suggest that the UK whole-economy productivity has been exceptionally weak since the start of the 2008/9 recession, and the emergence of

zombies (i.e. high survival rate of unviable businesses) may be a possible explanation for it. That is, monetary policy through maintaining a near-zero interest rates has hindered the forces of creative destruction, and hence dragging down the productivity levels.

The very nature of economics recessions implies low productivity levels, however, historical data indicate that shortly after the end of the previous recessions the UK economy started to recover its lost output and experienced an increase in productivity levels. Figure 2.5 shows the whole-economy labour productivity after UK recessions over the last 3 recessions. While it took 7 quarters since the start of the 1980/81 recession and only 3 quarters since the beginning of the 1990/91 recession for labour productivity to pick up and reach its pre-recession peak, 19 quarters since the start of the 2008/9 recession labour productivity level was about 2.3% below its pre-recession peak with a much flatter slope in comparison with the previous two recessions.

Figure 2.5 Labour Productivity after UK Recessions



Source: Office for National Statistics

The 2.3% is the actual labour productivity gap and if productivity was to follow its pre-recession rate of growth[67], the gap would have been almost 12%. Whereas, at the corresponding stage of the previous recessions productivity was higher than at the

[67] Following Barnett *et al*. (2014b), the growth rate is calculated between 1997 Q1 and the 2008 Q1 and projected forward from 2008 Q1.

start of the recession by 8.5% (for 1980/81 recession) and 12.7% (for the 1990/91 recession). Therefore, the gap between the productivity levels before and after the recent recession and more importantly its prolonged recovery is undeniable. This phenomenon is often referred to as 'the UK productivity puzzle' (BoE, 2012c).

Going into details of all the possible causes for the UK productivity puzzle and a detailed investigation of their individual effects on the whole-economy labour productivity is beyond the scope of this Thesis. However, a series of reports and studies published by the Bank of England (BoE) and other authorities such as Office for National Statistics (ONS) and the Insolvency Service, which attempt to investigate and solve the puzzle have suggested that the inefficient reallocation of resources plays a critical role in UK productivity puzzle (e.g. Benito *et al*, 2010; Patterson, 2012; BoE 2012c, 2013a & 2013d; Arrowsmith *et al*, 2013; Van Reenen, 2013; Barnett *et al*, 2014a & 2014b).

The aggregate labour productivity growth is not only determined by the productivity growth within businesses but also by the efficient reallocation of resources (capital and labour) between businesses and across economy. That is, if the reallocation of resources is impeded, it may lead to persistence in the efficiency differences across businesses, which could in turn lead to slower overall productivity growth (Caballero and Hammour, 2000; Disney *et al*, 2003; BoE 2013a & 2013b; Arrowsmith *et al* 2013; Barnett *et al*, 2014a & 2014b and Riley *et al*, 2014). The very nature of productivity growth requires that inefficient businesses must either become efficient or default in order to open room for more efficient and dynamic businesses, as suggested by Joseph Schumpeter (1942) and his idea of "creative destruction". That is, highly inefficient and weak businesses must fail in order to free up the resources locked-in with them that can be deployed in more productive and dynamic businesses with greater growth prospects elsewhere.

Preventing unviable businesses with little ability to invest from default and keeping zombies alive can impede the allocation of capital to the real economy by locking in funding in assets generating low or no returns and diverting away the credit that otherwise could have been available to potentially more productive and dynamic businesses (BoE, 2012d). Furthermore, the presence of firms benefiting from forbearance and shielded from market funding costs may crowd out healthy

competitors and new entrants and lead to weakness of productivity and sluggish economic growth.

In fact, this was the case for Japanese banks during the 1990s, where prolonged period of forbearance on non-performing loans to zombies led to economic stagnation and the Japanese "lost decade" (Hoshi and Kashyap, 2004; Hoshi, 2006; Caballero *et al*, 2008). Hoshi (2006) was among the first studies to investigate the impact of zombie firms on the Japanese economic stagnation in the 1990s. He finds that, the increase in the proportion of zombie firm in an industry is associated with a decline in job creation and an increase in job destruction, and the effects are particularly stronger for non-zombies. Hoshi (2006) further argues that, because zombies did not react to the unfavourable shocks that hit the Japanese economy in the 1990s as much as they should have, healthy firms were forced to adjust and thus suffered more from such negative shocks. In fact, in some cases, the distortion created by zombies may have been so large that some non-zombie firms were turned into zombies.

In their seminal study of the distortionary effect of zombie lending on Japan's economy, Caballero *et al*. (2008) model the presence of zombies as a constraint on the natural surge in destruction that would arise in the wake of an unfavourable technological, demand, or credit shock. Accordingly, they find that, zombies tend to distort productivity in different ways, including depressing market prices for their products, raising market wages by hanging on to the workers whose productivity at the current firms declined, and, more generally, congesting the markets where they participated. They also note that, the low prices and high wages in the zombie-dominant industries reduce the profitability and collateral value of the existing (and new) more productive firms, thereby impeding their growth opportunities and discouraging entry.

Similarly, Kwon *et al.* (2015) investigate the resource reallocation in Japan during the 1990s and find that, the contribution to productivity growth deteriorated during their analysis period. In particular they find that the misdirected lending by banks to zombies allowed them to avoid reducing production inputs, especially labour. Using counter-factual analysis they show that, without zombie lending, the annual aggregate productivity growth would have been higher by 1 pp during the 1990s.

There also have been empirical supports for the distortionary effect of zombies on productivity performance outside the context of Japanese economy and the 1990s. For example, a very recent study by McGowan *et al*. (2017) applies Caballero *et al*. (2008) framework to a broader sample of OECD countries over the period 2003-2013 and show that the prevalence of zombie firms impede labour productivity performance through market congestion and constraining the growth of more productive firms. That is, the industry capital sunk in zombie firms imposes a limit on the available capital and the expansion possibilities of healthy incumbent firms. Furthermore, the market congestion generated by zombies can create barriers to entry through inflated wages relative to productivity and depressing market prices[68]. Their estimation results based on counter-factual analysis suggest that, business investment (as a measure of growth) by non-zombie firms would have been on average 2 pp higher in 2013, had the share of industry capital sunk in zombie firms not risen from its 2007 level.

The inefficient allocation of resources in the UK is evident after the 2007 GFC, as mentioned in the Bank of England's November 2012 Inflation Report (2012c, p. 30):

> The crisis may also have prevented finance and other resources from being put to their most productive use within the economy, and, related to that, have impeded the reallocation of capital as the economy restructures. There is some evidence that net rates of return across sectors, relative to their 1997–2007 averages, have diverged since the crisis, indicating that capital is presently inefficiently allocated.

Furthermore, Barnett *et al*. (2014a) show that over the pre-crisis period (2002-2007) the average contribution of reallocation of resources[69] across UK businesses was 1.2 pp, while after the crisis (2008-2011) it fell to 0.5 pp, and that about a third of the weakness in labour productivity in the post-crisis period can be attributed to slower resource reallocation between businesses[70].

[68] Accordingly, such market congestions can lead to the widening of the average multifactor productivity gap between zombies and non-zombies.
[69] It is measured by the changes in firms' labour shares, which can be also interpreted as capturing movements in capital.
[70] Barnett *et al* (2014b) update the results of Barnett *et al* (2014a) by including 2012 data and show no significant change in results.

Accordingly, while we are not aware of any specific and thorough empirical investigation of the impact of zombies on the UK economic growth and productivity, if history tells us anything is that zombies can have a detrimental effect. That is, to the extent that the existence of zombies leads to inefficient reallocation of resources, they are expected to contribute to the lower than expected and the sluggish productivity and output recovery of the economy.

Overall, the results from R3 reports suggests that, there exists a substantial number of zombies among UK SMEs, that is, firms that are only able to pay the interest on their debts, but unable to reduce the debt itself.

However, as mentioned before, zombies as defined by R3 are essentially the "near-insolvency" firms that are still able to service their debts. Accordingly, while many of these near-insolvency firms may have been protected by low interest rates, support schemes, and loan forbearances, there is no reason to suggest that they have only emerged after the recent GFC, and thus have contributed towards the smaller-than-expected increase in aggregate insolvency after the 2008/9 recession (i.e., should have defaulted but have been able to survive).

We believe that a more appropriate definition of zombies must acknowledge that zombies, as the name suggests, are technically insolvent (i.e., half-dead) firms that have been prevented from insolvency (i.e., half-alive)! So that, our definition captures the insolvent nature of the zombies (i.e., reflecting that by definition they are not expected to be active and in operation, especially in a recessionary environment), as well as their survival (i.e., they have been prevented from default). Hence, this provides a plausible explanation for the smaller-than-expected increase in insolvencies after the 2008/9 recession.

Accordingly, in order to identify the "surviving insolvent" firms rather than "near-insolvency" firms, we use a more stringent criterion than R3 and define zombies as: *surviving technically insolvent firms that are unable to generate enough revenues to even pay the interest expenses on their borrowings, let alone the repayment of the*

principal amount[71]. Hence, these surviving insolvent firms, which would have most likely defaulted in previous recessions due to their inability to pay their financial obligations, can be claimed to have emerged and been able to survive after the 2008/9 recession. This was due to unprecedented low interest rates, different support schemes, and loan forbearances and thus, contributed to lower-than-expected corporate insolvencies.

Using this definition, it is interesting, timely, and warranted to investigate the existence of zombies in our sample and develop an empirical model to identify the determinants of zombieness status as well as estimating their impact on the probability of becoming a zombie, should we find any zombies in our sample. However, to the best of our knowledge, there have been no previous empirical attempts to identify zombies in a given sample or examine their characteristics and determinants. Hence, there is no pre-existing empirical literature to provide guideline in the choice of estimation technique or explanatory variables. Having said that, recalling that zombies are defined as the surviving *insolvent* firms, zombies and insolvent firms are very similar in definition. This is in the sense that in both cases, the firm is unable to pay its financial obligations and thus, the two terms capture the same underlying financial characteristics.

Consequently, in the following section, we provide a brief review of the corporate insolvency empirical literature to inform our choice of possible explanatory variables and estimation technique to be used in developing a model to identify the determinants of zombieness status and estimate their impact on the probability of becoming a zombie.

2.3.5.4. Empirical Literature of Zombies

Beaver (1966) and Altman (1968) are among the first attempts to investigate firm insolvency and since them follows a large literature on insolvency prediction. This results in a wide range of competing empirical models with different explained/explanatory variables and estimation methods. In what follows, we will

[71] Hereafter, the term zombie is used to refer to "surviving technically insolvent firms that are unable to generate enough revenues to even pay the interest expenses on their borrowings, let alone the repayment of the principal amount".

review the most commonly used estimation methods and different types of dependent and independent variables in the corporate insolvency literature.

2.3.5.4.1. Estimation Method

The most common analysis techniques that have been used in estimating insolvency models include: Discriminant Analysis (DA), Conditional Regression Analysis (CRA), and Neural Network Analysis (NNA). However, due to its complexity and decreased popularity in the literature, the NNA estimation method is not covered in this review[72].

Univariate Discriminant Models

Beaver (1966) has developed the first insolvency prediction model, using Univariate Discriminant Analysis (UDA) to test individual ratios' predictive abilities in classifying solvent and insolvent firms[73]. In a Univariate Discriminant Model (UDM), an optimal cut-off point is estimated for each of the variables separately, based on their values for each group. These cut-off points are then used to classify each firm in the sample into solvent/insolvent based on their values for the relevant variable (Hair *et al.*, 2010). Furthermore, UDA assumes a linear relationship between the dependent and the independent variable, which implies that UDMs fail to account for the possible non-linear relationships between some explanatory variables and firms' financial health condition.

However, given that using a single ratio model to estimate corporate insolvency is too simplistic to capture the complexity of financial failure, the applications of UDA have been very limited. Since Beaver (1966), there have been only a few other studies on corporate insolvency using this estimation technique (e.g., Pinches *et al.*, 1975 and Chen and Shimerda, 1981). Such overly simplified models could severely suffer from omitted variable problems and could lead to inconsistent and unreliable results, since the possible effect of all variables not being included will be captured by the error term. Nonetheless, UDMs may be appropriate when the objective is merely to

[72] For a detailed discussion of the neural networks and their applications in firm insolvency prediction, see Boritz *et al.* (1995) and Trigueiros and Taffler (1996).
[73] The term "solvent" is simply used to refer to firms that are not insolvent. It is the equivalent of the term 'non-bankrupt' commonly used in the US studies.

evaluate the predictive ability and significance of individual variables before they are included in a final multivariate model (Hair *et al.*, 2010).

Multivariate Discriminant Models

Altman (1968) was the first attempt to use Multivariate Discriminant Analysis (MDA) to develop an insolvency prediction model. Altman (1968: pp. 591-592) notes the following about MDA:

> MDA is a statistical technique used to classify an observation into one of several *a priori* groupings dependent upon the observation's individual characteristics. … MDA then attempts to derive a linear combination of these characteristics which "best" discriminates between the groups.

Multivariate Discriminant Models (MDMs) had been the most prominent approach used to estimate insolvency models in the 1970s and 1980s (e.g., Deakin, 1972; Blum, 1974; Altman *et al.*, 1977; Dambolena and Khoury, 1980; Taffler 1982; Gombola *et al.*, 1987; and Goudie and Meeks, 1991). In a MDM, several variables are combined into one single Multivariate Discriminant Score (MDS), which is calculated as the sum of the product of the variables and their coefficients. The MDS is then used to classify firms into different groups, using an optimal cut-off point. Firms are classified into solvent and insolvent groups, depending on which group they most closely resemble, subject to their MDS[74]. That is, if a firm's MDS is less than the cut-off point, it is classified as insolvent, and if the discriminant score exceeds or is equal to the cut-off point, firm is classified as solvent (Balcaen and Ooghe, 2006). Thus, the MDS is essentially an ordinal measure that allows the ranking of firms, with low values indicating poor financial health and vice versa.

Similar to UDA, MDA also assumes linear relationship between the independent variables and the dependent variable. Furthermore, it also requires normal distribution among independent variables and equal variance-covariance matrices of the independent variables across both groups of firms (Hair *et al.*, 2010). Although,

[74] When specific weights are assigned to the five financial ratios used in Altman (1968), the discriminant score is called the Z-score: $Z = .012X_1 + .014X_2 + .033X_3 + .006X_4 + .999X_5$. Where, X_1, X_2, X_3, X_4 and X_5 refer to *Working Capital/Total Assets*, *Retained Earnings/Total Assets*, *EBIT/Total Assets*, *Market Value Equity/Book Value of Total Debt*, and *Sales/Total Assets*, respectively.

violation of these assumptions can lead to biased and inconsistent estimates, they are often ignored by researchers as these assumptions are quite difficult and costly to satisfy in practice (Balcaen and Ooghe 2006). For instance, the normality assumption of independent variables could potentially prevent the use of dummy independent variables. Similarly, the assumption of equal dispersions of independent variables across both groups may be difficult to satisfy, especially in the existence of extreme values. While, winsorizing or trimming the data by deleting outliers are possible ways of dealing with non-normality and equal dispersions problem, they can lead to significant loss of information. The information loss could be particularly substantial when the two groups are significantly different in size and the extreme values belong to the smaller group, which is usually the case with insolvency data, as the number of insolvent firms is expected to be significantly smaller than that of solvent firms.

Logit/Probit Regression Models

Given that the rigid assumption required by MDA are often difficult to satisfy in practice, less demanding statistical techniques such as logit and probit regression models, also known as Conditional Probability Models (CPMs) have become increasingly popular in the insolvency literature (e.g., Ohlson 1980; Zmijewski 1984; Zavgren 1985; Gilbert *et al.*1990; Platt and Platt 1990; Lennox 1999; Becchetti and Sierra 2003; and Charitou *et al.*2004). CPMs are less restrictive than MDMs in the sense that, they do not require normality of independent variables or equal variance-covariance matrices, and they also allow for non-linear relationship between the set of explanatory variables and insolvency status of the firm (Lo, 1986). Ohlson (1980) and Zmijewski (1984) were among the first attempts to explain and predict corporate insolvency using CPMs: logit and probit model, respectively.

Although logit models and probit models are very similar in their estimation approach, the two vary in their assumption about the probability distribution. That is, while the logit model assumes the cumulative logistic distribution function, the probit model assumes a cumulative normal distribution function (Cramer, 2003). Accordingly, given the similarities between the two models and the significantly wider application of logit models in the insolvency literature, we will focus only on logit models.

Logit models are designed to estimate the probability of occurrence of a particular outcome. That is, while the dependent variable in MDM is a dummy variable indicating whether or not a firm belongs to a pre-specified group, the dependent variable in logit models is the odds ratios of the event of interest happening (i.e., probability of the event of interest (coded as 1) happening over the probability of not happening). Therefore, logit models may be more appropriate than MDMs when the focus is on the probability of insolvency rather than simple classification of insolvent and solvent firms (Barnes 1987). Logit models use the set of explanatory variables to estimate a probability score (logit score), indicating the probability of the firm becoming insolvent, or the firm's vulnerability to insolvency. The insolvency probability is assumed to follow a cumulative logistic distribution which implies that, an extremely healthy (weak) firm, in comparison to a firm that has an average financial health, must experience a proportionally larger deterioration (improvement) in its independent variables in order to deteriorate (improve) its insolvency probability score (Balcaen and Ooghe, 2006). Firm are classified into solvent and insolvent groups based on their logit score and a certain cut-off value.

Similar to MDMs, logit models are also based on the resemblance principle, in the sense that firms are assigned to the group they most closely resemble. That is, where a high logit score indicates a high insolvency probability (i.e., insolvent status is coded as 1 and solvent status is coded as 0), a firm is assigned to the insolvent group if its logit score is higher than the cut-off point and to the solvent group if its logit score is lower or equal to the cut-off point (Hair *et al.*, 2010).

As mentioned before, when applying logit analysis, no assumptions are made regarding multivariate normal distribution of the explanatory variables, equal dispersion matrices and linear relationship between the dependent and independent variables. However, as for any multivariate analysis techniques (such as MDA), logit models can be sensitive to high degrees of multicollinearity (high correlation among independent variables), which may result in unstable estimates (Gujarati, 2004; Hair *et al.*, 2010). Having said that, multicollinearity can be easily reduced or possibly eliminated by factor analysis or using alternative variables to capture the same effect. Furthermore, using stepwise estimation techniques available in different analysis

packages would automatically control for multicollinearity among independent variables.

Overall, given that logit model are less demanding in terms of required assumptions and can accommodate a wider range of variables due to their non-linear nature, they are deemed as the more appropriate estimation method to model corporate insolvency.

2.3.5.4.2. Dependent Variable

Corporate insolvency prediction studies vary in their definition of insolvency, depending on the purpose of the analysis, conditions of the firms in the analysis, and other sample characteristics such as the time period under examination (see, Dimitras *et al.*1996; Balcaen and Ooghe, 2006; and Bellovary *et al.*2007). While the great majority of the empirical insolvency studies have used the actual filing for insolvency or the ultimate failure of the firm to define insolvency, some other studies instead have used alternative financial distress criteria such as: several years of negative net operating income (e.g., Gilbert *et al.*1990 and Platt and Platt 2002), low interest coverage ratio (e.g., Asquith *et al.*1994 and Platt and Platt 2006), suspension of dividend payment (e.g., Lau 1987 and Ward 1994a), and major restructurings or layoffs (e.g., Hill *et al.*, 1996). A major advantage of the juridical definition of insolvency is its standardised and objective nature, which allows it to be easily applied to any analysis sample to classify firms into solvent and insolvent groups. The other advantage, which is particularly important for prediction models, is that, while the timing of other less objective definitions of insolvency cannot be accurately identified, using the actual filing for insolvency allows the moment of insolvency to be accurately dated.

Although the absolute majority of insolvency models formulate insolvency status by a dichotomous variable, where insolvency is coded 1 and non-insolvency (i.e., firm remains solvent) is coded 0, a few cases have used a multivariate dependent variable. That is, insolvency is defined as a multi-state process such that the dependent variable has more than two possible outcomes. For instance, Lau (1987) uses a five-state financial distress dependent variable to approximate the continuum of corporate financial health from financial stability to liquidation, instead of the conventional

solvent/insolvent dichotomy[75]. Using logit analysis to develop a multi-state model, the author estimates the probabilities of a firm entering each of the states. Similarly, in an attempt to identify early predictors of insolvency, Laitinen (1993) defines the insolvency process as a four-phase process: starting (i.e., a partial collapse in financial ratios); intervening (i.e., a slow decline or plateau in financial ratios); final (i.e., very low and poor financial ratios); and the exit phase (i.e., insolvency or total bankruptcy), and uses logit models to predict the probability of each of a firm entering each of the phases.

Over the past five decades, a significant number of independent or explanatory variables have appeared in the empirical studies of corporate insolvency, as possible determinants of insolvency or more generally determinants of firms' financial health. However, there has not been any consensus among insolvency studies, regarding the *significant* explanatory variables (Scott, 1981; Dimitras *et al.*, 1996; Bellovary *et al.*2007). Accordingly, lack of a strong theoretical basis for the selection of variables has caused the great majority of insolvency studies to adopt an empirical-based approach and choose the explanatory variables based on their popularity in the empirical literature (Balcaen and Ooghe, 2006). Consistent with this argument, surveys of insolvency literature suggest that, the definition of insolvency (i.e., actual insolvency vs. financial distress criteria) or the nature of the variable (i.e., dichotomous vs. multi-level) does not seem to affect the choice of explanatory variables included in insolvency models (Bellovary *et al.*, 2007). However, depending on sample characteristics, some variables have been found significant in some models and insignificant in others.

For instance, Gilbert *et al.* (1990) find that, financial ratios of insolvent firms are not significantly different than those of financially distressed firms. This in turn implies that, the same explanatory variables (representing different firm characteristics) as those used in models distinguishing between insolvent and solvent firms (i.e., models based on actual insolvency) may be also used in models distinguishing between financially distressed and solvent firms (i.e., models based on financial distress).

[75] The five financial states used by Lau (1987) are: state 0: financial stability; state 1: omitting or reducing dividend payment; state 2: technical default and default on loan payments; state 3: protection under Chapter X/XI of the Bankruptcy Act (complex reorganization arrangements with creditors); and state 4: bankruptcy and liquidation. States 1 to 4 are referred to as the states of increasing severity of financial distress.

Accordingly, the evident significant overlap among the independent variables of the models predicting financial distress, and those of the models predicting juridical insolvency, suggests that this has been the prevailing approach in the literature.

The same argument holds for multi-state insolvency models. For instance, Laitinen (1993) shows that the specific phases of insolvency process are not relevant for the choice of independent variables[76]. In particular, he finds that, while financial ratios in their level format can explain the final phase of insolvency, trends and differences of financial ratios are significant in the models estimating the probability of entering the intervening and starting phases of insolvency, respectively. Thus, although the formats of variables vary depending on the insolvency state, the same variables are used for all three models, corresponding to different insolvency states.

Accordingly, given that zombies are defined as surviving *insolvent* firms, and that firms are classified as zombies and non-zombies, the dependent variable in our estimation model is expected to be very similar in definition and format to the most commonly used dependent variable in the insolvency models; the insolvent/solvent dichotomous variable. Thus, it would be reasonable to consider independent variables that have been used in insolvency studies as the possible determinants in the probability of becoming a zombie.

2.3.5.4.3. Independent Variables

Conducting an extensive review of the insolvency prediction literature, Balcaen and Ooghe (2006) identify three broad types of independent variables used by insolvency models: financial, non-financial and macroeconomic variables. While, financial variables, typically in the form of financial ratios, are by far the most common type of explanatory variables, there have also been recognition of the possible impact of non-financial characteristics and the overall economic environment in which firms operate on their financial health status.

[76] The five explanatory variables used in Laitinen's multi-state model include: Return on Investment Ratio; Quick Ratio; Cash Flow/Net Sales; Shareholders Capital/Total Assets; and Cash Flow/Total Debt.

Financial Variables

Financial ratios are hard and objective measures that can be conveniently computed using publicly available information in firm's financial statements. While, the great majority of studies in the insolvency literature have used financial variables as the only type of explanatory variables in their models, there has been a significant variation in the choice of financial variables among these studies.

Using financial variables started with Beaver's (1966) attempt to assess the predictive abilities of 30 individual ratios in classifying insolvent firms, out of which he identifies *Net Income/Total Debt*, *Net Income/Sales*, *Net Income/Net Worth*, *Cash Flow/Total Debt*, and *Cash Flow/Total Assets* as the 5 ratios with the highest predictive ability of insolvency.

In its multivariate context, starting with Altman's (1968) z-score model, accrual-based financial ratios had been used as the only type of explanatory variables until the early 1980s (e.g., Deakin, 1972; Moyer, 1977; Altman *et al.* 1977; Taffler, 1982; and Zmijewski, 1984). As mentioned in the previous section, the number of financial ratios used as explanatory variables vary significantly among the empirical studies of corporate insolvency. For instance, while Taffler (1982) uses 50 different ratios in his insolvency model, Altman (1968) uses only 5 ratios and Zmijewski (1984) utilises even a smaller number of ratios, 3, to investigate the determinants of corporate insolvency[77]. However, despite their variation in number, generally the included financial ratios have been chosen to represent the same main financial characteristics of firms, such as: profitability, financial leverage, activity level, and liquidity position.

While majority of the early studies of corporate insolvencies had only included accrual-based ratios, given that firms' ability to generate cash from operation is critical for their survival, and the potential differences between net operating cash flow and net income, many studies have also included different operating cash flow-based ratios in their insolvency models (e.g., Gombola and Ketz 1983; Casey and Bartczak 1985; Gentry *et al.*, 1985; Gombola *et al.*, 1987; Aziz *et al.*1988; Ward

[77] The three ratios used by Zmijewski (1984) in his model include: Net Income/Total Assets, Total Debt/Total Assets and Current Assets/Current Liabilities.

1994b; Rujoub *et al.*, 1995; Sharma and Iselin 2003; and Jooste, 2007)[78]. In fact, the main objective of many of these studies has been to test which of the accrual-based financial ratios or the cash flow-based ratios are better able to explain insolvency. However, there seems to be little consensus and lack of general agreement among these studies to suggest superiority of one over another. For example, while Casey and Bartczak (1985) and Gombola *et al.* (1987) find that cash flow from operations do not improve the classification of solvent and insolvent firms, Aziz *et al.* (1988) and Sharma and Iselin (2003) find that cash-flow based ratios contain information content beyond accrual-based ratios, which could improve the performance of insolvency models!

A comprehensive review of insolvency prediction literature and model development by Bellovary *et al.*(2007) have identified the 42 most commonly used variables in the insolvency studies from 1966 to 2007[79]. The top 10 variables most common to multiple studies are *Net Income/Total Assets* (54 studies), *Current Ratio* (51 studies), *Working Capital/Total Assets* (45 studies), *Retained Earnings/Total Assets* (42 studies), *Earnings Before Interest and Taxes/Total Assets* (35 studies), *Sales/Total Assets* (32 studies), *Quick Ratio* (30 studies), *Total Debt/Total Assets* (27 studies), *Current Assets/Total Assets* (26 studies), and *Net Income/Net Worth* (23 studies).

Accordingly, given the prevailing empirical-based approach in choosing the explanatory variables in the literature, one must consider including a set of most commonly used financial variables in the empirical studies of corporate insolvency as possible explanatory variables when developing an insolvency prediction model.

Non-Financial Variables

Insolvency prediction models using only financial variables, implicitly assume that all the relevant factors affecting the insolvency or survival of firms, both internal and external, are captured by the included financial variables. Inclusion of non-financial or qualitative variables in insolvency models can improve their classification and predictive power as such factors could be used to detect the causes of insolvency

[78] Net operating cash flow may differ from net income for three main reasons: 'non-cash' expenses such depreciations or amortizations, timing differences and 'non-operating' gains and losses.

[79] They identify a total of 752 different variables used in the 165 studies surveyed in their paper, out of which 674 variables are used in only one or two studies. They highlighted the 42 most common variables that are utilised in five or more studies.

rather than its symptoms (Balcaen and Ooghe, 2006). For example, Peel *et al.* (1986) use four non-financial variables, the time lag between firm's financial year end and the date of the publication of its annual accounts, the number of directors' resignations, directors' appointments, and changes in the directors' shareholding in their insolvency model and find significant explanatory power for all of them. In particular, they show that, combining these non-financial variables with conventional financial ratios enhances the predictive power of models based on only financial variables. Similar results are found in Keasey and Watson's (1987) attempt to investigate the impact of different management behaviours indicators, firm's age, number of directors, and different time lag indicators for auditor's report and account submissions on corporate insolvency.

However, the majority of studies acknowledging the importance of non-financial variables in determining corporate insolvency tend to include both financial and non-financial variables in their models. Examples of non-financial variables and qualitative indicators used in these mixed models include: productive efficiency, level of diversification, profitability of the industry, market share, and events reflecting management actions, such as reductions in dividends, troubled debt restructurings, and violations of debt agreements (see, Opler and Titman, 1994; Amir and Lev, 1996; Ittner and Larcker, 1998; Becchetti and Sierra, 2003; Riley *et al.*, 2003; and Wu, 2004). Accordingly, in order to control for those firm characteristics that cannot be captured by financial variables and to cover a wider range of possible factors affecting firm's performance and financial health, one must consider including different financial and non-financial variables as explanatory variables in the development of the insolvency prediction model.

Macroeconomic Variables

Given that firms do not stand alone, the external environment to the firm can also have an impact on its performance (Dimitras *et al.*, 1996 and Richardson *et al.*, 1998). That is, changes in macroeconomic conditions such as economic growth rate, changes in interest rates and availability of credit may affect firms' performance and survivals. Thus, if such external factors are ignored and excluded from the models predicting the corporate insolvency, the corresponding models of insolvency are likely to suffer from

the omitted variable problem and may perform poorly when applied to a different economic environment than the one it was developed from (Bonfim, 2009).

Inclusion of macroeconomic variables in insolvency models was initially proposed by Desai and Montes (1982) and Rose *et al.* (1982) and since then, different proxy measures for overall economic conditions including GDP growth, inflation, credit availability, interest rates, exchange rate, and money supply have been adopted by many studies (e.g., Wadhwani, 1986; Goudie and Meeks, 1991; Richardson *et al.*, 1998; Liu, 2004; Altman *et al.,* 2005; Carling *et al.,* 2007; Bhattacharjee *et al.,* 2009; and Bonfim, 2009). Overall, their findings suggest that, movements in aggregate insolvency coincide with changes in macroeconomic performance, in the sense that negative macroeconomic shocks have been accompanied and followed by an increase in aggregate insolvency level and vice versa. For instance, in an attempt to determine the causes of aggregate insolvency, Wadhwani (1986) investigates the impact of inflation on aggregate insolvency rates in the UK over the period 1964-1981, and finds that higher inflation leads to a higher insolvency rate. Similarly, Liu (2004) conducts an investigation on the relationship between aggregate insolvency rates and interest rates, credit availability and inflation utilising a large dataset on UK firms over the period 1966-1999. The estimation results obtained using an Error-Correction Model (ECM), suggest that interest rates and inflation tend to have a strong positive association with aggregate insolvency, while there has been found a negative relationship between availability of credit and aggregate corporate insolvency rate.

However, while the previously mentioned studies have all been conducted in a macro-level context and investigate the impact of macroeconomic factors on aggregate insolvency, the overall macroeconomic conditions may affect individual firms differently depending on their individual characteristics. For instance, firms whose revenue-generating ability are relatively less sensitive to the overall economic conditions are less prone to insolvency than their otherwise similar counterparts when economic conditions change for the worse and vice versa. Therefore, given that all previously mentioned studies have focused on aggregate insolvency, it is interesting to investigate the possible impact of overall economic conditions on the firm-level insolvency.

2.3.5.5. Implication for Our Study

As discussed above, a unique type of firms called "zombies" seem to have come to existence after the recent GFC and the consequent economic recession. Zombies are unique in the sense that, they are neither fully insolvent (as are still active and in operating) nor in a solid financial standing (are unable to generate enough revenues to service their debts). Thus, their other financial characteristics such as capital structure may also be determined differently than those of non-zombies. Therefore, these unique firms must be controlled for when investigating the impact of the recent GFC on firms' capital structure, as failure to do so may lead to distorted and unreliable inferences regarding how different firms determine their capital structures.

Identifying the zombies in our analysis sample, we can investigate whether capital structure of zombies is determined differently than that of non-zombies by including a zombie dummy variable that takes a value of 1 if a firm is identified as zombie and 0 otherwise in our estimation model. Furthermore, since zombies are post-crisis phenomena, we can only define the zombie variable for the firm-year observations after the onset of the GFC (i.e., 2008, 2009, 2010, 2011 and 2012)[80].

Unfortunately, due to lack of theoretical and empirical evidence on the subject of zombies and the determination of their capital structure, there are no *a priori* expectations regarding the impact of being zombie on leverage ratios. However, recalling the discussion on possible causes of the emergence of zombies, to the extent that the banks' loan forbearances and the rescue packages offered by the government had involved additional lending to the zombies and significantly increased their leverage ratios, we would expect to find a positive relation between the zombie dummy variable and the leverage ratio, suggesting that zombies tend to have higher leverage ratios than non-zombies.

With respect to the determinants of zombieness status, three broad types of variables that have been used in insolvency models: financial, non-financial and macroeconomic variables, each capturing a different aspect of firm's financial health. Accordingly, an integrated model that includes a combination of the relevant financial, non-financial and macroeconomic variables can lead to more reliable

[80] For more details, see Section 3.2.

inferences about the determinants of zombieness status and their impact on the probability of becoming a zombie.

However, lack of a strong theoretical basis for the selection of variables and the prevailing empirical-based approach in choosing the explanatory variables based on their popularity in the empirical literature has led us to conclude that, the set of variables to use as determinants of the zombieness status of firms must be selected from a large pool of commonly used variables in the insolvency literature. We start with constructing an extensive set of variables that have appeared in previous insolvency studies and then narrow them down using different statistical criteria. This way, only the most significant variables with the highest explanatory power are remained to be included in the final estimation model of the probability of becoming a zombie.

Accordingly, an initial set of 50 potential explanatory variables is developed based on the frequency and appearance in insolvency prediction models, covering the three broad types of variables. Table 2.2, Table 2.3 and Table 2.4 present the potential financial, non-financial, and the macroeconomic explanatory variables and their definitions, respectively. The 39 financial variables in Table 2.2 are extracted from the comprehensive list of most commonly used variables in insolvency studies as identified by Bellovary *et al.*(2007), which cover all the main categories of financial ratios (i.e., leverage, profitability, liquidity, and activity ratios) as well as cash flow-based financial variables[81]. Furthermore, in order to cover a wider range of possible factors affecting firm's performance and financial health, a set of non-financial firm characteristics are also included in the initial list of explanatory variables. As can be seen from Table 2.3, they include: firm size (SIZE); a dummy variable controlling for firms' viability as assessed by its top management (CEOCHNG)[82]; a dummy variable controlling for restructuring activities (DISCNTDOP); a dummy variable controlling for payment of dividends (DVDND); and three dummy variables to control for the type of industry in which firm is operating (RTIL; CONSTRCTN; and

[81] Bellovary *et al.* (2007) identify a total of 752 different variables used in the 165 studies surveyed in their paper, out of which 674 variables are used in only one or two studies. They highlighted the 42 most common variables that are utilised in five or more studies.

[82] Following Peel *et al.* (1986), we include the dummy variable indicating whether the Chief Executive Officer (CEO) or equivalent resigned during the year is included as a proxy measure to capture the top management's assessment of the firm's viability, which is not necessarily reflected in conventional financial variables.

HTSLCTNG)[83]. Finally, to the best of our knowledge, there have been no firm-level insolvency models using macroeconomic factors as possible explanatory variables, and given that the overall macroeconomic conditions may affect individual firms differently depending on their individual characteristics, we cannot think of any reason why they should not be included in our model. Accordingly, to investigate the possible impact of the overall economic conditions on the probability of becoming a zombie, four macroeconomic variables that have commonly appeared in the insolvency literature are also included in the initial list of explanatory variables. As can be seen from Table 2.4, the included macroeconomic variables are: real Gross Domestic Product (GDP) growth rate to measure overall economic growth; average 3-month London Inter Bank Offered Rate (LIBOR) as a proxy to control for interest rates on borrowing; growth in net stock of lending to UK non-financial firms as a measure of credit availability; and Consumer Price Index (CPI) to control for inflation.

[83] Given the unprecedented collapse of house prices and drop in mortgage approvals after the recent recession, and the detrimental impact of recessions on consumer discretionary spending, firms that are more heavily exposed to such factors are more likely to suffer and face difficulties in meeting their financial obligations (Gittins and Luke, 2012; BoE, 2013c). Accordingly, in order to investigate whether such factors are in fact affecting the probability of becoming a zombie, we include three industry dummies to identify firms in the Retail, Construction and Hotels & Catering sectors.

Table 2.2 Financial Variables

Variable	*Definition*
TDTA	$Total\ Debt/Total\ Assets$
TDNW	$Total\ Debt/Net\ Worth$
TLTA	$Total\ Liabilities/Total\ Assets$
TLNW	$Total\ Liabilities/Net\ Worth$
NWTL	$Net\ Worth/Total\ Liabilities$
TCTA	$Total\ Capital/Total\ Assets$
RETA	$Retained\ Earnings/Total\ Assets$
LTDTA	$Longterm\ Debt/Total\ Assets$
NWTA	$Net\ Worth/Total\ Assets$
TMKVTD	$Total\ Market\ Value/Total\ Debt$
PM	$Net\ Profit(Loss)/Sales$
EBITS	$EBIT/Sales$
ROA	$Net\ Profit(Loss)/Total\ Assets$
ROE	$Net\ Profit(Loss)/Net\ Worth$
EBITTA	$EBIT/Total\ Assets$
OEOI	$Operating\ Expense/Operating\ Income$
WCTCE	$Working\ Capital/Net\ Worth$
WCS	$Working\ Capital/Sales$
CACL	$Current\ Assets/Current\ Liabilities$
QATA	$Quick\ Assets/Total\ Assets$
CATA	$Current\ Assets/Total\ Assets$
QACL	$Quick\ Assets/Current\ Liabilities$
CCL	$Cash\ \&\ Cash\ Equivalents/Current\ Liabilities$
CLTA	$Current\ Liabilities/Total\ Assets$
WCTA	$Working\ Capital/Total\ Assets$
CTA	$Cash\ \&\ Cash\ Equivalents/Total\ Assets$
NOCRDTINTVL	$(Quick\ Assets - Current\ Liabilities)/Daily\ Operating\ Expenses$
STA	$Sales/Total\ Assets$
NSTA	$Net\ Sales/Total\ Assets$
CAS	$Current\ Assets/Sales$
QAS	$Quick\ Assets/Sales$
INVS	$Inventory/Sales$
SINV	$Sales/Inventory$
CFO	$\ln(Operating\ Cash\ Flow)$
CFOTA	$Operating\ Cash\ Flow/Total\ Assets$
CFOS	$Operating\ Cash\ Flow/Sales$
CFOTD	$Operating\ Cash\ Flow/Total\ Debt$
CFOTL	$Operating\ Cash\ Flow/Total\ Liabilities$
CFOCL	$Operating\ Cash\ Flow/Current\ Liabilities$

Table 2.3 Non-Financial Variables

Variable	*Definition*
SIZE	$\ln(Total\ Assets)$
CEOCHNG	1 if Chief Executive Officer (CEO) or equivalent resigned during fiscal year, 0 otherwise
DISCNTDOPRTN	1 if firm sold, disposed or abandoned a business operation with a negative monetary impact, 0 otherwise
DVDND	1 if firm does not pay dividends, 0 otherwise
RTIL	1 if firm is in Retail Sector, 0 otherwise
CONSTRCTN	1 if firm is in Construction Sector, 0 otherwise
HTLSCTNG	1 if firm is in Hotels & Catering Sector, 0 otherwise

Table 2.4 Macroeconomic Variables

Variable	*Definition*
GDP	Real Gross Domestic Product (GDP) Annual Growth
LIBOR	Annual 3-month Libor
CREDIT	Annual Growth in Net Stock of Lending to UK Businesses
CPI	Annual Inflation by Consumer Price Index (CPI)

2.4. Concluding Remarks

This chapter provides a conceptual framework for our empirical analysis and is used to inform us in the choice of variables to be used in the estimation model. Firstly, we briefly review the main theories of capital structure and their main premises. Secondly, we provide a detailed review of the empirical findings on some of the most commonly used firm-specific determinants of capital structure. We then present some recent empirical studies on the impact of the recent Global Financial Crisis (GFC) on firms financing decisions. Finally, we introduce the concept of zombie firms as a post-crisis phenomenon and put it into context of firms' capital structure.

Reviewing the theories of capital structure, we emphasise the Modigliani-Miller irrelevance theory, the trade-off theory, the agency theory and the pecking order theory of capital structure. These theories are based on a set of conditional assumptions which makes one more appropriate in certain circumstances than others. While Modigliani and Miller's (1958) irrelevance theory proposes that, under perfect capital markets condition, the choice of capital structure is irrelevant to the firm's value, the existence of different market imperfections such as, bankruptcy risk, transaction costs, corporate taxes, costs of financial distress, information asymmetries, and conflicts of interest among stakeholders have led to the emergence of alternative and more practically applicable theories of capital structure.

Each of these theories proposes a different explanation for how firms make financing decisions and suggests different predictions regarding the determinants of capital structure. For example, the trade-off theory, developed by Kraus and Litzenberger (1973), proposes that the optimal debt ratio that maximises firm value is determined by balancing the tax advantages of debt against bankruptcy costs associated with debt financing. On the other hand, the agency theory of Jensen and Meckling (1976) proposes that the optimal capital structure of the firm is obtained at a debt-to-equity ratio that minimises total agency costs. Finally, unlike the other two theories, which are based on the existence of an optimal capital structure, Myers and Majluf's (1984) pecking order theory focuses on the hierarchy of the firm's financing sources. In particular, the theory suggests that it is only when internal resources are not available

or are insufficient that firms raise external finance. In this respect they do so in accordance to the riskiness of securities, implying the issuance of debt before equity.

When conducting a review of capital structure literature, we find that, previous empirical studies generally seem to agree that leverage is positively related to firm size and asset tangibility. But declines with an increase in firm profitability, growth opportunities, non-debt tax shields and business risk. In addition, there have also been strong support on the significant impact of the recent GFC on firms' capital structure among empirical studies.

Overall, the critical review of previous empirical studies of capital structure has led us to choose the following set of variables for our empirical analysis. The book debt-to-capital leverage ratio (total interest-bearing debt to total capital) is used as the measure of capital structure; proxy variables for growth opportunities (market-to-book ratio), firm size (natural log of total assets), degree of asset tangibility (tangible assets to total assets), profitability (return on assets), non-debt tax shields (depreciation and amortization expenses to total assets), and business risk (earnings' volatility) are used as the potential firm-specific determinants of capital structure; and a set of annual time dummies (equal to 1 if in specific year, 0 all other years) is used to capture the impact of the GFC on firms' capital structure. Finally, once zombies are identified in our sample, a dummy variable (equal to 1 if zombie, 0 otherwise) will be also used to capture the variation in capital structure that is attributable to zombie-specific characteristics.

Having obtained a better understanding of the underlying theories of capital structure and decided on the choice of analysis variables, we proceed with the discussion of the data and methodology that will be used in the analysis of zombies and determinants of capital structure. This will be the focus of Chapter 3.

3. Data and Methodology

3.1. Introduction

The main research objective of this Thesis is to investigate the impact of the recent Global Financial Crisis (GFC) and the firm-specific determinants of the capital structure on firms' leverage ratios. Furthermore, we aim to identify zombies in our analysis sample and investigate and identify the determinants of zombieness status. To achieve these objectives, it is important to choose an appropriate estimation method, and collect and analyse the appropriate data. This chapter provides details on the data and the choice of estimation method used to conduct our empirical analysis.

Based on the definition of zombies, we construct an Adjusted Interest Coverage Ratio (AICR) to measure the ability of firms to pay the interest expenses on their borrowing. Accordingly, a firm is identified as a zombie if it has $AICR < 1$ *and* still in operation for at least one year after meeting the technical insolvency criterion, hence ensuring both the insolvent nature and the surviving status of zombies are accounted for. Furthermore, having reviewed different estimation techniques to identify the determinants of zombieness status and estimate their impact on the probability of becoming zombie, logistic regression analysis is deemed as the most appropriate estimation method when the focus is on estimating the probability of the occurrence of an event (becoming a zombie in this case).

Our sample includes the constituents of the FTSE 250 Index over the period 2004-2012 and thus a dynamic panel model will be required to examine the determinants of firms' capital structure. Accordingly, we discuss the limitations of alternative estimation methods that may be used to estimate linear dynamic panel models. Given the endogeneity problems associated with the inclusion of the lagged dependent variables in dynamic models, standard estimates lead to inconsistent estimates. We then present alternative estimation methods that are able to control for this endogeneity problem in a dynamic panel model context. We show that, System Generalized Method of Moments (SYSGMM) leads to consistent and the most asymptotically efficient estimates. Based on the findings and discussions presented in Chapter 2, we specify the estimation models used in our analysis and their primary

objectives. Finally, in order to address the endogeneity problem associated with dynamic panel models, the potential endogeneity of the included regressors are determined by using a number of purpose-designed statistical tests.

The rest of the chapter is structured as follows. Section 3.2 presents details on the analysis data and sample construction process. Section 3.3 and Section 3.4 provide the justification for the choice of estimation method used for the empirical analysis of zombies and capital structure, respectively. Section 3.5 details the process of identifying endogenous variables and their respective appropriate instruments. Section 3.6 concludes the chapter.

3.2. Analysis Sample

Cross-sectional and comparative studies of capital structure, have consistently found evidence suggesting that country-specific factors such as; differences in economic developments (e.g., developed vs. developing), legal systems (e.g., civil law vs. common law), financial and institutional characteristics (e.g., market-based vs. bank-based), and tax codes tend to have a significant impact on firms' choice of capital structure (see, Rajan and Zingales, 1995; Booth *et al.*, 2001; Bancel and Mittoo, 2004; Antoniou *et al.*, 2008; and De Jong *et al.*, 2008). Accordingly, to avoid the impact of country-specific factors on findings, our analysis deliberately focuses on UK listed firms.

Furthermore, while using a general market index such as the FTSE AllShare Index (representing 98-99% of the UK market capitalisation) would provide us with a more reliable picture regarding the capital structure of typical UK listed firms, it could also lead to distorted results due to the significant differences in the availability and the ease of access to different sources of finance among its constituents[84]. Accordingly, we focus on the "smaller large firms" and use the data from the FTSE 250 Index (i.e., mid-cap stocks).

The choice of using the constituents of FTSE 250 Index (mid-cap stocks) is also motivated by the lack of empirical attempts to investigate their financing behaviour. That is, while Small and Medium-sized Enterprises (SMEs), large firms, and aggregate samples of all listed firms in a country or a database have been extensively covered by previous empirical studies of capital structure, we are not aware of any previous study to specifically investigate the impact of the recent financial crisis on the capital structure of mid-cap firms.

[84] FTSE Russell, the trading name of FTSE International Limited and Frank Russell Company defines the FTSE UK Index Series as follows: the FTSE 100 Index comprises the 100 most highly capitalised blue chip companies listed on London Stock Exchange, the FTSE 250 Index comprises mid-capitalised companies not covered by the FTSE 100 and represents approximately 15% of UK market capitalisation, and the FTSE SmallCap consists of companies outside of the FTSE 350 Index (combination of the FTSE 100 Index and the FTSE 250) and represents approximately 2% of the UK market capitalisation. FTSE AllShare Index is the aggregation of the FTSE 100, FTSE 250 and FTSE Small Cap Indices.

Finally, while most of the existing reports and surveys conducted with regards to the high firm survival and existence of zombies in the UK have been in the context of SMEs, to the best of our knowledge, there have been no attempts to identify and predict zombies specifically among larger firms. Thus, by investigating the existence of zombies among the constituents of the FTSE 250 Index, we hope to obtain a more comprehensive understanding of zombies in the UK through bringing large firms into the discussion of zombies.

However, a word of caution is in order. Since the FTSE 250 Index is a market-capitalisation index and is rebalanced accordingly, the constituents change from one year to another which could expose our analysis to a survivorship bias. Having said that, not much can be done to resolve the problem, as including firm-year observations for the periods when firm was not listed in the FTSE 250 Index would undermine the specific purpose of the analysis sample choice.

Generally, recessions associated with financial crises tend to be more sever and long lasting than normal recessions. If recessions associated with financial crises are globally synchronised, as it is the case with the 2008/9 recessions, they tend to last even longer and recoveries from such recessions are much more sluggish than that of normal recessions (IMF, 2009 and Reinhart & Rogoff, 2009). Consistent with this argument, the data from Bank of England on real GDP (as of the 3rd quarter of 2014) indicates that, it was only in the 2nd quarter of 2013 that the UK economy recovered its lost output and marginally passed the pre-crisis peak of £414,424m in the 1st quarter of 2008. Accordingly, we use 2012 as the upper limit of the analysis period. Furthermore, given the onset of the GFC in the 3rd quarter 2007 (BIS, 2009) and in order to have fairly balanced pre-crisis and post-crisis subsample periods, 2004 is chosen as the lower limit of our analysis period[85].

Therefore, we utilise a large panel data containing members of the FTSE 250 Index over the period 2004-2012, to conduct empirical analysis on zombies. Accordingly, a large set of firm-level and macro-level data needs to be collected.

[85] Furthermore, 2004 is preferred to 2003 (leading to balanced pre-crisis and post-crisis periods) in order to safeguard our results against possible distortions in data due to the consequences of the "dot-com" bubble burst and the economic slowdown of early 2000s, as the possible effect may be reflected in the forward lagged data.

However, given that the unprecedented high firm survival in the UK has only emerged after the onset of the GFC and during the 2008/9 recession, it implies that any factor that may have contributed towards it, such as the survival of insolvent firms (i.e., zombies), should be also considered in a post-crisis context. Furthermore, certain characteristics such as: significant increases in debt levels, deteriorated ability to meet short-term financial obligations or substantially high financing costs may be inferred as signs of severe financial distress, if observed in a post-crisis environment. However, the same characteristics may have a different interpretation in the prevailing booming economic conditions before the crisis. Accordingly, given that the empirical analysis of capital structure is conducted over the period 2004-2012, identification of zombies and investigation of the determinants of zombieness status is limited to the period 2008-2012.

3.2.1. Data Source

The macro data used are collected from a combination of sources; that is, while GDP growth and inflation rate are obtained from the World Bank Database, the 3-month LIBOR and net stock of lending to UK non-financial businesses are collected from the Bank of England and the Office for National Statistics, respectively. All macro-economic variables are seasonally adjusted to remove regular seasonal fluctuations and typical calendar effects (e.g., trading day), provide a better indication of the underlying movements, and enhance comparability of data over time[86].

All firm-level data are extracted from Bloomberg data platform and contains accounting and financial information for the constituents of the FTSE 250 Index as of the last working day of the year. The search criteria were set to provide original values as shown in the annual reports and convert all non-GBP values to GBP values[87].

[86] For more details regarding seasonal adjustment, see BoE (2010).

[87] Although the analysis sample only includes firms whose country of domicile is the UK, some firms in certain industries such as Oil, Gas & Consumable Fuels, Energy Equipment & Services, Metals & Mining, and Diversified Telecommunication Services have their financial statements in US dollar or Euro. Thus, to avoid inconsistencies, we use the GBP equivalent figures as provided by Bloomberg.

3.2.2. Sample Construction Reconciliation

The final sample analysis is constructed by applying different sampling criteria and filters to remove and mitigate possible factors that may distort the overall findings of the analysis. First, to ensure that the results are not distorted due to different accounting standards and tax treatments, firms are included on the condition that their main activities are concentrated in the UK domestic market, and those whose country of domicile is not UK are excluded from the sample. Indeed, as Lasfer (1995) notes, since domestic firms are unlikely to have borrowed from overseas markets, their capital structure is also unlikely to be distorted by the fluctuations in the exchange rate and the use of debt to manage currency exposure. Furthermore, Bancel and Mittoo (2004) and Antoniou *et al*. (2008), among other cross-sectional studies, find that country-specific factors such as differences in economic developments (e.g. developed vs. developing), legal systems (e.g. civil law vs. common law), financial and institutional characteristics (e.g. market-based vs. bank-based) and tax codes have a significant impact on firms' choice of capital structure. Second, financial and utility firms are excluded because of the different nature of their capital structures. That is, financial and utility sectors are highly regulated and the leverage ratio of the firms operating in these sectors reflect the regulation-specific factors such as the minimum capital requirement or insurance schemes which are not relevant to firms in other sectors. Accordingly, their capital structure may not be strictly comparable to that of non-financial and non-utility firms. For instance, Fama and French (1992) show that, while highly leveraged capital structure is a common characteristic of financial and utility firms, it is more likely to be a sign of financial distress for non-financial firms.

Third, to avoid inconsistencies and distortions due to different financial year ends, for firms with financial year ends in the second half of the calendar year (July – December) the same year data is used and for firms with financial year ends in the first half of the calendar year (January – June) next year data is used[88]. Fourth,

[88] For instance, if a firm is listed on the FTSE 250 Index as of 31st December 2008 and has a March financial year end, the 2009 financial statements which covers the period 1st April 2008 to 31st March 2009 will be used for the year 2008. If the same firm has a financial year end in September, then the 2008 financial information will be used. The logic behind this adjustment is simple: if the financial statements of the firm contain more than six months of the current year, they mostly represent the current year performance of the firm, but where financial information reflect less than six months of the current year (hence containing more than six months of the previous year) they are a better reflection of the performance and the financial position of the firm in the previous year than the current year.

leverage ratios are required to lie in the closed unit interval (i.e., [0,1]) and all firm-level variables are winsorised at the upper and lower one-percentiles to mitigate the effect of outliers and eradicate errors in the data. Finally, firms with missing data on any of the analysis variables are eliminated. These restrictions lead to a final sample of 1,163 firm-year observations on the UK based non-financial and non-utility firms that were members of the FTSE 250 Index in at least one year during the period 2004-2012.

Although we acknowledge the limitations of this approach, it seems as the only valid and practical option to address different financial year ends of the firms. Any conclusion from our analysis will be made with consideration of this limitation.

3.3. Estimation Method (Zombies)

With respect to the analysis of zombies, we aim to achieve three objectives. The first objective is to introduce a zombie indicator using publicly available financial information, and identify the zombies that may exist in our sample. However, this indicator is only helpful to identify current zombies (i.e., *ex post*) and cannot be used to predict the probability of becoming a zombie. Therefore, the second objective is to identify the determinants of the zombieness status of a firm and, the third objective is to estimate impact of the respective determinants on the probability of becoming a zombie. Stata (version 13.1) data analysis and analytical software is used to perform the econometric analysis.

3.3.1. Identifying Zombies

The Association of Business Recovery Professionals (R3) defines zombies as those firms that are only able to pay the interest on their debts and not reduce the principal amount (R3, 2013)[89]. It is also the commonly used definition by professional bodies such as Bank of England, National Office for Statistics, and insolvency practitioners. As discussed in Section 2.3.5, although this definition may be helpful in identifying near-insolvency firms (i.e., firms that are struggling to pay their principal debts and still have not failed on their financial obligations), it cannot be used to identify the *surviving insolvent* firms. That is, firms that meet the definition of insolvency (i.e., cannot pay their financial obligations when due) but have not been declared as insolvent and are still actively operating. Accordingly, in order to identify the surviving insolvent firms rather than the near-insolvency firms, we use a more rigid criterion than R3 and define zombies as *"surviving technically insolvent firms that are unable to generate enough revenues to even pay the interest expenses on their borrowings, let alone the repayment of the principal amount"*.

R3 identifies zombies using the data obtained from 502 telephone interviews with the owners or financial directors of firms, asking them about the firms' financial conditions. However, using such qualitative measures obtained via direct contact with

[89] This term should not be confused with the Asian Stock Market Zombies or Z-shares, which is used to refer to "*the newish companies that trade little relative to their size, because their so-called free float is held mostly by cornerstone investors*" (Hughes, 2016).

the top management of the FTSE 250 constituents is not a valid and practical option for us. As a result, we proceed with using the publicly available information to construct a proxy variable to identify zombies that reflects their definition.

Accordingly, the Interest Coverage Ratio (ICR), calculated as the ratio of Operating Income to Interest Expenses, can be used to objectively measure firms' ability to pay the interest expense on their borrowings and identify technically insolvent firms in our sample. Furthermore, in order to ensure the surviving status of zombies, a technically insolvent firm is identified as zombie if for at least one year after meeting the technical insolvency criterion it is still operating as a listed, active, non-acquired and non-merged entity.

However, the caveat to using conventional ICR is that it fails to account for two important items: the capitalised interest expenses (i.e., the interest on borrowing used to finance asset construction) and the interest income of the firm. To control for such factors, we calculate an Adjusted Interest Coverage Ratio (AICR) by making the following two adjustments. The first adjustment is with regards to the denominator and the way interest expense is measured. That is, instead of non-capitalised interest expense used in the conventional ICR, we use Total Interest Expense that includes both capitalised and non-capitalised interest expenses as the denominator of AICR. The argument for using only non-capitalised interest expense in the denominator of conventional ICR is that, since capitalised interest expense is already included in the value of assets, it should not be treated as a financial liability and be included in the interest expense of the firm. However, we are interested in measuring the ability of the firm to service the interest on its total borrowing, regardless of whether it is used to construct assets that may take time to get ready for their intended use or finance an immediate purchase of new equipment or buildings etc. Accordingly, excluding the capitalised interest expense from the denominator may cause the ICR to overestimate the ability of the firm to pay its financial obligations and could even lead to misclassification of zombies as healthy firms. Therefore, Total Interest Expense which includes both capitalised and non-capitalised interest expenses will be used as the denominator of AICR.

The second adjustment is applied to the numerator of conventional ICR by adding Interest Income to Operating Income figure. A preliminary analysis of our data

indicates that, the majority of firms report a positive value for this additional source of income in their income statements. Furthermore, interest income and interest expense typically have the same sources or are very closely related. For instance, if the majority part of the borrowing is due to retirement plan obligations then majority of the interest income is coming from the retirement plan too. Similarly, the income may come from the interest earned on cash at bank, which is the main source of borrowing and the associated interest expense[90]. Therefore, given that interest income is not included in the operating income figure, calculating ICR in its conventional format may lead to an underestimation of the ability of the firm to pay its financial obligations and in some cases could even lead to misidentification of healthy firms as zombies[91]. Thus, in order to avoid such underestimations or misidentifications, the sum of Interest Income and Operating Income is used as the numerator of AICR.

Accordingly, the following AICR is used to measure the ability of firms to pay the interest expenses on their borrowing:

$$AICR_{it} = \frac{Operating\ Income_{it} + Interest\ Income_{it}}{Total\ Interest\ Expense_{it}}$$

Recalling the definition of zombies (i.e., surviving technically insolvent firms that are unable to generate enough revenues to even pay the interest expenses on their borrowings, let alone the repayment of the principal amount), a firm is identified as zombie if it has an $AICR < 1$ (i.e., is technically insolvent as it is unable to generate enough revenues to cover their financial obligations) *and* is still operating as a listed, active, non-acquired and non-merged entity for at least one year after meeting the technical insolvency criterion (i.e., is surviving). Furthermore, since interest coverage ratio is only relevant to firms with positive financial obligations, firms with negative net interest expense (i.e., net interest income) are excluded from the AICR calculation.

[90] The reason for large interest income from cash at bank may be because firms wish to take advantage of the tax deductibility of interest expense and benefiting from tax shields, thus, although they have significant cash resources at their disposals, they prefer to borrow the money from banks and earn interest on the cash at bank.

[91] For example, a firm with an operating income smaller than its total interest expense by default have an $ICR < 1$, suggesting that it cannot afford to pay its interest payments and therefore is identified as a zombie. However, the same firm may also have some interest income that can be used to pay its financial liabilities, and in some cases the interest income may be large enough to result in an $ICR > 1$.

3.3.2. Determinants of the Zombieness Status

The second and third objectives of the zombie analysis are to identify the determinants of the zombieness status of the firms and to estimate impact of the respective determinants on the probability of a firm becoming a zombie, respectively. As discussed in Section 2.3.5, logistic regression analysis is deemed as the most appropriate estimation method when the focus is on estimating the probability of occurrence of an event (becoming a zombie in our case).

3.3.2.1. Binary Probability Models

The zombieness status of a firm can be formulated as a dichotomous variable: zombie or non-zombie. Unlike the usual regression models with continuous dependent variables, where the object is to estimate the expected value of the dependent variable given the values of the regressors, in the case of the dichotomous dependent, the objective is to find the probability of something happening, and hence the estimated coefficients would reflect the impact of independent variables on the likelihood of the outcome coded as 1 happening. Hence, regression models with dichotomous dependent variable are often known as binary probability models. Although it does not matter which group is assigned the value of 1 or 0, given that we are interested in estimating the probability of a firm becoming a zombie, zombies are coded as 1 and non-zombies are coded as 0.

Accordingly, the probability of a firm becoming a zombie can be presented by the following regression model, which is also known as the Linear Probability Model (LPM):

$$y_{it} = \alpha_0 + \sum_{j=1}^{k} \beta_j X'_{j,it} + \varepsilon_{it}. \quad (3.1)$$

Where, y_{it} takes the value of 1 if a firm is zombie and 0 otherwise; X_{it} is the vector of k explanatory variables; α_0 and βs are the parameters to be estimated; and ε_{it} is the error term which is assumed to follow a normal distribution with mean zero and variance σ^2 (i.e., $\varepsilon_{it} \sim (0, \sigma^2)$.

Recalling the discussion about the probability models, we can define the conditional expectation of y_{it} given X_{it} as the conditional probability of the event of interest happening, given the explanatory variables. This can be written as:

$$E(y_{it}|X_{it}) = \Pr(E(y_{it} = 1|X_{it}). \quad (3.2)$$

Assuming $E(\varepsilon_{it}) = 0$, to ensure unbiased estimates, we can re-write Eq. (3.1) as:

$$E(y_{it}|X_{it}) = \alpha_0 + \sum_{j=1}^{k} \beta_j X'_{j,it}. \quad (3.3)$$

Furthermore, defining the probability of the event of interest happening as: $\Pr(E(y_{it} = 1|X_{it}) = P_{it}$, and consequently the probability of the event of interest not happening as: $\Pr(E(y_{it} = 0|X_{it}) = (1 - P_{it})$, the following is implied regarding the distribution (probability) of y_{it}:

Table 3.1 Probability Distribution of the Binary Dependent Variable

y_{it}	Probability
0	$1 - P_{it}$
1	P_{it}
Total	1

Given that y_{it} can only take two values (i.e., follow a binomial distribution), we can write:

$$E(y_{it}|X_{it}) = [1 \times (P_{it})] + [0 \times (1 - P_{it})] = P_{it}. \quad (3.4)$$

Substituting Eq. (3.4) into Eq. (3.3) will yield:

$$P_{it} = \alpha_0 + \sum_{j=1}^{k} \beta_j X'_{j,it}. \quad (3.5)$$

Finally, given that any probability measure is restricted to the 0-1 interval, $P_{it} = E(y_{it}|X_{it})$ must also lie between the 0 and 1. Thus, the following must hold:

$$0 \leq E(y_{it}|X_{it}) \leq 1. \quad (3.6)$$

The first and the most convenient approach to estimate the linear probability model presented in Eq. (3.1) is to use the Ordinary Least Squares (OLS) estimation method.

However, there are at least three problems associated with estimating the LPM model presented in Eq. (3.1) using OLS[92]. First, even without any formal tests, we can argue that the normality assumption of the residuals is violated for Eq. (3.1). This is because, similar to the dependent variable (y_{it}), the residuals (ε_{it}) also follow a binomial distribution as there are only two possible values for the residuals: $(1 - \alpha_0 - \sum_{j=1}^{k} \beta_j X'_{j,it})$ and $(-\alpha_0 - \sum_{j=1}^{k} \beta_j X'_{j,it})$, for $y_{it} = 1$ and $y_{it} = 0$, respectively. Second, the variance of the residuals does not fulfil the homoscedasticity condition. That is, given the properties of the binomial distribution, the variance of the residuals, conditional on the explanatory variables, is $Var(\varepsilon_{it}|X_{it}) = (\alpha_0 + \sum_{j=1}^{k} \beta_j X'_{j,it})(\alpha_0 - \sum_{j=1}^{k} \beta_j X'_{j,it})$. Thus, the variance of the residuals is non-constant, meaning that the homoscedasticity assumption of the residuals does not hold. Third and most importantly, recalling Eq. (3.6), while the conditional probability of $y_{it} = 1$ given X_{it} must lie between 0 and 1, there is no guarantee than the fitted values of y_{it} , $\hat{y}_{it} = \hat{\alpha}_0 + \hat{\beta}_j X'_{j,it}$, will necessarily fulfil this restriction.

It should be noted that, given that non-normality of the residuals does not lead to inconsistent or biased estimates and is typically not a concern in large samples, the violation of the normal distribution of residuals assumption may not be a major concern for the estimation of LPMs. Furthermore, heteroskedasticity-robust standard errors can be used to control for the heteroskedasticity problem. However, there are no remedies to overcome the third problem, as one cannot constrain the OLS estimated probabilities of y_{it} to lie between 0 and 1, using the conventional techniques at hand and without using mathematical programming techniques (Gujarati, 2004).

In addition, the linear nature of the LPM makes it an unattractive model, as it unrealistically assumes that the probability of the event of interest occurring (i.e., $\Pr(E(y_{it} = 1|X_{it}) = P_{it})$ increases linearly with X_{it} the (i.e., the incremental effect of the explanatory variables on the probability of the event of interest occurring are constant, irrespective of their respective actual values) (Argesti, 2002). Such problematic properties make the OLS technique and the LPMs inappropriate for the analysis of a binary dependent variable.

[92] For a more detailed discussion of the linear probability models and their associated problems, see Aldrich and Nelson (1986) and Long (1997).

However, the solution is to use a probability model that: 1) constrains the fitted values of the dependent variable (i.e., $E(y_{it} = 1|X_{it}) = P_{it}$) to the 0-1 interval, and 2) assumes that the relationship between the fitted values of the dependent and the independent variables is non-linear (i.e., as Aldrich and Nelson (1984: p. 26) define: "y_{it} approaches zero at slower and slower rates as X_{it} gets small and approaches one at slower and slower rate as X_{it} gets very large") (Gujarati, 2004 and Greene, 2008). These are the main features of the logit and probit (or normit) models which are non-linear and use Maximum Likelihood (ML) estimation, which constrains the fitted values to lie between the logical limits of 0 and 1.

3.3.2.2. Logit Models

The two common standard alternative binary outcome models to the LPM are the logit model and the probit model. Although both the logit and the probit model use maximum likelihood as their estimation methods, the two vary in their specified functional forms for probability as a function of regressors. That is, while the logit model assumes the cumulative logistic distribution function, the probit model assumes a cumulative normal distribution function[93]. Given the similarities between the two models and to the wider empirical applications of the logit models, we will focus only on logit models.

Logit models, developed by David Cox (1985), are specifically designed to deal with binary dependent variables. As suggested by Baum (2006), using a latent variable is a useful approach to binary probability models. Substituting y_{it} with a latent variable, we can re-write Eq. (3.1) as:

$$y_{it}^{*} = \alpha_0 + \sum_{j=1}^{k} \beta_j X'_{j,it} + \varepsilon_{it}. \quad (3.7)$$

Where, y_{it}^{*} is an unobservable magnitude of the probability of the event of interest occurring (i.e., $\Pr(y_{it} = 1)$), and is linearly related to the set of explanatory variables, X_{it}. The difference between the two binary probability models presented in Eq. (3.7)

[93] Furthermore, the coefficients on the two models are not directly comparable, as the logistic distribution has a variance of $\frac{\pi^2}{3}$ as opposed to the normalised variance of 1 for the cumulative normal distribution. Accordingly, the coefficient estimates obtained from the logit model must be multiplied by $\frac{\sqrt{\pi}}{3}$ to be comparable with those obtained from the probit model. For more details, see Cramer (2003) and Greene (2008).

and Eq. (3.1) is only in the dependent variable. That is, while in Eq. (3.1) we examine the binary variable as they are, in Eq. (3.7) we analyse a latent variable for which we observe a binary realisation. Accordingly, given that y_{it} denotes whether or not the firm is zombie, y_{it}^{*} denotes the probability of the firm becoming a zombie.

While the probability of the firm becoming a zombie (i.e., $\Pr(y_{it}=1)$) cannot be observed, we can observe whether firm is a zombie (i.e., $y_{it}=1$) or a non-zombie (i.e., $y_{it}=0$):

$$\begin{cases} y_{it}=1 \quad if \quad y_{it}^{*}>0 \\ y_{it}=0 \quad if \quad y_{it}^{*}\leq 0 \end{cases}. \tag{3.8}$$[94]

Recalling the definition of $y_{it}^{*}=\Pr(y_{it}=1)$, substituting Eq. (3.8) into Eq. (3.7) will yield:

$$P_{it}=\Pr(y_{it}=1|X_{it})=\Pr(y_{it}^{*}>0|X_{it})$$

$$=\Pr\left(\varepsilon_{it}>-\left(\alpha_0+\sum_{j=1}^{k}\beta_j X'_{j,it}\right)\middle|X_{it}\right). \tag{3.9}$$

For ease of exposition, let's define $Z_{it}=\alpha_0+\sum_{j=1}^{k}\beta_j X'_{j,it}$. Accordingly, assuming the distribution of ε_{it} is symmetric, we can write[95]:

$$\Pr(\varepsilon_{it}>-Z_{it})=\Pr(y_{it}=1|X_{it})=\Psi(y_{it}^{*}). \tag{3.10}$$

Where, $\Psi(.)$ is a Cumulative Distribution Function (CDF). For the logit model, $\Psi(.)$ is the logistic distribution function which can be written as:

$$P_{it}=\Pr(y_{it}=1|X_{it})=\frac{1}{1+e^{-Z_{it}}}=\frac{e^{Z_{it}}}{1+e^{Z_{it}}}. \tag{3.11}$$

While Eq. (3.11) model the probability of becoming a zombie, we can easily convert it to model the model the probability of a firm not becoming a zombie (i.e., non-zombie):

[94] It should be noted that, multiplying y_{it}^{*} by any positive constant does not change y_{it}, thus, if y_{it} is observable, we can estimate the βs in Eq. (3.7) only up to a positive multiple. Hence, in order to fix the scale of y_{it}^{*}, it is customary to assume $Var(\varepsilon_{it})=1$ (Maddala and Lahiri, 2009).

[95] ε_{it} is assumed to have a symmetric distribution (i.e., $\Pr(\varepsilon_{it}>-Z_{it})=1-\Pr(\varepsilon_{it}<-Z_{it})$), as recalling Eq. (3.2), $P_{it}=(1-P_{it})$ holds.

$$1 - P_{it} = \frac{1}{1+e^{Z_{it}}}. \quad (3.12)$$

From Eq. (3.11) it can be easily verified that, since Z_{it} ranges from -∞ to +∞, P_{it} is guaranteed to lie within the range of 0 and 1, and that it is non-linearly related to $Z_{it} = \alpha_0 + \sum_{j=1}^{k} \beta_j X'_{j,it}$, hence satisfying the two requirements to overcome the problems faced by the LPM and OLS estimation.

The non-linear nature of the logit model requires the use of the ML estimation in an iterative manner to find the most likely estimates for the coefficients. Unlike the OLS estimation method, which minimises the sum of the squared differences between the actual and predicted values of the dependent variable, ML maximises the likelihood that an event will occur[96]. From Eq. (3.11) and Eq. (3.12), we can write:

$$\frac{P_{it}}{1-P_{it}} = \frac{1+e^{Z_{it}}}{1+e^{-Z_{it}}} = e^{Z_{it}}. \quad (3.13)$$

Where, $\frac{P_{it}}{1-P_{it}}$ is the *odds ratio* of becoming a zombie against becoming a non-zombie (i.e., not becoming a zombie). Taking the natural log of Eq. (3.13) will yield:

$$L_{it} = \ln\left(\frac{P_{it}}{1-P_{it}}\right) = Z_{it} = \alpha_0 + \sum_{j=1}^{k} \beta_j X_{j,it}. \quad (3.14)$$

Where, L_{it}, called the logit, denotes the *log of the odds* ratio of a firm becoming a zombie. Eq. (3.10) presents the general form of logit models. It can be seen from Eq. (3.14) that although L_{it} is a linear function of the set of explanatory variables (X_{it}), the probabilities themselves are not, which resolves the linearity problem faced by the LPM. The logit regression analysis is performed via the **`xtlogit`** command in Stata, estimating Eq. (3.14) using ML estimation method.

3.3.2.3. Individual vs. Average Probabilities

Recalling that our analysis is conducted on an unbalanced panel data and since panel data relate to the same individual units over time, there is bound to be heterogeneity in these units (Greene, 2008). For example, firms tend to differ in their management

[96] Explaining the mechanism of Maximum Likelihood Estimation is beyond the scope of this Thesis, however, it is amply covered in other sources such as: Chapter 21 in Greene (2008), Hair *et al.* (2010), and StataCorp (2015).

competence and quality, reputation, political influence, geographical locations, capital intensity etc., which generally do not change over time. Similarly, there may be time-specific factors such as macroeconomic factors or events in a particular year that affect all the firms in the analysis sample. For instance, general shocks to the financial market, availability of credit, implementation of expansionary or contractionary monetary and fiscal policies etc. Accordingly, as long as these unobserved factors are slowly changing (if not strictly time invariant) or they affect most individuals (if not strictly firm invariant) their impact on the probability of becoming a zombie is absorbed by the firm- and time-specific effects, respectively[97]. Thus, an appropriate estimation method for models with firm- and time-heterogeneity must allow controlling for such effects.

The pooled OLS estimator assumes independence within firms and ignores the possible time-specific effects that are common across all firms. Consequently, the possible unobserved firm- and time-specific effects are captured via the time-varying disturbance term, ε_{it}, which may lead to omitted variable bias (see, Hsiao, 2003 and Greene, 2008).

The dependence among observations of a firm over time can be better illustrated by looking at the persistence in the dependent variable over time. Table 3.2 reports the year-to-year transition of the firms' zombieness status. As can be seen from Table 3.2, there is a considerable persistence in the zombieness status of firms from one year to the next. That is, almost 94% of the firms that are detected as non-zombie in one year also maintain their non-zombie status in the next, while about 36% of those that are identified as zombies in one year also maintain their zombie status in the next!

Thus, the high degree of persistence in the dependent variable may be an indication of high interdependence in the observations of a given firm. Accordingly, given that the pooled estimators assume independence across firms and over time and hence

[97] In microeconometric applications, the term firm-specific (time-specific) effects are also referred to as many other names, such as unobserved firm (time) heterogeneity, and individual (time) effects. As such, we use these terms interchangeably in this Thesis. A more detailed discussion of the individual- and time-specific effects is provided in Section 3.4.

ignoring the panel nature of the data, we must use a panel estimator that allow for controlling the firm-specific and time-specific effects that may exist in the data[98].

Table 3.2 Year-to-Year Transition of the Firms' Zombieness Status

Zombie	*Zombie*		Total
	0	*1*	
0	93.55	6.45	100.00
1	64.29	35.71	100.00
Total	91.12	8.88	100.00

The three alternative approaches to estimate logit models in a panel context are the Fixed Effects (FE), Random Effects (RE) and Population Averaged (PA), which are performed in Stata via the **`fe`**, **`re`**, and **`pa`** options, respectively, after the **`xtlogit`** command.

Due to the short analysis period (i.e., $T = 5$), the FE method will generate inconsistent estimations. This is because, it can only estimate 5 unobserved random variable parameters, and given their joint estimation with the coefficient parameters (βs), the inconsistency of the unobserved random variable parameter will lead to inconsistent estimation of βs (Hsiao, 2003; Baltagi, 2005; and Cameron and Trivedi, 2010). Furthermore, since the FE estimators rely on within variations and not between variations, it can only provide the coefficient estimates on the time-varying regressors, and not the time-invariant variables. For example, industry dummy variable or other firm-specific characteristics that do not change over time will be dropped from the estimation model, resulting loss of information and hence non-efficient estimates (Baum, 2006).

The other two alternative panel estimation methods are the RE and the PA logit models. The RE estimator estimates the individual (i.e., firm specific) probabilities by estimating the using the following model:

$$\Pr(y_{it} = 1|X'_{it}, \mu_i) = \alpha_0 + \sum_{j=1}^{k} \beta_j X_{j,it} + \mu_i + \nu_{it}. \quad (3.15)^{99}$$

[98] While using the robust standard error logit model, via using the **vce(robust)** option, can correct standard errors for any dependence over time for a given firm (i.e., presence of heteroskedasticity), it still fails to address the firm-level effects (Baltagi, 2005 and Greene, 2008).

Where, μ_i denotes the firm-specific effect and represents the combined effect of all omitted firm-specific variables that causes some firms to be more likely to become zombie than others; and ν_{it} denotes the time-varying error component.

Eq. (3.15) indicates that, controlling for individual effects, the RE model measures the probability of the event of interest happening, conditional on the explanatory variables *and* the individual-specific effects that may have contributed to the change in the probability of the event of interest happening for a specific panel unit.

On the other hand, the PA estimator estimates the overall (i.e., population averaged) probabilities:

$$\Pr(y_{it} = 1|X'_{it}) = \alpha_0 + \sum_{j=1}^{k} \beta_j X_{j,it} + \varepsilon_{it}. \quad (3.16)$$

Where, $\varepsilon_{it} = \mu_i + \nu_{it}$. As can be seen from Eq. (3.16), while controlling for the individual effects (μ_i) as part of the error term (ε_{it}), the PA logit model *does not* condition the probability of the event of interest happening to individual effects, as it examines the averaged probability of the event of interest happening for individual panel units. In other words, the average probabilities can be obtained by averaging the individual probabilities over the individual-effects distribution (Neuhaus *et al.*, 1991). In fact, the empirical difference between the PA and RE model is because the average of non-linear functions is not the same as the non-linear function of the averages.

Furthermore, since the objective of our analysis is to identify the determinants of zombieness *across* the constituents of the FTSE 250 Index, and not what makes *individual* firms more likely to become zombie, we are interested in estimating the overall probability of a firm becoming a zombie. Furthermore, the individual probabilities may well vary substantially across firms and accordingly, we proceed using the PA specification in our logit regression analysis[100].

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[99] Technically, the estimator fits $L_{it} = \ln\left(\frac{\Pr(y_{it} = 1|X'_{it})}{\Pr(y_{it} = 0|X'_{it})}\right)$, however, for the ease of exposition, we only present the underlying basis of the model: $\Pr(y_{it} = 1|X'_{it}, \mu_i)$.

[100] Furthermore, the computation and interpretation of the marginal effects, which are used to quantify the impact of the explanatory variables on the probability of the event of interest happening, are easier for the PA models as opposed to the RE models, where complications arise due the presence of the individual effects in the model (Cameron and Trivedi, 2009).

Stata's **`xtlogit`** command treats the time-specific effect as a component of the error term and specifies a correlation matrix for the within-group observations for each panel unit to account for the individual-specific effects[101]. In fact, another advantage of PA over RE model stem from their robustness to the choice of within-group correlation. That is, unlike the RE models that are very sensitive to the type of within-group correlations, the PA approach provides consistent estimates of the regression coefficients and of their robust variances; even if the assumed within-group correlation is misspecified (see, Liang and Zeger, 1986 and Hu *et al.*, 1998)[102]. Furthermore, the **`vce(robust)`** option can be used to correct standard errors for any dependence over time for a given firm (i.e., presence of heteroskedasticity) and obtain heteroskedasticity-robust coefficient estimates.

[101] The type of within-group correlation can be specified by using the **corr(.)** option, where one can choose from a wide range of correlation patterns, such as: equal correlations, no correlations, unstructured correlations, autoregressive correlations etc.

[102] The standard assumed within-group correlation by the PA estimator is **exchangeable** (i.e., equal) correlations, reflecting the average individual effects. Similarly, if they are specified to be **independent** (i.e., no correlation), then the model become pooled, and if the correlations are specified as **unstructured**, then there are no constraints placed on the within-group correlations (StataCorp, 2015).

3.4. Estimation Method (Capital Structure)

As discussed in Section 3.2, our empirical analysis is conducted on an unbalanced panel data. Unlike time-series and cross-section data that contain information on one or more variables over a period of time and on several individual units at the same point in time respectively, panel data contain information on the same cross-sectional unit over a number of periods. In our case, the panel data contain information on a large number of the FTSE 250 Index constituents over the period 2004-2012.

Panel data can enrich empirical analysis in ways that may not be possible if pure cross-section or time series data are used. For example, by combining time series of cross-section observations, panel data offer more informative data, more variability, less collinearity amongst variables and more reliable parameter estimates (Gujarati and Porter, 2010). Furthermore, observing different individuals (e.g., firms, banks, countries) over time allows panel data regressions to capture the variations over both the units and time, hence they are able to control for individual differences across the panel units and time (see, Hsiao, 2003 and Baltagi, 2005). Finally, panel data can relate the individual's experiences and behaviour at one point in time to other experiences and behaviour at another point in time. Hence, allowing estimation of dynamic models where the dependent variable for an individual depend in part on its values in previous periods, an option which is not feasible with pure cross-section or pure time-series datasets (Baltagi, 2005)[103]. Despite the apparent benefits, panel data have limitations such as their inability to uncover nuances, qualitative coherence and identify causal links (Gujarati and Porter, 2010).

Recalling the discussion in Section 2.3.2, to construct a complete dynamic specification that allows for the possible effect of the Autoregressive process on the stochastic term and the implications of adjustment costs, a 1-period lagged dependent variable is included in the model. Accordingly, the following dynamic model is used as the general model specification to investigate the determinants of firms' capital structures:

[103] Other advantages of panel data include: ability to identify and measure effects that cannot be detected by pure cross-section or pure time-series data, facilitating the construction and testing of more complicated behavioral models, and greater measurement accuracy (see, Hayashi, 2000; Hsiao, 2003; Baltagi, 2005; and Gujarati and Porter, 2010).

$$y_{\mathrm{it}} = \alpha_0 + \alpha_1 y_{\mathrm{i,t-1}} + \sum_{k=1}^{K} \beta_{\mathrm{k}} \mathrm{X'_{k,it}} + \mu_{\mathrm{i}} + \lambda_{\mathrm{t}} + \varepsilon_{\mathrm{it}}. \quad (3.17)$$

Where, y_{it} is a measure of leverage ratio of firm i in year t; $y_{i,t-1}$ denotes the 1-year lagged leverage ratio; X_{it} represents the vector of k possible determinants of leverage; μ_i represents time-invariant unobservable firm-specific effects; λ_t represents firm-invariant unobservable time-specific effects which are common to all firms and can change through time; ε_{it} is the idiosyncratic disturbance term (i.e., error term) which varies across both time and individuals and is assumed to be serially uncorrelated with mean zero and constant variance: $\varepsilon_{it} \sim i.i.d.\ N(0, \sigma^2)$; α_0 is the constant; α_1, and β_k, are the unknown parameters to be estimated.

Since panel data relate to individual units over time, there is bound to be heterogeneity in these units (Greene, 2008). For instance, firms tend to differ in their management competence and quality, reputation, political influence, geographical locations, capital intensity, etc., which generally do not change over time. Similarly, there may be time-specific factors such as macroeconomic factors or events in a particular year that affected all the firms in the analysis sample; for instance, general shocks to the financial market, credit crunches, implementation of expansionary or contractionary monetary and fiscal policies etc. Therefore, if significant enough, these unobserved individual- and time-specific factors may play a role in explaining the firms' choice of capital structure[104]. Consistent with this argument, Lemmon *et al.* (2008) finds that, as long as these unobserved factors are slowly changing, if not strictly time invariant, or they affect most individuals, if not strictly firm invariant, their impact on capital structure is absorbed by the firm- and time-specific effects, respectively. Accordingly, an appropriate estimation method for models with firm- and time-heterogeneity must allow controlling for such effects.

There are a number of alternative estimation methods to estimate model presented in Eq. (3.17). The common estimators include pooled Ordinary Least Squares (OLS), Random Effect (EF), Fixed Effect (FE), and Generalised Method of Moments (GMM) estimation methods. However, we will show in the following sections that only the

[104] In microeconometric applications, the terms firm-specific (time-specific) effects are also referred to as many other names, such as the unobserved firm (time) heterogeneity and unobserved individual (time) effects. Accordingly, these terms are used interchangeably in this Thesis.

GMM method will provide consistent and efficient parameter estimates of the dynamic panel models such as the estimation model presented in Eq. (3.17).

3.4.1. Pooled Ordinary Least Squares

The first and simplest approach to estimate Eq. (3.17) is to ignore the panel structure of the data and apply pooled Ordinary Least Squares (OLS) estimator. The standard OLS assumes linearity, no-perfect collinearity among independent variables, exogeneity of all the independent variables, no serial correlation in the error term, normal distribution of the error terms and homoscedasticity of the errors (Wooldridge, 2010).

The pooled OLS estimator also assumes independence within firms over time and ignores the possible time-specific effects that are common across all firms. Consequently, the possible unobserved firm- and time-specific effects are captured via the time-varying error term, ε_{it}, hence leading to an omitted variable bias (Hsiao, 2003). Furthermore, we must also be cautious of the efficiency loss of the pooled OLS estimator due to the presence of serial correlation in the idiosyncratic error term. This is quite likely to be the case in the dynamic capital structure context, as Lemmon *et al.* (2008: p. 1594) note:

> In so far as financial adjustment is costly, economic shocks are persistent, or autocorrelated independent variables are omitted from the specification, one might suspect the presence of serial correlation in the error structure.

Accordingly, estimating a dynamic panel model such as Eq. (3.17) via pooled OLS, which fails to control for the unobserved heterogeneity and the possible serial correlation in the error structure, yields "biased" and "inconsistent" results (Baltagi, 2005; Greene, 2008)[105].

Wooldridge (2010) notes that, the key condition required to obtain consistent OLS estimates is the strict exogeneity assumption:

[105] An estimator is biased if the expected value of parameter estimate is different from the true value. An estimator is said to be consistent if it is unbiased or if the bias shrinks as the sample size increases (Greene, 2008).

$$E(y_{it} \mid x_{i1}, \dots, x_{iT}, \mu_i) = E(y_{it} \mid X_{it}, \mu_i) = \beta X'_{it} + \mu_i. \quad (3.18)$$

Eq. (3.18) implies that, once X_{it} and μ_i are controlled for, X_{is} has no partial effect on y_{it} for $s \neq t$. The strict exogeneity assumption can be stated in terms of idiosyncratic errors, which is also known as the "zero-conditional-mean" or the "mean independence" assumption:

$$E[\varepsilon_{it} \mid X_{is},\ \mu_i] = 0, \qquad s, t = 1, 2, \dots, T. \quad (3.19)$$

That is, the error term must be uncorrelated with the observable regressors of all past, current and future time periods of the same individual[106]. If assumption in Eq. (3.19) holds, then each regressor is necessarily exogenous. However, if a regressor is correlated with ε_{it}, or the assumption in Eq. (3.19) fails to hold, then the regressor is said to be endogenous[107]. Assuming that variable x_{i1} in Eq. (3.18) is endogenous, we can write:

$$Cov(x_{i1}, \varepsilon_{it}) = E[\varepsilon_{it} \mid X_{is}] \neq 0. \quad (3.20)$$

When at least one of the regressors is correlated with the error term, such as in Eq. (3.20), the model is said to have an endogeneity problem.

The three common sources of endogeneity in applied econometrics are: simultaneity, omitted variables, and measurement error (Baltagi, 2005)[108]. The distinctions among the three possible forms of endogeneity are not always apparent. In fact, in many cases an equation can have more than one source of endogeneity (Wooldridge, 2010).

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[106] As Wooldridge (2010) demonstrates mathematically, the zero conditional mean assumption in Eq. (3.19) is sufficient for the strict exogeneity assumption, as it is much stronger than the no contemporaneous correlation assumption between regressors and the error term, which is often used to define strictly exogenous variables: $E(\varepsilon_{it} \forall X_{it}) = 0, t = 1, \dots, T$.

[107] While traditionally the term 'endogenous' is used to refer to variables that are determined within the context of a model, it is now used more broadly to describe any situation where an explanatory variable is correlated with the error term (Wooldridge, 2010).

[108] *Simultaneity* or 'two-way causality' arises when at least one of the explanatory variables in the right-hand side of the model is itself determined partly as a function of the explained variable. Consequently, where there is a two-way causality between the explanatory variable(s) and the dependent variable, those regressors and the error term are generally correlated. The *omitted variables* problem refers to situations where an omitted variable of interest, which is captured as part of the unobservable component of the error term, may also be correlated with one of the included regressors, hence causing a correlation between the respective regressor and the error term. Finally, *measurement error* arises due an imperfect measure of the variable of interest. This error in measurement is effectively captured by the error term. Consequently, it may lead to a correlation between the included imperfect measure of the variable of interest and the error term, depending on how the imperfect measure and the actual variable of interest are correlated.

Accordingly, in order to avoid possible misidentification, we use rigid statistical tests to detect endogenous variables in our model. This is discussed in great details in Section 3.5.

Moreover, under the strict exogeneity assumption of OLS, the error term is also assumed uncorrelated with the individual- and time-specific effects (Baltagi, 2005). However, given that individual effects, μ_i, reflect the unobserved heterogeneity among individual firms and are constant over time, they are likely to be correlated with the vector of other firm-specific regressors that vary over time, X_{it} (Greene, 2008; Maddala and Lahiri, 2009). However, the existence of such effect causes problem with using pooled OLS estimator, which is also noted by Greene (2008: p. 287): "*if u_i is unobserved, but correlated with X_{it}, then the least squares estimator of β is biased and inconsistent as a consequence of an omitted variable*". That is, given that the unobserved firm heterogeneity is captured by the error term, the correlation between the unobserved firm-heterogeneity and the included regressors leads to correlation between the error term and regressors, violating the strict exogeneity assumption, and hence leading to biased and inconsistent estimates[109].

The two commonly used alternative panel estimation methods that allow controlling for firm and time heterogeneity are the Random-Effect (RE) and the Fixed-Effect (FE) estimation methods. While both the RE and the FE models assume that the unobserved individual effects are uncorrelated with the time-varying error term, they differ in their assumption about the correlation between the unobserved heterogeneity and the included regressors. The FE model controls for the unobserved firm-heterogeneity by allowing each firm to have its own intercept value that does not vary over time and assumes μ_i are correlated with the included regressors. The RE model, on the other hand, controls for individual differences in the error term by treating them as random errors and further assumes that μ_i is uncorrelated with the included regressors, which is also referred to as the orthogonality condition (Gujarati and Porter, 2010)[110].

[109] The Breusch and Pagan's (1980) Lagrange Multiplier test can be used to test the existence of unobserved heterogeneity in the data and thus, test the appropriateness of using pooled OLS estimation method. The result of the Breusch-Pagan test is discussed in Section 4.3.3.4.1.

[110] It should be noted that, both the FE and the RE estimation methods only allow the intercepts to vary across panel units and/or across time, but assume the slope coefficients to be the same across panel

Similar to pooled OLS and as for any OLS estimator, for either RE and FE estimates to be consistent, the strict exogeneity assumption must hold (Baltagi, 2005). However, as we show in the following two sections, the strict exogeneity assumption of OLS rules out lagged dependent variables, suggesting that neither of the RE and FE estimation methods are appropriate to use in a dynamic model context such as Eq. (3.17). This is because the lagged dependent regressor in Eq. (3.17), $y_{i,t-1}$, is correlated with the individual-specific effects (μ_i), and hence with the current error term, ε_{it}. Therefore, the lagged dependent regressor violates the strict exogeneity assumption and leads to biased and inconsistent estimates of OLS estimators. Having said that, we will briefly discuss the alternative OLS estimators, RE and FE, to show their limitations and to justify our choice of estimation methodology.

To avoid unnecessary complications, we use a simplified version of our estimation model, Eq. (3.17), in the following discussion of the choice of estimation method. The simplified model is a simple dynamic model where only individual effects, μ_i, are present and it includes only one time-varying regressor, x_{it}. Although the arguments regarding the appropriateness of different estimators are generalizable to any multivariate dynamic model with unobserved time-specific effects, they involve a more complicated mathematical presentation. Accordingly, the simplified version of Eq. (3.17) can be written as:

$$y_{it} = \alpha_0 + \alpha_1 y_{i,t-1} + \beta x_{it} + \mu_i + \varepsilon_{it}. \tag{3.21}$$

3.4.2. Random Effects Model

RE models use the Generalized Least Square (GLS) estimation procedure and they effectively treat the individual-level effects as additional random errors, hence the term Random Effects. Accordingly, assuming Eq. (3.21), the RE model can be written as:

$$y_{it} = \alpha_0 + \alpha_1 y_{i,t-1} + \beta x_{it} + \varepsilon_{it}, \qquad \varepsilon_{it} = \mu_i + \nu_{it}. \tag{3.22}$$

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units. They impose restrictions on the model in Eq. (3.17) of $\beta_{kit} = \beta \; \forall \; i, t, k > 1$. That is, only the constant is allowed to differ across i and the relationship between the explanatory variables and the dependent variable is assumed to be the same for all panel units. This is because, if the relationship between explanatory variables and the dependent variable is assumed to be different for each panel unit, then there would be no justification to use a single equation for the sample and instead, separate regressions must have been run for each panel unit.

Where, ε_{it} is called the 'composite-error term'. As mentioned above, in addition to the strict exogeneity of regressors that is required for consistent estimates, RE models also assume orthogonality to hold between the individual random effects (μ_i) and other regressors. Recalling that strict exogeneity of regressors is the most critical assumption to obtain consistent estimates, and that individual random effects are included in the composite error process of the RE models, orthogonality of the individual effects is equally critical to obtain consistent estimates using the GLS estimator. However, both of these assumptions are violated when estimating the dynamic models such as the model presented in Eq. (3.22). To see why, it suffices to write Eq. (3.22) for period $t-1$:

$$y_{i,t-1} = \alpha_0 + \alpha_1 y_{i,t-2} + \beta x_{i,t-1} + \varepsilon_{i,t-1}, \qquad \varepsilon_{i,t-1} = \mu_i + \nu_{i,t-1}. \tag{3.23}$$

Thus, since the time-invariant random effect (μ_i) enters every value of y_{it} by construction, it causes the lagged dependent regressor ($y_{i,t-1}$) to become correlated with the current period composite error term (ε_{it}). This violates both the orthogonality condition and the strict exogeneity assumption (Baum, 2006)[111]. Consistent with this argument, Wooldridge (2010) shows that, ε_{it} is uncorrelated with the observable regressors (including the lagged dependent variable) if and only if μ_i is also uncorrelated with each of them, which is not the case with RE models.

3.4.3. Fixed Effects Model

As noted before, unlike the RE model which assumes orthogonality between individual effects and regressors, the FE estimator assumes arbitrary correlation between μ_i, which are called "Fixed Effects", and the observed regressors included in the model. That is, the FE estimator acknowledges that since fixed effects reflect the unobserved heterogeneity among individual firms and are constant over time, they are likely to be correlated with other firm-specific characteristics that vary over time (Baltagi, 2005). Accordingly, in order to avoid violation of the strict exogeneity assumption and obtain unbiased and consistent estimates, one must eliminate the fixed-effect unobserved heterogeneity that causes the correlation between the error term and the regressors (Wooldridge, 2010). There are 3 alternative approaches to

[111] This problem is also known as the "Nickell bias" problem, which will be discussed in greater details in Section 3.4.3.2.

apply FE estimators and remove unobserved heterogeneity: 1) using Least Squares with Dummy Variables (LSDV); 2) demeaning the estimation model (within-transformation); and 3) first-differencing the estimation model (first-difference transformation).

3.4.3.1. Least Squares Dummy Variables

If the unobservable time-invariant individual effects are estimated by including a dummy variable in the model for every individual firm in the sample, the estimator is referred to as the "Least Squares Dummy Variables" (LSDV) estimator. The LSDV estimator is effectively the pooled OLS estimator that allows for an arbitrary correlation between the error term and regressors by including $N-1$ dummy variables, identifying the individual panel units[112]. Introducing a dummy variable for each firm in the sample to Eq. (3.21) yields:

$$y_{it} = \alpha_0 + \sum_{j=1}^{N-1} \theta_j D_{ji} + \alpha_1 y_{i,t-1} + \beta x_{it} + \varepsilon_{it}. \quad (3.24)$$

Where, D_{ji} denotes the vector of $N-1$ dummy variables identifying the individual panel units. Accordingly, μ_i drops out because of the perfect collinearity with D_{ji}.

However, as can be seen from Eq. (3.24), we now have $N-1$ additional parameters, and thus at large values of *N* the LSDV estimator may not be feasible or may lead to inefficient estimates. That is, adding a parameter for every panel unit would imply a significant loss of degrees of freedom (Greene, 2008). Furthermore, despite removing the μ_i the model, the LSDV estimator fails to satisfy the strict exogeneity assumption required for consistent estimates (Baltagi, 2005). To see why, it suffices to write Eq. (3.23) for period $t-1$:

$$y_{i,t-1} = \alpha_0 + \sum_{j=1}^{N-1} \theta_j D_{ji} + \alpha_1 y_{i,t-2} + \beta x_{i,t-1} + \varepsilon_{i,t-1}. \quad (3.25)$$

As can be seen from Eq. (3.25), since y_{it} is a function of the firm-specific dummy variable (D_{ji}), it appears in all values of y_{it} of the same firm at different time periods. This causes a correlation between the lagged dependent regressor ($y_{i,t-1}$) and the

[112] The number of individual dummies is $N-1$ rather than N as one of the individual dummies is dropped because of the included constant term in them model, α_0.

current error term hence violating the strict exogeneity. Furthermore, this correlation does not vanish as N gets larger, nor does it vanish as T increases (Bond, 2002). Accordingly, the alternative solutions to estimate FE models are to remove the individual-level effects from the model through within transformation or first differencing.

3.4.3.2. Within-Transformation

The within transformation or demeaning involves subtracting the individual's mean value of the dependent variable and each regressor from the respective variable. Accordingly, the within transformation of Eq. (3.21) yields:

$$(y_{it} - \bar{y}_i) = \alpha_1(y_{i,t-1} - \bar{y}_{i1}) + \beta(x_{it} - \bar{x}_i) + (\varepsilon_{it} - \bar{\varepsilon}_i). \quad (3.26)$$

Where, $\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}$, $\bar{y}_{i1} = \frac{1}{T}\sum_{t=1}^{T} y_{i,t-1}$, $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{it}$, and $\bar{\varepsilon}_i = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_{it}$ [113]. Eq. (3.26) is also known as the "within-unit estimator" or simply the "within estimator", and it removes both the constant term and the individual-effect from the regression[114]. The within estimator is also more efficient and preferred to the LSDV as it avoids an unnecessary increase in the degrees of freedom (Greene, 2008). However, it should be noted that, although the within transformation has eliminated μ_i, the model in Eq. (3.26) still suffers from an endogeneity problem as the demeaning process induces a correlation between the within-transformed lagged dependent regressor $(y_{i,t-1} - \bar{y}_{i1})$ and the within-transformed error term $(\varepsilon_{it} - \bar{\varepsilon}_i)$ (Baltagi, 2005). This is because, $y_{i,t-1}$ component of $(y_{i,t-1} - \bar{y}_{i1})$ is correlated with $\varepsilon_{i,t-1}$, which implies a correlation with $\bar{\varepsilon}_i$ component of $(\varepsilon_{it} - \bar{\varepsilon}_i)$. That is, when subtracting $\bar{\varepsilon}_i$, we are subtracting a term which is the average of T terms, and one of those terms is $\varepsilon_{i,t-1}$. Accordingly, the resulted estimates based on within transformation are biased and inconsistent.

Nickell (1981) shows that, the correlation between $(y_{i,t-1} - \bar{y}_{i1})$, and $(\varepsilon_{it} - \bar{\varepsilon}_i)$, imposes a downward bias, also known as the "Nickell bias" on the within estimators.

[113] A word of caution is in order. One cannot include time-invariant explanatory variables in FE models, as if x_{it} does not vary over time for any individual, then $(x_{it} - \bar{x}_{it})$ would be zero and thus removed from Eq. (3.26).

[114] As α_0 and μ_i are assumed to be fixed, we have $\alpha_0 = \bar{\alpha}_0$ and $\mu_i = \bar{\mu}_i$, respectively, hence removing $(\alpha_0 - \bar{\alpha}_0)$ and $(\mu_i - \bar{\mu}_i)$ from the equation.

In particular, he demonstrates mathematically that as $N \to \infty$, the inconsistency of the coefficient on the within-transformed lagged dependent regressor in Eq. (3.26), α_1, is of order $1/T$, which may be sizable if T is small. Furthermore, Baum (2006) shows that, even for reasonably large values of T, the bias will be $-(1+\alpha_1)/(T-1)$, which may still be a sizable value. Moreover, the Nickell bias cannot be removed by including additional regressors. In fact, as Baum (2006: p. 233) notes: *"if the regressors are correlated with the lagged dependent variable to some degree, their coefficients may be seriously biased as well"* [115]. However, Bond (2002) and Roodman (2009a) propose that, given that pooled OLS estimators and within-transformed estimators are likely to be biased in opposite directions, one might hope that possible consistent estimators will lie between the two, or at least not be significantly higher than the former or significantly lower than the latter.

3.4.3.3. First-Differencing

Finally, the alternative transformation to wipe out the individual effects and a solution to the Nickell bias problem associated with dynamic models is to take first difference of the original model (Greene, 2008). First-difference (FD) transformation of Eq. (3.21) removes the fixed-effect and its associated omitted-variable bias, yielding:

$$\left(y_{it} - y_{i,t-1}\right) = \alpha_1\left(y_{i,t-1} - y_{i,t-2}\right) + \beta\left(x_{it} - x_{i,t-1}\right) + \left(\varepsilon_{it} - \varepsilon_{i,t-1}\right). \tag{3.27}$$

Accordingly, Eq. (3.27) can be written as:

$$\Delta y_{it} = \alpha_1 \Delta y_{i,t-1} + \beta \Delta x_{it} + \Delta\varepsilon_{it}. \tag{3.28}$$

However, while first differencing eliminates the fixed effects, the FD transformed lagged regressor ($\Delta y_{i,t-1}$), is still correlated with the FD transformed error term ($\Delta\varepsilon_{it}$). This is because $\varepsilon_{i,t-1}$ component of $\Delta\varepsilon_{it}$, which is now a first-order Moving Average process ($MA(1)$), is by construction correlated with $y_{i,t-1}$ component of $\Delta y_{i,t-1}$, and hence causing the correlation between the FD transformed lagged dependent regressor

[115] Having said that, Bond (2002) argue that, while the correlation between the $(y_{i,t-1} - \bar{y}_{i1})$ and $(\varepsilon_{it} - \bar{\varepsilon}_i)$ does not vanish as N gets larger, the contribution of each time period to the individual mean becomes negligibly smaller as T increases, such that when $T \to \infty$, the within estimator of α_1 and β become consistent.

and the FD transformed error term[116]. Accordingly, the dependence of $\Delta y_{i,t-1}$ on $\Delta\varepsilon_{it}$ implies that the FD estimates are also inconsistent and biased, with the direction of the bias being downward and typically greater than that found for the within estimator (Bond, 2002)[117].

Thus, even with the fixed effect removed, the FD transformed error terms are still correlated with the FD transformed lagged dependent regressor through the contemporaneous terms of y in period $t+j$ and $j = 1, 2, ...$ (Baltagi, 2005). Recalling the strict exogeneity condition discussed in Section 3.4.1, x_{it} is said to be strictly exogenous if the error term is uncorrelated with the observable regressors of all past, current and future time periods of the same individual. Thus, if x_{it} is said to be strictly exogenous, we can write:

$$E[x_{it}, \varepsilon_{is}] = 0 \text{ for all } t \text{ and } s. \tag{3.29}$$

Where, $s, t = 1, 2, \ldots, T$. However, we already know that the strict exogeneity condition does not always hold. In particular, x_{it} is said to be endogenous (i.e., not strictly exogenous) if the current error term is uncorrelated with future values of x_{it} but may be correlated with its current and lagged values. Thus, if x_{it} is said to be endogenous, we can write:

$$\begin{cases} E[x_{it}, \varepsilon_{is}] \neq 0 \text{ for all } s \leq t \\ E[x_{it}, \varepsilon_{is}] = 0 \text{ for all } s > t \end{cases}. \tag{3.30}$$

However, if the current period error term is uncorrelated with the current and lagged values of x_{it} but may be correlated with its future values, x_{it} is said to be "predetermined" (Greene, 2008). It is predetermined in the sense that it is fixed in the current period, but may be influenced by the current unpredictable errors in the future periods (Wooldridge, 2010). Thus, if x_{it} is said to be predetermined, then:

$$\begin{cases} E[x_{it}, \varepsilon_{is}] \neq 0 \text{ for all } s < t \\ E[x_{it}, \varepsilon_{is}] = 0 \text{ for all } s \geq t \end{cases} \tag{3.31}$$

[116] To see why FD error term is $MA(1)$, it suffices to write $\Delta\varepsilon_{it}$ for $t = 2, 3$, and 4: $\Delta\varepsilon_{i2} = \varepsilon_{i2} - \varepsilon_{i1}$, $\Delta\varepsilon_{i3} = \varepsilon_{i3} - \varepsilon_{i2}$, and $\Delta\varepsilon_{i4} = \varepsilon_{i4} - \varepsilon_{i3}$. As we will show in Section 3.4.5, GMM can easily accommodate first order serial correlations in the FD error term.

[117] However, Bond (2002) and Baum (2006) show that the within transformation and the first-difference transformation and hence their corresponding estimators coincide in the special case when $T = 3$.

As can be seen from Eq. (3.30) and Eq. (3.31), the only difference between predetermined variables and endogenous variables is that the latter allow for contemporaneous correlation (i.e., x_{it} and ε_{it}), whereas the former do not.

Accordingly, the lagged dependent regressor ($y_{i,t-1}$) in Eq. (3.21) falls into the definition of a predetermined variable as presented in Eq. (3.31). That is, while the current error term (ε_{it}) is uncorrelated with the current and lags of the regressor ($y_{i,t-1}, y_{i,t-2}, y_{i,t-3}, \ldots$), it is correlated with the future value of the regressor (y_{it}). Thus, it is due to the endogeneity of the lagged dependent regressor that the OLS estimators (i.e., pooled OLS, RE, and FE) do not produce consistent estimates in a dynamic panel model. However, with μ_i removed, a straightforward Instrumental Variables (IV) estimator can be used to control for the endogeneity problem in Eq. (3.28) (Baltagi, 2005).

3.4.4. Anderson-Hsiao Estimator

Instrumental Variables (IV) estimation is a method of estimation that is widely used in many econometric applications, when endogeneity of the explanatory variables is suspected. While there are formal tests for identifying endogenous variables, even without testing for endogeneity, we know that the FD transformed lagged dependent regressor in a dynamic model such as Eq. (3.28) is not strictly exogenous as it is correlated with FD transformed error term. As noted by Bond (2002), the fundamental idea behind IV method is that, one can obtain consistent estimates if the actual realised values of the endogenous variable, which are correlated with the error term, can be replaced by its predicted values that are still related to the endogenous variable but are uncorrelated with the error term.

The predicted values are obtained by projecting the endogenous variable on a set of appropriate instruments. An appropriate IV is an observable variable excluded from the model (i.e., not correlated with the dependent variable), which satisfies the following two conditions (Wooldridge, 2010)[118]. The first condition involves the relationship between the IV and the endogenous variable. In particular, it requires that in a linear projection of the endogenous variable (i.e., a regression of the endogenous

[118] The process of identifying appropriate IVs is discussed in more details in Section 3.5.

variable on the IV candidate and all other exogenous variables in the model), the coefficient on the IV is non-zero and significant[119]. That is, the instrument must be *informative* of the endogenous variable. Assuming X and Z to be the endogenous variable and the instrument respectively, we can express the first condition as:

$$Cov(Z, X) \neq 0. \tag{3.32}$$

The second condition, which is usually referred to as the *validity* condition, requires the IV to be uncorrelated with the error term. That is, the IV must be exogenous. Accordingly, we can express the validity condition of IVs as:

$$Cov(Z, \varepsilon_{it}) = 0. \tag{3.33}$$

Anderson and Hsiao (1981 & 1982) developed a new estimator to control for the endogeneity problem and obtain consistent estimates of Eq. (3.28). They propose that, once fixed effects are removed by first differencing transformation, $\Delta y_{i,t-2}$ or simply $y_{i,t-2}$ may be used as appropriate instruments for the FD transformed lagged dependent regressor, as they both are correlated with $\Delta y_{i,t-1}$ but orthogonal to $\Delta \varepsilon_{it}$[120].

The Anderson-Hsiao (AH) estimator is performed in two stages. In the first stage, the endogenous variable is regressed on a set of explanatory variables, which contains the instrument of interest and all other exogenous variables included in the original model. Then, in the second stage, the projected values of the endogenous variable replace its actual values (Bond, 2002 and Baum *et al.*, 2003). Accordingly, using instrumental variables, the AH approach, also known as the "first-differenced IV" (FDIV) estimator, will lead to consistent estimates for the FD model in Eq. (3.28) so far as the original error term is not serially correlated (Baltagi, 2005; Greene, 2008; Wooldridge, 2010).

[119] Wooldridge (2010) points out that, while the first condition is often loosely described as "IV must be correlated with the endogenous variable", it merely implies that, the IV is partially correlated with the endogenous variable once the other exogenous variables have been netted out. That is, the IVs are required to have explanatory power for (each of) the endogenous variable(s) *after* conditioning on all the remaining exogenous variable(s).

[120] However, evaluating the performance of the Anderson-Hsiao (AH) estimator in the context of simple dynamic error components models with an autoregressive exogenous variable, Arellano (1989) finds that, the estimator that uses differenced instrument (i.e., $\Delta y_{i,t-2}$) has a singularity point and very large variances over a significant range of parameter values. In contrast, the estimator that uses instruments in levels (i.e., $y_{i,t-2}$) has no singularities and much smaller variances. Accordingly, given the superiority of using lagged levels as instruments instead of lagged differences, the subsequent literature only use lagged levels when applying the AH estimator.

3.4.5. Arellano-Bond Estimator

It should be noted that, while the FDIV estimates of the parameters in the model (3.28) are *consistent*, they may not necessarily be *efficient*. This is because the FDIV estimator does not make use of all the available moment conditions and, does not take into account the $MA(1)$ process and the differenced structure of the error terms (Ahn and Schmidt, 1995; Bond, 2002; and Greene, 2008)[121]. Consistent with this, subsequent studies to Anderson and Hsiao (1982), such as Holtz-Eakin *et al.* (1988) and Arellano and Bond (1991), have noted that while the only valid instrument for $\Delta y_{i,t-1}$ that can be used in the FDIV estimator is $y_{i,t-2}$, further lags of $y_{i,t-1}$ are also *appropriate* instruments.

The Generalised Method of Moments (GMM), developed by Hansen (1982), provides a convenient framework for obtaining asymptotically efficient estimators of the dynamic panel models such as Eq. (3.28) by exploiting additional moment restrictions. The GMM estimator is based on moment functions, which depend on observable random variables and unknown parameters. Accordingly, one can find a GMM estimator of the true parameter by finding the elements of the parameter space which sets linear combinations of the sample cross products 'as close to zero as possible' (Hall, 2005). In addition, using GMM to estimate dynamic models has become increasingly popular because of its advantages over using OLS. That is, it facilitates dealing with important modelling concerns such as fixed effects and endogeneity of regressors, while avoiding dynamic panel bias. Furthermore, the flexible framework of GMM allows accommodation of unbalanced panels and multiple endogenous variables (Baltagi, 2005).

Accordingly, building on the work of Anderson and Hsiao (1982) and using GMM estimation techniques, Arellano and Bond (1991) developed a consistent and more efficient estimator for the parameters of dynamic panel models. The new estimator utilises additional instruments obtained by using the orthogonality conditions that

[121] In fact, defining Z as a $(T-2) \times m$ block diagonal matrix whose sth block is given by $(y_{i1} \dots y_{is})$ and $(s = 1, \dots, T-2)$, Arellano and Bond (1991) show that the AH estimator will lead to inefficient estimates, because $y_{i,t-2}$ is a linear combination of Z.

exist between the lagged values of the dependent variable and error term[122]. That is, instead of using only the instrument $y_{i,t-2}$ for all t as suggested by the AH estimator, Arellano and Bond (1991) propose using an increasing more number of lagged instruments as $t \to T$. In particular, they show that, given the predetermined nature of the lagged dependent regressor, the vector of $y_{i,1}, y_{i,2}, y_{i,3}, \dots, y_{i,s}$ where $s = 1, \dots, T-2$, can be used as appropriate instruments for $\Delta y_{i,t-1}$, as they all satisfy both the strong correlation with the endogenous variable condition (i.e., are informative) and the zero correlation with the error term condition (i.e., are valid)[123].

Accordingly, by specifying the model as a system of difference equations such as Eq. (3.28), one per period, the Arellano-Bond (AB) estimator, also known as the "Difference-GMM" (DIFGMM), allows using more instruments in later periods, where more lagged values of the instruments are available (Baltagi, 2005; Wooldridge, 2010). In addition, the GMM framework of the AB estimator also allows incorporating the serially correlated structure of the errors in the FD equations (Maddala and Lahiri, 2009)[124]. That is, by acknowledging the $MA(1)$ structure of the FD error term ($\Delta\varepsilon_{it}$) and hence the orthogonality of $\Delta\varepsilon_{it}$ to the past history of the FD transformed lagged dependent regressor ($\Delta y_{i,t-1}$), the first valid instruments to use by DIFGMM starts from the first lag of the FD transformed lagged dependent regressor (i.e., $y_{i,t-2}, y_{i,t-3}$, ...).

However, while DIFGMM leads to a significant increase in efficiency, using limited Monte Carlo simulations, Arellano and Bond (1991) document evidence of a "finite sample bias" also known as the "small sample bias". In particular, they find the estimated standard errors of the 2-step GMM estimator to be downward biased, and

[122] Although the first-differenced GMM estimator is often considered the work of Arellano and Bond (1991), they in fact popularized the work of Holtz-Eakin *et al.* (1988). Holtz-Eakin *et al.* (1988) expanded on the Anderson-Hsiao approach, showing how to implement it to estimate a vector autoregression with time-varying parameters. Arellano and Bond (1991) then use Monte Carlo studies to evaluate a GMM estimator that is very similar to the Holtz-Eakin *et al.* (1988) recommendation.

[123] Arellano and Bond (1991) further note that, the vector $y_{i,1}, y_{i,2}, y_{i,3}, \dots, y_{i,s}$, where $s = 1, \dots, T-2$ is the full set of instruments only when the equation contains individual effects, lagged dependent variables and no strictly exogenous variables. However, if the model also contains other strictly exogenous regressor, say x_{it}, then all values of x_{it} are valid instruments and thus, the full set of instruments will include $y_{i,1}, y_{i,2}, y_{i,3}, \dots, y_{i,s}$ as well as $x_{i,1}, x_{i,2}, x_{i,3}, \dots\ x_{i,s}$ where $s = 1, \dots, T-2$. See Arellano and Bond (1991), for more details on the construction of the instrument matrix.

[124] Assuming the original error term (ε_{it}) is serially uncorrelated, the FD transformed error term ($\Delta\varepsilon_{it}$) follows an $MA(1)$ process (i.e., is correlated with $\Delta\varepsilon_{i,t-1}$) because $Cov(\varepsilon_{it} - \varepsilon_{i,t-1}, \varepsilon_{i,t-1} - \varepsilon_{i,t-2}) = -Cov(\varepsilon_{i,t-1}, \varepsilon_{i,t-1}) \neq 0$.

thus recommending against using the 2-step GMM estimator. Nevetheless, Windmeijer (2005) worked out a finite-sample correction for the 2-step standard errors, using a correction term, based on Taylor series expansion that accounts for the estimation of the weight matrix, and shows that this correction term provides a more accurate approximation in finite samples when all the moment conditions are linear[125].

3.4.6. Arellano-Bover/Blundell-Bond Estimator

So far, we have established that the AB estimator is more efficient than the AH estimator, as it uses all moment conditions based on the assumption $E(y_{is}, \Delta\varepsilon_{it}) = 0$ for $s < t - 2$ in the FD transformed Eq. (3.28).

However, recent econometric studies has suggested that the AB estimator may suffer from a problem of "weak instruments" or "weak identification", and that additional moment conditions based on level equations may lead to an estimator with improved precision and better finite-sample properties (e.g., Arellano and Bover, 1995; Blundell and Bond, 1998; Stock *et al.*, 2002; and Roodman, 2009b)[126]. In particular, Arellano and Bover (1995) show that, the lagged instruments used in DIFGMM could be poor instruments for first differences if the variables are close to being a random walk, and that the absence of information concerning the parameters in the level variables causes substantial loss of efficiency. Similarly, Blundell and Bond (1998) find that, the instruments used by the DIFGMM estimator contain little information about the endogenous variables in first differences, and that the DIFGMM estimator performs poorly and leads to biased estimates, especially for short sample periods and persistent data. They attribute the bias and the poor precision of the DIFGMM estimator to the problem of weak instruments.

In fact, expanding the work of Arellano and Bover (1995), Blundell and Bond (1998) develop a substantially more efficient estimator than the AB estimator by imposing an additional restriction on the initial conditions process, $E(\Delta y_{i,t-1}, \mu_i) = 0$, under which all the moment conditions available can be exploited by a linear GMM

[125] For more details regarding the finite sample bias problem, see Windmeijer (2005).
[126] The weak instrument problem is related to the first condition of IV validity and it refers to situations where instruments are only weakly correlated with the included endogenous variables. For a detailed discussion of weak instruments in GMM, see Stock *et al.* (2002).

estimator in a system of first-difference and levels equations[127]. That is, rather than using the first differences to eliminate the fixed effects as in DIFGMM, the Arellano-Bover/Blundell-Bond (AB/BB) estimator allows the instruments to be exogenous to the fixed effects. Thus, the additional moment restriction allows using both the first differences of the level predetermined and endogenous variables and the lagged levels of the first differenced predetermined and endogenous variables as instruments (Roodman, 2009a).

Accordingly, the AB/BB estimator, also known as "System GMM" (SYSGMM), estimates the model both in levels and first-differences, where the equations in first differences are instrumented by lagged levels and the equations in levels are instrumented using the first difference. Thus, by using both differenced and level instruments in a GMM context, SYSGMM exploits all the information available in the sample, and will lead to significantly more efficient estimates than the DIFGMM, which only allows instruments to be constructed in the form of lagged levels (Baltagi, 2005; Baum, 2006; Roodman, 2009a; and Wooldridge, 2010). Consistent with this argument, using Monte Carlo simulations, Blundell *et al.* (2000) show that, while the DIFGMM estimator with weakly exogenous covariates suffers from large finite sample bias and low precision, simulations for the SYSGMM estimator exhibit smaller finite sample bias and significant improvement in precision levels.

Similar to the DIFGMM, the consistency of the SYSGMM is also based on the absence of second order correlation in the FD transformed errors (i.e., absent of first-order correlation in original error terms)[128]. However, if the hypothesis of no serial correlation of error term is rejected, one can add more lags of the dependent variable as regressors in the hope that this will eliminate any serial correlation in the error[129]. Recall the orthogonality of the FD error term ($\Delta\varepsilon_{it}$) to the past history of the FD transformed lagged dependent regressor ($\Delta y_{i,t-1}$) implies that $y_{i,t-2}$ will be the first available valid instrument to use by DIFGMM estimator. Thus, if ε_{it} itself has first-order serial correlation, then $\Delta\varepsilon_{it}$ follows an $MA(2)$ process, and hence the first valid

[127] They assume a simple case where the model is just identified, hence includes only one endogenous variable (i.e., the lagged dependent regressor) and one instrument.
[128] Both the **xtdpdsys** command and **xtabond2** command assume that the original model errors, ε_{it}, are serially uncorrelated.
[129] The alternative solution is to use the **xtdpd** command, an acronym for dynamic panel data, which allows for some autocorrelation in the idiosyncratic errors, ε_{it} (StataCorp, 2015). The **xtdpd** command also allows predetermined variable to have a more complicated structure.

instruments for the FD equation start from the second lag of the FD transformed lagged dependent regressor (i.e., $y_{i,t-3}, y_{i,t-4}$, ...). As Baum (2006: p. 233) notes: "*even if we believed that* ε *might be following and* $AR(1)$ *process, we could still follow this strategy, "backing off" one period and using the third and fourth lags of* y". The similar logic holds for the level equations. That is, if ε_{it} has a first-order correlation, then $\Delta y_{i,t-1}$ is no longer a valid instrument for the level equation, and the first valid instruments start with the of the FD of the first lag of the lagged dependent regressor (i.e., $\Delta y_{i,t-2}$, $\Delta y_{i,t-3}$, ...) (Baltagi, 2005 and Roodman, 2009a).

Having discussed the problems associated with estimating dynamic panel models for different estimation methods and their shortcomings in dealing with them, SYSGMM seems to be the most asymptotically efficient and superior method that leads to consistent estimates of the unknown parameters[130].

3.4.7. Estimation Models

Having decided on the analysis data and estimation method, we now specify the estimation models. Applying the general model specification presented in Eq. (3.17) to the set of analysis variables derived from the review of the empirical literature of capital structure (see, Section 2.3), the following will be estimated as our "base" model:

$$Leverage_{it} = \alpha_0 + \beta_1 L.LVG_{it} + \beta_2 GRT_{it} + \beta_3 PRF_{it} + \beta_4 TNG_{it} + \beta_5 SIZ_{it} + \beta_6 NDTS_{it} + \beta_7 RSK_{it} + \gamma_1 YR_{2004} + \gamma_2 YR_{2005} + \gamma_3 YR_{2006} + \gamma_4 YR_{2008} + \gamma_5 YR_{2009} + \gamma_6 YR_{2010} + \gamma_7 YR_{2011} + \gamma_8 YR_{2012} + \mu_i + \varepsilon_{it}. \quad (3.34)$$

Where, $Leverage_{it} = \frac{Total\ Debt_{it}}{Total\ Debt_{it} + Total\ Equity_{it}}$ denotes book leverage ratio; $L.LVG_{it} = \frac{Total\ Debt_{t-1}}{Total\ Debt_{t-1} + Total\ Equity_{t-1}}$ denotes the 1-year lagged book leverage ratio; $SIZ_{it} = \ln(Total\ Assets_{it})$ denotes firm size; $GRT_{it} =$

[130] While the standard SYSGMM is performed by the **xtdpdsys** command in Stata, in 2003 David Roodman developed an improved version of official Stata's estimator **xtdpdsys**, which allows for the same specification as the SYSGMM approach and also reports the Windmeijer's finite sample bias corrected standard errors for the two-step estimates, and is available in Stata through the user-written command **xtabond2**. Accordingly, given the advantages of the Roodman's estimator over the AB/BB estimator, we use **xtabond2** to estimate our capital structure models. For an excellent guideline on the mechanics of the **xtabond2** command, see Roodman (2009b).

$\frac{Book\ Value\ Total\ Assets_{it} - Book\ Value\ Equity_{it} + Market\ Value\ Equity_{it}}{Book\ Value\ Total\ Assets_{it}}$ denotes growth opportunities; $TNG_{it} = \frac{Net\ Fixed\ Assets_{it}}{Total\ Assets_{it}}$ denotes asset tangibility; $PRF_{it} = \frac{EBITDA_{it}}{Total\ Assets_{it}}$ denotes profitability; $NDTS_{it} = \frac{Depreciation\ and\ Amortization\ Expense_{it}}{Total\ Assets_{it}}$ denotes non-debt tax shields; $RSK_{it} = \frac{annual\ \%\ change\ in\ EBIT_{it}}{average\ \%\ change\ in\ EBIT_{i}}$ denotes business risk; YRs are the annual time dummies, α_0 is the constant; μ_i represents time-invariant unobservable firm-specific effects; ε_{it} is the idiosyncratic error term; and βs and γs are the unknown parameters to be estimated[131].

The primary purpose of Eq. (3.34) is to investigate the impact of the recent Global Financial Crisis (GFC) and each of the included firm-specific determinants of capital structure on the leverage ratios of the constituent of the FTSE 250 Index during the period 2004-2012. Accordingly, the set of 6 firm specific determinants of the capital structure are included to examine how much of the firms' leverage ratio is explained by the variation in these factors and thus, their coefficients will indicate the relative change in the leverage ratio when a given variable is changed by 1 unit. Furthermore, the 1-year lagged leverage ratio is included to account for the dynamic nature of firms' capital structure decisions and thus its coefficient measures the explanatory impact of previous period's leverage ratio on the current periods' ratio, while controlling for transaction and other adjustment costs. Finally, a set of annual time dummy variables the period 2004-2012, with 2007 (the onset of the GFC) as the base year, are included for to capture the impact of the recent GFC on firm's leverage ratio, while controlling for the firm-specific determinants of capital structure. Accordingly, the coefficient on the year dummies indicate the relative change in the leverage ratios in a given year compared with 2007 that is due to the time-specific overall economic conditions in the respective years[132].

As discussed extensively in Section 2.3.5, a unique type of firms called "zombies", seems to have come to existence after the recent GFC and the consequent economic recession. We define zombies as *surviving technically insolvent firms that are unable*

[131] The construction of all of the variables used in this study is detailed in Table 7.1 in the Appendix.

[132] Each annual time dummy acts as an aggregate measure containing all macroeconomic variables external factors in the respective year. Furthermore, It should be noted that, the inclusion of annual time dummies (YRs) effectively leads to the removal of the firm-invariant unobservable time-specific effects (λ_t) which was included in the general specification model presented in Eq. (3.17).

to generate enough revenues to even pay the interest expenses on their borrowings, let alone the repayment of the principal amount.

Zombies are unique in the sense that, they are neither fully insolvent (as are still active and in operating) nor having a solid financial standing (are unable to generate enough revenues to service their debts). Thus, their other financial characteristics such as capital structure may also be determined differently than those of non-zombies. For instance, the capital structure of zombies may have been affected by the unprecedented level of banks' forbearances on non-performing loans and different government-sponsored support schemes that have been offered in the period after the recent GFC and consequent economic recession. Thus, as part of the investigation on the impact of the recent GFC on capital structure, we are also interested to test whether the capital structure of zombies is determined differently than that of non-zombies.

Given that the unprecedented high firm survival in the UK has only been documented after the onset of the GFC and consequent economic recession, it implies that any factor that may have contributed towards it, such as the emergence of zombies, should be also considered in a post-crisis context (see, Section 2.3.5). Furthermore, while certain characteristics such as: significant increases in debt levels, deteriorated ability to meet short-term financial obligations or substantially high financing costs may be inferred as signs of severe financial distress, if observed in a post-crisis environment, the same characteristics may have a different interpretation in the prevailing booming economic conditions before the crisis. Consequently, once zombies are identified in out sample, the following "zombie" model will be estimated for the period 2008-2012:

$$Leverage_{it} = \alpha_0 + \beta_1 L.LVG_{it} + \beta_2 GRT_{it} + \beta_3 PRF_{it} + \beta_4 TNG_{it} + \beta_5 SIZ_{it} + \beta_6 NDTS_{it} + \beta_7 RSK_{it} + \beta_8 ZMB_{i,t-1} + \gamma_1 YR_{2008} + \gamma_2 YR_{2009} + \gamma_3 YR_{2010} + \gamma_4 YR_{2011} + \gamma_5 YR_{2012} + \mu_i + \varepsilon_{it} \quad (3.35)$$

Where, $ZMB_{\mathrm{i,t-1}}$ denotes a dummy variable that takes a value of 1 if a firm is identified as zombie at the beginning of a given year, and 0 otherwise[133]. Accordingly, the coefficient on the zombie dummy variable would indicate the

[133] The zombie dummy variable is 1 year lagged, in order to ensure that it capture the effect of being zombie on the leverage ratio and avoid the distortion due the changes in firms' financial condition during the year.

difference between the leverage ratios of zombies relative to those of non-zombies, holding all other variables constant. As such, a significant positive or negative coefficient would suggest the existence of some additional factors specific to zombies that exert a significant impact on their capital structure decisions.

Furthermore, given that the analysis period of the zombie model is limited to the years after the GFC, it can also be used to assess the empirical relevance of the commonly used firm-specific determinants of capital structure in a post-crisis environment. That is, since the same firm-specific determinants of capital structure are used in both the base model (covering both the pre-crisis and the post-crisis periods) and the zombie model (covering only the post-crisis period), changes in the signs or statistical significance of their respective coefficients in the zombie model as opposed to the base model can be inferred as certain firm-specific determinants of capital structure losing their empirical relevance or reversing in their impact in a post-crisis environment.

However, in order to address the endogeneity problem associated with the estimation of dynamic models such the base and the zombie model, we must identify the endogenous regressors for each model before proceeding with the estimation results.

3.5. Determination of Endogenous Regressors

We attempt to test the potential endogeneity of the included regressors by using purpose-designed statistical tests. Accordingly, all included firm-specific regressors in the base model and the zombie model, except for the lagged dependent regressor, which by construction is a predetermined variable, are treated as not strictly exogenous and are tested for potential endogeneity[134]. However, the process of detecting the endogenous regressors and choosing appropriate instruments are intertwined. That is, one must first assume that a regressor is endogenous and thus find appropriate instruments for that regressor, to be able to test for the endogeneity of the respective regressor.

Recalling that appropriate IVs must be highly correlated with the endogenous variable but uncorrelated with the error term, the possible instrument candidates can be either external (i.e., conceptually unrelated to the endogenous variable) or internal (i.e., based on lagged values of the instrumented variable) to the immediate dataset. Furthermore, the strictly exogenous variables can be used as their own instruments, as they are already uncorrelated with the error term (Baum *et al.*, 2003).

The internal nature of financing decisions and their substantial impact on all other aspects of the firm makes difficult to find valid external instruments that are exogenous to the model and thus are not considered as omitted variables (Ozkan, 2001). Although a limited number of external instruments are identified for some of the variables, consistent with the standard practice in the empirical applications of the GMM, most instrument candidates are internal and include lagged values of the specified endogenous variables[135]. This choice is in line with Roodman's (2009b: p. 100) comment regarding the SYSGMM estimator command:

> Finally, because the estimators are designed for general use, they do not assume that good instruments are available outside the immediate dataset. In effect, it is assumed that the *only available instruments are "internal"—*

[134] Given the dichotomous nature of year dummy variables, and that they each only enter into one time-period equation (i.e., value of 1 for one period and 0 for all other periods), they are uncorrelated with the idiosyncratic error term and thus are treated as exogenous.

[135] The external candidate instruments include: *Inventory Turnover* for *SIZ*, *Research & Development Expenses* for *TNG*, *Payout Ratio* for *PRF*, *Effective Tax Rate and Income Tax Expense* for *NDTS*, *Unlevered Beta* and *Risk Premium* for *RSK*. See Table 3.3 and Table 3.4 for more details.

based on lags of the instrumented variables. However, the estimators do allow inclusion of external instruments.

Given the assumed correlation between the specified endogenous variable and the error term, the standard treatment is to use lag 2 and above as instruments (Baum, 2006 and Roodman, 2009b). Furthermore, following the standard in the econometric literature and the discussions above, the lagged dependent regressor (1-year lagged book leverage ratio) is treated as a predetermined variable, and hence is instrumented by its own first lag.

While using lagged values of the endogenous variables is a more convenient solution than finding external instruments, it also has limitations. In particular, an issue of concern, which could affect inferences about parameters estimates of the IV and GMM estimators, is having "too many" instruments relative to the sample size. This is because, as T increases, the number of available lags to be used as instruments increases too, which could easily lead to generating a great many instruments for each endogenous regressor or what Roodman (2009a) refers to as "instrument proliferation". Consistent whit this argument, Baum (2006) shows that the number of instruments increases quadratically in the number of periods for DIFGMM and, by extension, it is far worse for SYSGMM, given the simultaneous estimation of level and difference equations.

The possible downsides to having too many instruments, however, were noticed a long time ago by Sargan (1958) who finds that, the magnitude of the errors involved in the asymptotic approximation are proportional to the number of instrumental variables, meaning that having too many instruments can have significant impact on the efficiency of the estimates. Similarly, Roodman (2009a: p. 139) notes that: "s*imply by being numerous, instruments can overfit instrumented variables, failing to expunge their endogenous components and biasing coefficient estimates towards those from non-instrumenting estimators*". Consequently, to the extent that including further lags of the endogenous variable in the instrument set introduces more information, it should improve efficiency, however, it may also lead to larger finite sample bias of the IV estimator due to the smaller sample size caused by the increasing unavailability of longer lagged values (Hahn and Hausman, 2002 and Roodman, 2009b).

Accordingly, we do the following to avoid or minimize the consequences of instrument proliferation: first, given that the endogeneity test is conducted for one regressor at a time (i.e., one specified endogenous variable), the alternative instrument sets start by including 2 instruments, which is large enough for the model to be overidentified, and small enough to minimize the likelihood of instrument proliferation and loss of efficiency. Second, when choosing among competing *appropriate* instruments, the preference will be towards the instrument sets with smaller number of instruments. Finally, following Baum (2006) and Roodman (2009b), we also set a maximum number of lagged levels to be included as instruments for the predetermined variable[136].

The user-written **`ivreg2`** command (Baum *et al.*, 2003 & 2007) is used to conduct the tests for detecting endogeneity of the regressors and identifying the appropriate set of instruments. In particular, the **`ivreg2`** command with the option **`gmm2s robust endog`** is used to implement the 2-step efficient GMM estimation with IVs and report 4 post-estimation tests: 3 tests for the relevance, strength of relevance and validity of instruments, and 1 test for the endogeneity of the regressors.

In order to improve reliability and setting a stricter criteria for our choice of instruments and identification of endogenous variables, we use a lower significant level for the tests where the rejection of the null is the satisfactory outcome or the cost of making type 1 error (i.e., rejecting a true null) is significant (e.g., the test for the relevance), and a higher significance level for the tests where the failure to reject is the satisfactory outcome or the cost of making type 2 error (i.e., failing to reject a false null) is significant (e.g., the test for validity of instruments and the test for endogeneity of the regressors). Having said that, we have no control over the significance level used for testing the strength of relevance, as the test statistics are compared against the critical values computed by Stock and Yogo (2005), which are only reported for 5% significance level.

[136] This will be discussed in more details in Section 4.3.4.1, where we determine the optimal estimation specification.

3.5.1. Underidentification Test

The first condition that must be satisfied for appropriate instruments is the relevance condition (i.e., the first-stage regression equation is identified)[137]. That is, there must be a correlation between the endogenous variable and the instruments, controlling for the effect of all other included regressors in the model. The underidentification test reported after the **`ivreg2`** is a Lagrange Multiplier (LM) test with the null hypothesis that the equation is underidentified (i.e., instruments are not relevant) and the Kleibergen-Paap's (2006) rank statistics is used as the test statistics for the underidentification[138].

Accordingly, failure to reject the null hypothesis would suggest that the model is underidentified and hence instruments are not relevant (Baum *et al.*, 2007). However, a rejection of the null should be treated with caution, as rejecting that the instruments are not correlated with the endogenous variable is not an indication of how strong is the correlation between them. That is, relevant instruments can still be only weakly correlated with the endogenous regressor.

As discussed above, in order to make it more difficult to misidentify instruments as relevant, we use 1% significance level (*p-value* of 0.01) as the threshold for testing the underidentification test, where rejection of the null implies that instruments satisfy the relevance condition.

3.5.2. Weak-Identification Test

Given that the partial correlation of the instruments with the endogenous regressor determines the asymptotic variance of the estimator, if the explanatory power of the relevant instruments is "weak", the asymptotic variance of the IV estimator can be quite large (Wooldridge, 2010). Accordingly, weak correlation between instruments and the endogenous regressor can lead to substantial estimation biases and the poor performance of IV/GMM estimators (Staiger and Stock, 1997 and Stock *et al.*, 2002).

[137] The first-stage regressions are reduced form regressions of the specified endogenous variable on its instrument as well as all other exogenous variables included in the original model. For more details, see Section 3.4.4.

[138] For estimations with assumed *i.i.d.* errors, the Anderson LM and Cragg-Donald Wald statistics are used as the underidentification test statistics. For more details, see Kleibergen and Paap (2006).

The second post-estimation test, referred to as the weak-identification test, addresses the strength of the instruments relevance and the correlation between them and the endogenous regressor. In particular, it tests the null that a given group of instruments is weak against the alternative that it is strong.

For estimations with more than one instrument and, to account for the presence of the exogenous regressors, the joint statistical significance of all the instruments in the first-stage regression must be considered (Cameron and Trivedi, 2010). Accordingly, the *Kleibergen-Paap Wald statistic*, which is a joint significance test of the instruments in first-stage regression, is used to test the strength of the identification[139].

Weak instruments are detected by comparing the *Kleibergen-Paap Wald statistic* to the critical values, proposed by Stock and Yogo (2005), corresponding to the maximum 10% distortion in the IV estimator compared to an OLS estimator. Accordingly, the *Kleibergen-Paap statistics* greater than the critical value for 10% maximal IV size would suggest evidence against the presence of weak instruments[140].

3.5.3. Test of Overidentifying Restrictions

The final condition that must hold to ensure the appropriateness of the instruments is the validity condition (i.e., instruments are exogenous to the error term). The validity of instruments can only be tested in an overidentified model, where the number of instruments exceeds that of the endogenous regressors (Hayashi, 2000).

The test of overidentifying restrictions reported after **`ivreg2`**, also known as the Sargan-Hansen test, tests the joint null hypothesis that instruments are valid (i.e., uncorrelated with the error term), and that the excluded instruments are correctly excluded from the estimated model against the alternative that they are not (StataCorp, 2015). Furthermore, the reported test statistic for the efficient GMM estimator (specified via the **`gmm`** option) is the *Hansen's J statistic*, which is the minimised value of the GMM criterion function (Baum *et al.*, 2007).

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[139] When errors are assumed to be *i.i.d.*, the Cragg-Donald (1993) Wald F-statistic is used instead. For more details, see Stock and Yogo (2005).

[140] While, Bound *et al.* (1995) and Staiger and Stock (1997) proposed the rule of thumb that the F statistic must be at least 10 for an instrument to be valid, more recent work such as Stock *et al.* (2002) and Stock and Yogo (2005) suggest that depending on the number of instruments, the critical value can be even higher.

Accordingly, we test whether the *Hansen's J statistic* is "small enough" to be consistent with the orthogonality condition (i.e., no correlation with the error term) of the instruments (Wooldridge, 2010 and Cameron and Trivedi, 2010). Thus, a rejection of the null hypothesis must cast doubt on the validity of the instruments.

Recalling the problems associated with having too many instruments, Roodman (2009a) notes that the test for validity of instrument is also sensitive to the number of instruments, and gets weaker as the number of instruments increases. He therefore argues that, while using the conventional significance levels such as (5% or 10%) may be conservative when deciding on the statistical significance of a coefficient estimate, they are too *liberal* when used for testing the validity of instruments (i.e., ruling out correlation between instruments and the error term). Accordingly, following his advice, we use the *p-value* of 0.25 (25% significance level) as our lower limit for the rejection of the null as it implies at least one in four chances that one would observe a test-statistic of the same magnitude. Following the same logic, *p-values* of 1.00 should also be treated with major caution.

3.5.4. Endogeneity Test of Regressors

As noted at the beginning of the section, in order to test the endogeneity of the regressors, one must first identify a set of appropriate instruments for each specified endogenous regressor. Instruments are considered appropriate if *all* of the following conditions are met:

- The null hypothesis that the model is underidentified is rejected (i.e., instruments are relevant).
- The null hypothesis that relevant instruments are weakly correlated with the specified endogenous regressors is rejected (i.e., instruments are not weak).
- The null hypothesis that instruments are uncorrelated with the error term fails to be rejected (i.e., instruments are valid).

Recalling Eq. (3.30), a regressor is said to endogenous (i.e., not strictly exogenous), if it is correlated with the error term, implying that the zero-conditional-mean assumption (i.e., $E(\varepsilon_{it} \forall X_{it}) \neq 0, t = 1, \dots, T$) fails to hold. Accordingly, as Baum *et al.* (2003) proposes, when testing for endogeneity of regressors, we must actually test

whether a variable meet the zero-conditional-mean assumption. Accordingly, the final post-estimation test reported by **`ivreg2`** command (using the **`endog`** option) is the test of endogeneity of the regressors, which tests the null hypothesis that the specified endogenous regressor can actually be treated as exogenous.

The reported test statistic is chi-squared statistic, which is referred to as the "difference-in-Hansen" statistic, and is defined as the difference of the Hansen statistic of the equation with the smaller set of instruments, where the specified endogenous regressor is treated as endogenous, and the equation with the larger set of instruments, where the specified endogenous regressor is treated as exogenous (Baum *et al.*, 2007). Accordingly, using a 10% significance level, a difference-in-Hansen statistic with $p\text{-}value < 0.1$ implies a rejection of the null hypothesis, meaning that the specified endogenous regressor is actually endogenous and must be treated accordingly. However, recalling that the results of the endogeneity test are only valid so far as the instruments used to estimate the second-stage regression are appropriate, the results of the endogeneity test must be considered together with the previously discussed post-estimation tests[141].

Table 3.3 and Table 3.4 report the results of the post-estimation tests and detail the criteria for the choice of appropriate instruments for each of the specified endogenous regressors of the base model and the zombie model, respectively. The choice of instruments is deemed appropriate and hence the endogeneity test is considered reliable, if the outcomes of the first three post-estimation tests are signified by a tick.

As can be seen from the Tables 3.3, we fail to reject the null hypothesis that the specified endogenous regressor can be treated as exogenous for all the regressors in the base model, except for RSK. That is, PRF, GRT, SIZ, TNG, and $NDTS$ are identified as exogenous, while RSK indicates endogeneity. While the two instrument sets (*Lag 2, Lag 3, Lag 4*) and (*Lag 3, Lag 4*) are both identified as appropriate instruments for *RSK*, the stronger results for the underidentification, weak-identification and the overidentification tests for the instrument set (*Lag 3, Lag 4*)

[141] The second-stage regression is the regression of the re-estimation of the original model where the actual values of the endogenous regressors are replaced with their projected values obtained from the first-stage regression.

suggest that it is a more appropriate instrument set than (*Lag 2*, *Lag 3*, *Lag 4*)[142]. Furthermore, as (*Lag 3*, *Lag 4*) include a smaller number of lags, it will lead to fewer instruments in the estimation model, and hence implying smaller information loss and finite sample bias problem. Accordingly, we use *Lag 3* and *Lag 4* of *RSK* as the appropriate set of instruments to control for the endogeneity problem in our estimation model.

As can be seen from Table 3.4, following the same criteria as for the base model, none of the specified endogenous regressors of the zombie model seem to have failed the endogeneity tests, suggesting they can all be treated as exogenous variables when estimating the zombie model. Next chapter will present the estimation results and discussion.

[142] The results are highlighted in bold in the last panel of Table 3.3.

Table 3.3 Choice of Instruments and Test of Endogeneity – Base Model

		Outcome of the Post-estimation Test			
Variable	*Choice of instruments*	***Underidentification:*** *(Reject: relevant instruments; Fail to reject: irrelevant instruments)*	***Weak-identification:*** *(K-P statistic > 10% maximal IV size Critical Value: strong instruments; K-P statistic < 10% maximal IV size Critical Value: weak instruments)*	***Overidentification:*** *(Reject: invalid instruments; Fail to reject: valid instruments)*	***Endogeneity:*** *(Reject: endogenous variable; Fail to reject: exogenous variable)*
GRT	*L2 & L3*	24.968 0.000 ✓	20.206 > C.V ✓	0.353 0.552 ✓	1.204 0.272 Exogenous
	L2, L3, L4	22.582 0.000 ✓	6.649 < C.V ×	1.029 0.598 ✓	0.951 0.329 Exogenous
	L2 & L4	22.219 0.000 ✓	8.937 < C.V ×	0.006 0.938 ✓	1.191 0.275 Exogenous
	L3 & L4	9.122 0.011 ×	33.393 > C.V ✓	0.025 0.875 ✓	5.110 0.024 Endogenous
	L2, L3, L4, L5	30.455 0.000 ✓	21.673 < C.V ×	8.037 0.045 ×	0.320 0.571 Exogenous
	L3, L4, L5	19.062 0.000 ✓	10.792 < C.V ×	6.099 0.047 ×	1.414 0.235 Exogenous
	L2 & L5	33.207 0.000 ✓	30.507 > C.V ✓	2.339 0.268 ×	0.596 0.440 Exogenous
	L3 & L5	18.853 0.000 ✓	15.239 < C.V ×	0.011 0.918 ✓	4.786 0.029 Endogenous
	L4 & L5	8.056 0.018 ×	17.390 < C.V ×	4.664 0.031 ×	7.243 0.007 Endogenous

		Outcome of the Post-estimation Test			
Variable	*Choice of instruments*	***Underidentification:***	***Weak-identification:***	***Overidentification:***	***Endogeneity:***
SIZ	*IT, L2*	176.664 0.000 ✓	863.568 > C.V ✓	0.321 0.571 ✓	7.170 0.007 Endogenous
	IT, L3	117.275 0.000 ✓	419.169 > C.V ✓	0.003 0.958 ✓	0.848 0.357 Exogenous
	IT, L2, L3	122.615 0.000 ✓	477.814 > C.V ✓	0.028 0.986 ✓	1.483 0.223 Exogenous
	L2 & L3	171.740 0.000 ✓	1174.692 > C.V ✓	0.241 0.623 ✓	0.000 0.996 Exogenous
	L2, L3, L4	127.768 0.000 ✓	829.965 > C.V ✓	0.494 0.781 ✓	0.101 0.750 Exogenous
	L2 & L4	127.779 0.000 ✓	1254.250 > C.V ✓	0.000 0.983 ✓	0.029 0.865 Exogenous
	L3 & L4	112.500 0.000 ✓	613.865 > C.V ✓	0.601 0.438 ✓	0.246 0.620 Exogenous
	L2, L3, L4, L5	98.877 0.000 ✓	431.656 > C.V ✓	1.767 0.622 ✓	1.253 0.263 Exogenous
	L3, L4, L5	99.643 0.000 ✓	296.761 > C.V ✓	0.579 0.749 ✓	0.063 0.802 Exogenous
	L2 & L5	88.766 0.000 ✓	1498.669 > C.V ✓	0.004 0.947 ✓	2.324 0.127 Exogenous
	L3 & L5	100.188 0.000 ✓	438.244 > C.V ✓	0.000 0.987 ✓	0.075 0.784 Exogenous
	L4 & L5	78.968 0.000 ✓	309.756 > C.V ✓	0.087 0.768 ✓	0.663 0.416 Exogenous

		Outcome of the Post-estimation Test			
Variable	*Choice of instruments*	***Underidentification:***	***Weak-identification:***	***Overidentification:***	***Endogeneity:***
TNG	*R&D, L2*	127.867 0.000 ✓	1689.691 > C.V ✓	0.010 0.920 ✓	0.042 0.838 Exogenous
	R&D, L3	103.737 0.000 ✓	1297.176 > C.V ✓	0.467 0.494 ✓	0.002 0.964 Exogenous
	R&D, L2, L3	105.086 0.000 ✓	891.101 > C.V ✓	0.434 0.805 ✓	0.005 0.945 Exogenous
	L2 & L3	136.697 0.000 ✓	2090.434 > C.V ✓	0.478 0.490 ✓	0.062 0.803 Exogenous
	L2, L3, L4	103.684 0.000 ✓	1008.215 > C.V ✓	1.253 0.534 ✓	0.111 0.739 Exogenous
	L2 & L4	104.308 0.000 ✓	1511.701 > C.V ✓	0.622 0.430 ✓	0.021 0.885 Exogenous
	L3 & L4	103.102 0.000 ✓	1465.512 > C.V ✓	1.665 0.197 ×	0.460 0.497 Exogenous
	L2, L3, L4, L5	75.736 0.000 ✓	627.006 > C.V ✓	1.985 0.576 ✓	0.240 0.624 Exogenous
	L3, L4, L5	73.023 0.000 ✓	794.334 > C.V ✓	1.601 0.449 ✓	0.458 0.499 Exogenous
	L2 & L5	75.478 0.000 ✓	1199.525 > C.V ✓	1.198 0.274 ✓	0.637 0.425 Exogenous
	L3 & L5	72.938 0.000 ✓	1036.351 > C.V ✓	1.508 0.220 ×	0.461 0.497 Exogenous
	L4 & L5	69.721 0.000 ✓	1209.319 > C.V ✓	0.939 0.333 ✓	1.301 0.254 Exogenous

		Outcome of the Post-estimation Test			
Variable	*Choice of instruments*	***Underidentification:***	***Weak-identification:***	***Overidentification:***	***Endogeneity:***
PRF	*PO, L2*	32.195 0.000 ✓	20.882 > C.V ✓	1.617 0.313 ✓	0.391 0.532 Exogenous
	PO, L3	26.484 0.000 ✓	12.470 < C.V ×	5.644 0.018 ×	0.053 0.818 Exogenous
	PO, L2, L3	27.811 0.000 ✓	10.775 < C.V ×	4.993 0.082 ×	0.813 0.367 Exogenous
	L2 & L3	36.571 0.000 ✓	20.215 < C.V ✓	0.030 0.862 ✓	0.117 0.732 Exogenous
	L2, L3, L4	7.245 0.065 ×	2.324 < C.V ×	1.601 0.449 ✓	0.317 0.573 Exogenous
	L2 & L4	7.413 0.025 ×	3.682 < C.V ×	1.661 0.198 ×	0.269 0.604 Exogenous
	L3 & L4	1.995 0.369 ×	1.039 < C.V ×	0.045 0.832 ✓	0.681 0.409 Exogenous
	L2, L3, L4, L5	3.552 0.470 ×	0.743 < C.V ×	1.057 0.788 ✓	5.698 0.017 Endogenous
	L3, L4, L5	1.219 0.748 ×	0.425 < C.V ×	0.648 0.723 ✓	3.612 0.057 Endogenous
	L2 & L5	1.733 0.420 ×	0.815 < C.V ×	0.066 0.797 ✓	3.328 0.068 Endogenous
	L3 & L5	0.856 0.652 ×	0.457 < C.V ×	0.301 0.583 ✓	1.609 0.205 Exogenous
	L4 & L5	0.059 0.971 ×	0.029 < C.V ×	0.029 0.864 ✓	1.951 0.162 Exogenous

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		Outcome of the Post-estimation Test			
Variable	*Choice of instruments*	***Underidentification:***	***Weak-identification:***	***Overidentification:***	***Endogeneity:***
NDTS	*ETR, L2*	77.402 0.000 ✓	23.018 > C.V ✓	4.674 0.031 ×	0.274 0.601 Exogenous
	ETR, L3	58.956 0.000 ✓	29.148 > C.V ✓	1.536 0.215 ×	0.576 0.448 Exogenous
	ETR, L2, L3	63.640 0.000 ✓	31.355 > C.V ✓	4.309 0.116 ×	0.548 0.459 Exogenous
	ITE, L2	80.436 0.000 ✓	23.493 > C.V ✓	0.111 0.740 ✓	0.330 0.566 Exogenous
	ITE, L3	75.880 0.000 ✓	17.069 < C.V ×	0.052 0.819 ✓	0.028 0.867 Exogenous
	ITE, L2, L3	81.670 0.000 ✓	33.901 > C.V ✓	1.171 0.557 ✓	0.454 0.500 Exogenous
	L2 & L3	79.137 0.000 ✓	48.407 > C.V ✓	0.099 0.753 ✓	0.189 0.664 Exogenous
	L2, L3, L4	68.756 0.000 ✓	204.607 > C.V ✓	1.599 0.450 ✓	0.934 0.334 Exogenous
	L2 & L4	66.692 0.000 ✓	336.254 > C.V ✓	0.448 0.503 ✓	0.932 0.334 Exogenous
	L3 & L4	59.152 0.000 ✓	36.150 > C.V ✓	0.008 0.929 ✓	0.815 0.367 Exogenous
	L2, L3, L4, L5	44.713 0.000 ✓	178.195 > C.V ✓	1.225 0.747 ✓	5.702 0.017 Endogenous
	L3, L4, L5	44.470 0.000 ✓	157.038 > C.V ✓	1.031 0.597 ✓	2.290 0.130 Exogenous
	L2 & L5	43.387 0.000 ✓	323.458 > C.V ✓	0.069 0.793 ✓	6.878 0.009 Endogenous
	L3 & L5	44.471 0.000 ✓	228.803 > C.V ✓	1.022 0.312 ✓	1.918 0.166 Exogenous
	L4 & L5	36.330 0.000 ✓	27.179 > C.V ✓	0.862 0.353 ✓	2.102 0.147 Exogenous

		Outcome of the Post-estimation Test			
Variable	*Choice of instruments*	***Underidentification:***	***Weak-identification:***	***Overidentification:***	***Endogeneity:***
RSK	*β, L2*	1.327 0.515 ×	0.403 < C.V ×	0.090 0.764 ✓	0.369 0.544 Exogenous
	β, L3	2.104 0.349 ×	5.226 < C.V ×	0.450 0.502 ✓	2.999 0.083 Endogenous
	β, L2, L3	3.689 0.297 ×	21.141 < C.V ×	0.907 0.635 ✓	2.741 0.098 Endogenous
	RP, L2	2.975 0.226 ×	1.551 < C.V ×	0.794 0.373 ✓	0.699 0.403 Exogenous
	RP, L3	4.379 0.112 ×	7.418 < C.V ×	1.129 0.288 ✓	6.559 0.010 Endogenous
	RP, L2, L3	7.527 0.057 ×	26.063 > C.V ✓	1.960 0.375 ✓	5.405 0.020 Endogenous
	L2 & L3	4.185 0.123 ×	31.972 > C.V ✓	0.868 0.352 ✓	4.530 0.033 Endogenous
	L2, L3, L4	10.187 0.007 ✓	133.196 > C.V ✓	0.574 0.751 ✓	6.750 0.009 Endogenous
	L2 & L4	1.923 0.382 ×	6.045 < C.V ×	0.000 0.996 ✓	4.186 0.041 Endogenous
	L3 & L4*	**13.998** **0.003 ✓**	**406.618** **> C.V ✓**	**0.063** **0.802 ✓**	**6.937** **0.002 Endogenous**
	L2, L3, L4, L5	9.524 0.049 ✓	9.483 < C.V ×	5.958 0.114 ×	0.216 0.642 Exogenous
	L3, L4, L5	9.462 0.024 ✓	8.937 < C.V ×	4.894 0.087 ×	0.126 0.722 Exogenous
	L2 & L5	4.407 0.110 ×	5.354 < C.V ×	6.100 0.014×	0.001 0.976 Exogenous
	L3 & L5	9.384 0.009 ✓	14.638 < C.V ×	4.873 0.027×	0.156 0.693 Exogenous
	L4 & L5	3.328 0.189 ×	5.151 < C.V ×	2.504 0.114 ×	1.785 0.182 Exogenous

Where, *L2*, *L3*, *L4*, and *L5* denotes 2-year lag, 3-year lag, 4-year lag and 5-year lag of the potential endogenous regressor, respectively; *β* denotes unlevered beta; *RP* denotes risk premium; *ETR* denotes effective tax rate; *ITE* denotes income tax expense; *PO* denotes the payout ratio; *R&D* denotes the research and development expenses; and *IT* denotes inventory turnover.

* The optimal instrument set, considering the selection criteria for appropriate instruments.

Table 3.4 Choice of Instruments and Test of Endogeneity – Zombie Model

		Outcome of the Post-estimation Test			
Variable	*Choice of instruments*	***Underidentification**: (Reject: relevant instruments; Fail to reject: irrelevant instruments)*	***Weak-identification:** (K-P statistic > 10% maximal IV size Critical Value: strong instruments; K-P statistic < 10% maximal IV size Critical Value: weak instruments)*	***Overidentification:** (Reject: invalid instruments; Fail to reject: valid instruments)*	***Endogeneity:** (Reject: endogenous variable; Fail to reject: exogenous variable)*
GRT	*L2 & L3*	16.392 0.000 ✓	39.529 > C.V ✓	0.086 0.769 ✓	0.007 0.932 Exogenous
	L2, L3, L4	10.864 0.013 ×	14.421 < C.V ×	4.722 0.094 ×	0.084 0.773 Exogenous
	L2 & L4	8.709 0.013 ×	19.765 < C.V ×	4.970 0.026 ×	0.052 0.820 Exogenous
	L3 & L4	11.075 0.004 ✓	22.046 > C.V ✓	0.837 0.428 ✓	0.266 0.606 Exogenous
	L2 & L5	9.121 0.011 ×	4.037 < C.V ×	0.793 0.373 ✓	0.992 0.319 Exogenous
	L3 & L5	9.794 0.008 ✓	5.244 < C.V ×	0.946 0.331 ✓	0.342 0.559 Exogenous

		Outcome of the Post-estimation Test			
Variable	*Choice of instruments*	***Underidentification:***	***Weak-identification:***	***Overidentification:***	***Endogeneity:***
SIZ	*IT, L2*	78.557 0.000 ✓	808.175 > C.V ✓	1.463 0.227 ×	0.059 0.808 Exogenous
	IT, L3	46.621 0.000 ✓	277.131 > C.V ✓	0.777 0.378 ✓	0.261 0.609 Exogenous
	IT, L2, L3	46.710 0.000 ✓	376.473 > C.V ✓	0.728 0.695 ✓	0.143 0.705 Exogenous
	L2 & L3	75.754 0.000 ✓	749.241 > C.V ✓	0.167 0.683 ✓	0.192 0.661 Exogenous
	L2, L3, L4	43.794 0.000 ✓	357.381 > C.V ✓	5.742 0.057 ×	1.364 0.243 Exogenous
	L2 & L4	45.783 0.000 ✓	503.122 > C.V ✓	4.794 0.029 ×	1.989 0.159 Exogenous
	L3 & L4	43.198 0.000 ✓	297.279 > C.V ✓	4.683 0.031 ×	2.023 0.155 Exogenous
	L2 & L5	23.216 0.000 ✓	205.869 > C.V ✓	0.527 0.468 ✓	0.015 0.902 Exogenous
	L3 & L5	21.346 0.000 ✓	107.899 > C.V ✓	0.866 0.352 ✓	0.107 0.744 Exogenous

		Outcome of the Post-estimation Test			
Variable	*Choice of instruments*	***Underidentification:***	***Weak-identification:***	***Overidentification:***	***Endogeneity:***
TNG	*R&D, L2*	78.763 0.000 ✓	821.426 > C.V ✓	0.312 0.576 ✓	3.800 0.051 Endogenous
	R&D, L3	50.161 0.000 ✓	782.899 > C.V ✓	1.556 0.212 ×	0.043 0.836 Exogenous
	R&D, L2, L3	49.139 0.000 ✓	857.914 > C.V ✓	1.650 0.438 ✓	0.036 0.850 Exogenous
	L2 & L3	55.493 0.000 ✓	1111.506 > C.V ✓	0.260 0.610 ✓	0.191 0.662 Exogenous
	L2, L3, L4	34.796 0.000 ✓	998.581 > C.V ✓	2.032 0.362 ✓	0.707 0.401 Exogenous
	L2 & L4	35.561 0.000 ✓	1660.969 > C.V ✓	0.570 0.450 ✓	0.750 0.387 Exogenous
	L3 & L4	33.637 0.000 ✓	854.535 > C.V ✓	2.094 0.148 ×	0.032 0.858 Exogenous
	L2 & L5	16.184 0.000 ✓	746.833 > C.V ✓	3.847 0.050 ×	2.247 0.134 Exogenous
	L3 & L5	15.730 0.000 ✓	496.057 > C.V ✓	5.751 0.017 ×	1.462 0.227 Exogenous

		Outcome of the Post-estimation Test			
Variable	*Choice of instruments*	***Underidentification:***	***Weak-identification:***	***Overidentification:***	***Endogeneity:***
PRF	*PO, L2*	8.689 0.013 ×	15.101 < C.V ×	0.181 0.671 ✓	2.263 0.133 Exogenous
	PO, L3	5.597 0.006 ✓	21.455 < C.V ✓	0.360 0.548 ✓	1.860 0.173 Exogenous
	PO, L2, L3	5.870 0.118 ×	11.769 < C.V ×	5.926 0.052 ×	0.796 0.372 Exogenous
	L2 & L3	4.928 0.005 ✓	22.496 < C.V ✓	0.640 0.424 ✓	1.913 0.167 Exogenous
	L2, L3, L4	3.756 0.289 ×	1.303 < C.V ×	2.436 0.296 ✓	0.019 0.892 Exogenous
	L2 & L4	3.650 0.161 ×	2.032 < C.V ×	0.387 0.534 ✓	0.206 0.650 Exogenous
	L3 & L4	1.692 0.429 ×	0.723 < C.V ×	3.078 0.079 ×	0.002 0.967 Exogenous
	L2 & L5	9.604 0.008 ✓	6.748 < C.V ×	1.820 0.177 ×	2.911 0.088 Endogenous
	L3 & L5	3.993 0.136 ×	1.732 < C.V ×	0.126 0.722 ✓	3.184 0.074 Endogenous

		Outcome of the Post-estimation Test			
Variable	*Choice of instruments*	***Underidentification:***	***Weak-identification:***	***Overidentification:***	***Endogeneity:***
NDTS	*ETR, L2*	35.926 0.000 ✓	172.201 > C.V ✓	0.953 0.329 ✓	1.005 0.316 Exogenous
	ETR, L3	35.273 0.000 ✓	237.792 > C.V ✓	0.458 0.499 ✓	0.498 0.480 Exogenous
	ETR, L2, L3	34.847 0.000 ✓	191.711 > C.V ✓	0.471 0.790 ✓	0.032 0.858 Exogenous
	ITE, L2	48.851 0.000 ✓	123.866 > C.V ✓	0.157 0.692 ✓	0.131 0.717 Exogenous
	ITE, L3	40.839 0.000 ✓	147.074 > C.V ✓	0.030 0.863 ✓	2.158 0.142 Exogenous
	ITE, L2, L3	41.649 0.000 ✓	151.943 > C.V ✓	1.827 0.401 ✓	0.013 0.910 Exogenous
	L2 & L3	39.852 0.000 ✓	211.932 > C.V ✓	0.655 0.418 ✓	0.492 0.483 Exogenous
	L2, L3, L4	23.523 0.000 ✓	109.169 > C.V ✓	2.855 0.240 ×	0.657 0.418 Exogenous
	L2 & L4	20.082 0.000 ✓	69.424 > C.V ✓	1.308 0.253 ✓	0.019 0.890 Exogenous
	L3 & L4	22.121 0.000 ✓	140.692 > C.V ✓	1.708 0.191 ×	1.126 0.289 Exogenous
	L2 & L5	9.266 0.009 ✓	100.398 > C.V ✓	1.524 0.217 ×	0.001 0.982 Exogenous
	L3 & L5	8.536 0.014 ×	78.000 > C.V ✓	3.396 0.065 ×	0.660 0.416 Exogenous

		Outcome of the Post-estimation Test			
Variable	*Choice of instruments*	***Underidentification:***	***Weak-identification:***	***Overidentification:***	***Endogeneity:***
RSK	*β, L2*	1.136 0.567 ×	1.049 < C.V ×	11.114 0.001 ×	2.554 0.110 Exogenous
	β, L3	7.624 0.022 ×	29.733 > C.V ✓	7.721 0.006 ×	1.648 0.199 Exogenous
	β, L2, L3	7.303 0.063 ×	5.449 < C.V ×	6.505 0.039 ×	1.269 0.260 Exogenous
	RP, L2	3.806 0.149 ×	3.704 < C.V ×	0.177 0.674 ✓	2.880 0.090 Exogenous
	RP, L3	5.973 0.051 ×	23.471 > C.V ✓	0.033 0.855 ✓	0.898 0.343 Exogenous
	RP, L2, L3	8.639 0.035 ×	6.542 < C.V ×	0.259 0.878 ✓	2.047 0.153 Exogenous
	L2 & L3	6.975 0.031 ×	8.679 < C.V ×	0.001 0.970 ✓	1.785 0.182 Exogenous
	L2, L3, L4	5.766 0.124 ×	45.876 > C.V ✓	0.718 0.698 ✓	2.694 0.101 Exogenous
	L2 & L4	5.118 0.007 ✓	25.953 < C.V ✓	0.499 0.480 ✓	1.241 0.291 Exogenous
	L3 & L4	5.656 0.005 ✓	71.725 > C.V ✓	0.308 0.579 ✓	1.080 0.318 Exogenous
	L2 & L5	2.577 0.276 ×	10.628 < C.V ×	0.293 0.589 ✓	0.686 0.408 Exogenous
	L3 & L5	3.900 0.142 ×	30.664 > C.V ✓	0.195 0.659 ✓	3.494 0.062 Endogenous

Where, *L2*, *L3*, *L4*, and *L5* denotes 2-year lag, 3-year lag, 4-year lag and 5-year lag of the potential endogenous regressor, respectively; *β* denotes unlevered beta; *RP* denotes risk premium; *ETR* denotes effective tax rate; *ITE* denotes income tax expense; *PO* denotes the payout ratio; *R&D* denotes the research and development expenses; and *IT* denotes inventory turnover.

3.6. Concluding Remarks

Having identified the analysis variables in Chapter 2, this chapter provides details on the data and the choice of estimation method used to conduct our empirical analysis. Based on the definition of zombie firms, we construct an indicator to capture both the insolvent nature and the surviving status of zombies. Furthermore, having reviewed different estimation techniques to identify the determinants of zombieness status and estimate their impact on the probability of becoming zombie, logistic regression analysis is deemed as the most appropriate estimation method when the focus is on estimating the probability of the occurrence of an event (becoming a zombie in this case).

Using a panel data on the constituents of the FTSE 250 Index over the period 2004-2012 and in order to control for the dynamic nature of the capital structure decisions, we estimate a linear dynamic panel model to investigate the determinants of capital structure. In an attempt to identify the appropriate estimation method and develop an empirical framework for our analysis, we provide a critical evaluation of the properties of different estimation methods available to estimate linear dynamic panel models. These include the pooled Ordinary Least Squares, Random Effect, Fixed Effect, First Difference/Instrumental Variable (FDIV), Difference Generalised Method of Moments (DIFGMM), and System GMM (SYSGMM). We show that the existence of unobserved individual effects in linear dynamic models causes a correlation between the lagged dependent variable and the error term, which violates the strict exogeneity assumption, and hence make the estimates of standard estimators inconsistent.

One approach to remove the individual effects is to within transform (demean) the model by subtracting the individual's mean value of the dependent variable and each regressor from the respective variable. However, while the within transformation removes the individual effects, it induces a correlation between the within-transformed lagged dependent regressor and the within-transformed error term, creating a bias (Nickell bias) in the estimate of the coefficient of the lagged dependent regressor, which cannot be removed by including additional observations.

The alternative solution is to first-difference (FD) the model and use instrumental variables to control for the endogeneity problem. While, Anderson and Hsiao's (1982) estimator (FDIV) leads to consistent estimates by using the first lag of the FD lagged dependent regressor, it may not be efficient, as it fails to use all of the available moment conditions. Using the GMM framework, Arellano and Bond (1991) develop a more efficient estimator (DIFGMM), which uses an increasing more number of lagged instruments as further lags become available. However, DIFGMM has been shown to suffer from poor precision, if instruments are weakly correlated with the endogenous variable. Arellano and Bover (1995) and Blundell and Bond (1998) develop a more advanced and superior estimator (SYSGMM), which overcomes the shortcomings of DIFGMM by imposing an additional restriction on the initial conditions process, under which, all of the available moment conditions can be exploited by a linear GMM estimator in a system of first-difference and levels equations. Accordingly, by using both the first differences of the level variables and the lagged levels of the first differenced variables as instruments, SYSGMM exploits all the available information in the sample, and hence leads to consistent and the most efficient estimates of the linear panel model. We next specify our two estimation models, the "base model" and the "zombie model", and their included regressors.

Finally, we attempt to identify the endogenous regressors and their respective appropriate instruments for each model by performing a series of statistical tests. Accordingly, while the proxy variable for business risk (*RSK*) is identified as the only endogenous variable in the base model, we find no endogenous variable among the regressors of the zombie model. Furthermore, the 3rd and the 4th lag of the *RSK* variable are identified as the appropriate set of instruments to use in the final estimation of the base model.

4. Results and Discussion

4.1. Introduction

Having established the framework for the empirical analysis of the Thesis in the previous chapter, in this chapter we provide the main findings and present a discussion of the estimation results. First, we identify 42 firm-year zombie observations in our sample using the identification criteria developed in Chapter 3. We then use logit regression analysis to identify the possible determinants of zombieness status and estimate their significance. Employing a range of econometric techniques, our results show that, highly indebted firms with low profitability and cash-generating ability are more likely to become zombies than highly profitable firms with greater cash-generating ability and lower financial leverage. In addition, we find evidence that, firms whose CEO (or equivalent) resigns during the fiscal year and do not make dividend payments are more likely to become zombies than the more viable and non-financially constrained firms without drastic changes in their top management and regular dividend payments.

The descriptive statistics and correlation matrices of the main analysis variables are provided to obtain a better understanding of the data and, allow a preliminary assessment of the impact of the recent GFC on firms' leverage ratios. In order to demonstrate the empirical procedure of choosing the final estimator and model specification, we start by presenting the estimation results of the static versions of the base and the zombie model specified before. However, as discussed in Section 2.3.2, in order to capture the dynamic nature of the capital structure decisions and, to control for the existence of transaction costs and other associated adjustment costs, we conduct our main analysis of capital structure using dynamic models.

A number of GMM-specific post-estimation tests are performed to ensure the estimation models are correctly specified, and then different information criteria measures are used to choose the optimum specifications for each model. Accordingly, the estimation results for the base model are presented first, where the firm-specific determinants of leverage and the impact of the recent GFC on firms' leverage ratios are discussed. The estimation results of the zombie model are presented next, with the

focus of discussion being on the coefficient on the zombie dummy variable and the empirical relevance of the firm-specific determinants of capital structure in a post-crisis context. Finally, we test the robustness of our findings by re-estimating both the base and the zombie model using an alternative measure of capital structure.

The rest of the chapter is structured as follows. Section 4.2 reports the estimation results and discusses the findings of our zombie analysis. In Section 4.3 we present the estimation results for both the base model and the zombie model of capital structure and test the robustness of our main empirical findings. Section 4.4 concludes the chapter.

4.2. Results (Zombies)

4.2.1. Identifying Zombies

As discussed in Section 3.3.1, the following Adjusted Interest Coverage Ratio (AICR) is used to measure the ability of firms to pay the interest expenses on their borrowing:

$$AICR_{it} = \frac{Operating\ Income_{it} + Interest\ Income_{it}}{Total\ Interest\ Expense_{it}}$$

Recalling the definition of zombies, a firm is identified as zombie if it has $AICR < 1$ (i.e., is technically insolvent as it is unable to generate enough revenues to cover their financial obligations) *and* is still operating as a listed, active, non-acquired and non-merged entity for at least one year after meeting the technical insolvency criterion (i.e., is surviving)[143]. Using these criteria, a total of 42 firm-year zombie observations are identified in our sample during the period 2008-2012 representing 29 firms from 10 industries, based on the Global Industry Classification Standard (GICS)[144].

After the initial identification of zombies, an extensive search task was conducted. This involved a thorough examination of the annual reports and an internet search on each of the zombie candidates using the main financial news media and platforms including Financial Times, Bloomberg and the Business section of BBC News website. The search period covered 1 year before and 1 year after the actual period for which firms had met the zombie criteria. This rather time-consuming task was deemed necessary to ensure that the identified zombie candidates did indeed suffer from severe financial distress over an extended period of time. It was also necessary to avoid misidentifying firms that had merely experienced a temporary negative shock to their operations and thus faced difficulties with meeting their financial obligations.

Checking through individual annual reports, articles and announcements in the financial news confirmed the sever insolvency issues experienced by all the identified zombies. There has been ample evidence in the financial news regarding the renegotiations of the zombies with their creditors, mostly in the form of granting

[143] Since interest coverage ratio is only relevant to firms with positive financial obligations, firms with negative net interest expense (i.e., net interest income) are excluded from the AICR calculation.
[144] The names of zombies, the industry they belong to, and the year for which they are detected as zombies are presented in Table 7.2 in the Appendix.

waivers to breach of pre-agreed loan covenants, switching to an interest-only loan, offering payment holidays, and loan restructurings such as lowering the interest rate and extending the maturity.

Although there have been some other firms, mostly in the peer group of the identified zombies, which had indicated the same distress signs and experienced the similar financial difficulties, they are not detected as zombies by our measure because of their marginally $AICR > 1$. While we are aware that they may share many of the "zombieistic" characteristics and their inclusion increases the relevant size of our zombie group, we continue with our strict threshold to make sure that only the surviving technically insolvent firms are identified as zombies. This helps to enhance the reliability of our results.

4.2.2. Determinants of the Zombieness Status

The estimation results of logit models can be presented in different formats: logit coefficients and odds ratios. The default format in Stata is logit coefficients, which is the log of odds ratios. Interpretation of results based on the absolute values of log odds ratios is quite inconvenient. Accordingly, logit coefficients are commonly used to indicate only the direction and the significance of the impact of explanatory variables on the probability of the outcome of interest occurring, and then marginal effects are estimated to quantify the magnitude of such impacts.

4.2.2.1. Univariate Logit Analysis

As discussed in Section 2.3.5.4, due to the limited empirical literature on zombies, in order to estimate a multivariate model for the probability of becoming a zombie, we must first identify the individually significant variables from the pool of commonly used determinants of the probability of insolvency as suggested by the corporate insolvency literature. A univariate logit regression analysis can be conducted to evaluate the explanatory power of individual variables and identify individually significant determinants of the zombieness status. Accordingly, based on the discussion in Section 2.3.5.4, we will estimate the following univariate model for each of the variables presented in Table 2.2, Table 2.3, and Table 2.4:

$$Zombie_{it} = \alpha_0 + \beta x_{it} + \varepsilon_{it}. \quad (4.1)$$

Where, $Zombie_{\mathrm{it}}$ denotes the log of odds ratio of becoming a zombie (i.e., $Zombie_{it} = \ln\left(\frac{\Pr(y_{it}=1)}{\Pr(y_{it}=0)}\right)$) with y_{it} takes value of 1 if a firm is identified as zombie (i.e., $AICR_{it} < 1$) and 0 otherwise (i.e., $AICR_{it} \geq 1$); x_{it} denotes the potential explanatory variable of interest; ε_{it} is the idiosyncratic error term; and α_0 and β are the unknown parameter to be estimated.

In order to identify the significant univariate determinants of the zombieness that should be included in the final model, all individual variables are judged against the significance level of their coefficients. This is essentially equivalent to the Wald test

in multivariate analysis[145]. That is, if a variable indicates a significance level of less than the 10% threshold, they are deemed as a significant determinant of the probability of becoming a zombie.

Table 4.1 reports the estimation results of the univariate logit analysis of the explanatory variables with statistically significant coefficient estimates. Where, *Coef.* denotes the β in Eq. (4.1) and indicates the change in the estimated logit (i.e., log of odds ratio of becoming a zombie) for a unit change in the value of the given regressor; the *Robust Std. Err*. are the Huber-White heteroskedasticity-robust standard errors associated with the coefficients, and the *z* and *Prob* > | *z* |, respectively, are the z-statistics and the 2-tailed p-values that are used for testing the null hypothesis that the coefficient is zero.

As can be seen from Table 4.1, the estimation results of the univariate logit models identify 11 variables with a statistically significant impact on the probability of becoming a zombie. The directions and signs of the coefficients on all of the significant variables seem to be consistent with the findings of insolvency prediction models and are intuitively understandable. For example, the positive coefficient on *TDTA* suggests that, financial leverage is an important determinant of zombieness status of firms, such that, *ceteris paribus*, the greater the debt burden, the greater is the likelihood of firm to fail on its financial obligations and hence becoming technically insolvent. The negative coefficients on *EBITS*, *ROA* and *ROE*, suggest that more profitable firms are less likely to face difficulty with meeting their financial obligations and are therefore less likely to become zombie. Similarly, the negative signs of *NSTA* and *CFOTA* are also in line with the expectation that, the higher the ability of the firm to generate cash flow from its operation and the higher the firms' activity level, the less likely is the firm to struggle to generate enough revenues to cover its interest expenses and become technically insolvent.

Turning to the non-financial variables, although large firms are generally less likely to face difficulties in meeting their financial obligations than small firms, the negative coefficient on *SIZE* suggests that, among moderately large firms (constituents of the FTSE 250 Index), the relatively smaller firms are more likely to face financial

[145] The *Wald-statistic* is used to test the null hypothesis that all the coefficients except for the constant are jointly zero, against the alternative that they are not.

difficulties and become zombie. As discussed in Section 2.3.5.4, the dummy variable to control for the CEO (or equivalent) resignation during the year, *CEOCHNG*, is used as a proxy measure to capture the top management's assessments of the firm's viability which are not necessarily reflected in conventional financial variables. Accordingly, the positive coefficient on *CEOCHNG* suggests that, firms whose CEO (or equivalent) resigns during the fiscal year are more likely to become zombies than more viable firms not suffering from such drastic changes in their top management. Furthermore, the positive coefficient on the dummy variable to control for dividend payment behaviour of firms, *DVDND*, indicates that, firms that do not pay dividends, or more specifically, cannot afford to pay dividends, are more likely to become zombie than their non-financially constrained counterparts that can make regular dividend payments. Similarly, the reported positive coefficient on *RTIL*, suggests that firms that belong to the retail sector are more likely to become zombies than firms operating in any other sector. This finding is not surprising given the significant exposure of the retail sector to consumer discretionary spending and the expected detrimental impact of the economic recessions and GDP contractions on consumer discretionary spending. Consistent with this argument, the reports published by R3 indicate that Retail sector show the highest number of firms struggling to meet their financial obligations[146].

[146] In fact, in their July 2012 report, the retail sector was identified as the most troubled sector overall, with around 31, 000 firms (18%) claiming that they would default on their debts in the event of a rise in interest rates, 30, 000 firms (17%) struggling to pay their debts when they fall due, and 29, 000 firms (16%) admitting that they have had to renegotiate their payments terms with creditors.

Table 4.1 Univariate Regression Results

Zombie	*Coef.*	*Robust Std. Err.*	*z*	*P* > | *z* |
TDTA	0.021	0.010	2.050	0.041
EBITS	-1.016	0.368	-2.760	0.006
ROA	-0.265	0.115	-2.290	0.022
ROE	-0.001	0.001	-1.720	0.085
NSTA	-0.012	0.007	-1.850	0.064
CFOTA	-0.086	0.035	-2.450	0.014
SIZE	-0.586	0.244	-2.400	0.017
CEOCHNG	0.955	0.368	2.590	0.010
DVDND	2.111	0.375	5.640	0.000
RTIL	1.165	0.566	2.060	0.040
GDP	-0.117	0.069	-1.690	0.091
Obs.				513*
No. of groups				164
Obs. per group:			*min*	1
			avg	3.1
			max	5

Where, the analysis period is 2008-2012; $Zombie = \ln(\frac{\Pr(y_{it}=1)}{\Pr(y_{it}=0)})$ denotes the log of odds ratio of becoming a zombie (i.e., $AICR = \frac{Operating\ Income + Interest\ Income}{Total\ Interest\ Expense} < 1$); $TDTA = \frac{Total\ Debt}{Total\ Assets}$ denotes leverage ratio; $EBITS = \frac{Earnings\ Before\ Inerest\ \&\ Taxes}{Sales}$, $ROA = \frac{Net\ Profit\ (Loss)}{Sales}$, and $ROE = \frac{Net\ Profit\ (Loss)}{Net\ Worth}$ denote measures of profitability; $NSTA = \frac{Net\ Sales}{Total\ Assets}$ denotes activity ratio; $CFOTA = \frac{Operating\ Cash\ Flow}{Total\ Assets}$ denotes cash-generating ability; $SIZE = \ln(Total\ Assets)$ denotes firm size; *DVDND* is a dummy variable that takes value of 1 if firm does not make dividend payment during the year and 0 otherwise; *RTIL* is a dummy variable that takes value of as 1 if firm belongs to the Retail sector and 0 otherwise; *CEOCHNG* is a dummy variable that takes value of 1 if CEO (or equivalent resigned) during the year and 0 otherwise; *GDP* denotes the annual growth in the Real Gross Domestic Product (GDP); and *Robust Std. Err*. denotes the Huber-White heteroskedasticity-robust standard errors; and

**The default listwise deletion method used by Stata implies that if there is a missing value for any variable in the logistic regression, the entire case will be excluded from the analysis. Accordingly, due to missing values, the total number of observations that are used in the univariate of CEOCHNG and DVDND are 427 and 511, respectively.*

Finally, while the insolvency literature suggests that macroeconomic variables tend to have a significant impact on aggregate insolvency, the results of our univariate analysis do not suggest a strong support for such effects at the firm-level during our analysis period. In fact, as can be seen from Table 4.1, the only significant macroeconomic variable is GDP growth. This finding is also consistent with the smaller-than-expected increase in aggregate insolvency level after the 2008/9 recession in the UK.

Having discussed the direction of the impact of individually significant factors in determining the probability of becoming a zombie, one must note that statistically significant variables based on a univariate model may not necessarily enter in the final multivariate model. That is, the presence of other significant variables in the multivariate model may prevent a particular variable from displaying incremental information content, and thus it may drop out of the final model. Furthermore, high correlations amongst explanatory variables (i.e., multicollinearity) could also lead to distortions in model estimates (Hair *et al.*, 2010). For example, the existence of a high degree of multicollinearity among independent variables could lead to large standard errors, which in turn distort *p*-values (Gujarati and Porter, 2010). Accordingly, the estimation results of models with highly correlated independent variables are likely to be unstable and imprecise, as *p*-values may change significantly depending on removing or retaining other highly correlated variables[147].

Having performed the univariate analysis and detected individually significant determinants of zombieness, we proceed with identifying the joint significant determinants in a multivariate context.

[147] Although, Stata automatically drops the problematic variables if multicollinearity is detected, for illustration purpose, the Pearson correlation matrix of all the individually significant variables as suggested by the univariate analysis and the test of multicollinearity among the respective variables are presented in Table 7.3 and 7.4 in the Appendix. There is no evidence of troublesome pairwise correlation or multicollinearity among the individually significantly determinants of zombieness.

4.2.2.2. Stepwise Multivariate Logit Analysis

In order to identify the determinants of zombieness status in a multivariate model and obtain the optimum combination of individually significant explanatory variables, we employ the stepwise logit model technique. In stepwise logit estimations, the inclusion or exclusion of variables are based on likelihood ratio tests using a pre-specified minimum significance level threshold (StataCorp, 2015). The two alternative procedures to perform the stepwise estimation are the backward-stepwise and the forward-stepwise methods. The standard method for stepwise estimation in Stata is the backward-stepwise, and given that we have already the full list of individually significant variables, backward-stepwise is a more appropriate estimation technique. Recalling the results reported in Table 4.1, the following model is used to perform the backward-stepwise estimations:

$$Zombie_{it} = \alpha_0 + \beta_1 TDTA_{it} + \beta_2 EBITS_{it} + \beta_3 ROA_{it} + \beta_4 ROE_{it} + \beta_5 NSTA_{it} + \beta_6 CFOTA_{it} + \beta_7 SIZE_{it} + \beta_8 CEOCHNG_{it} + \beta_9 DVDND_{it} + \beta_{10} RTIL_i + \beta_{11} GDP_t + \varepsilon_{it}. \quad (4.2)$$

In order to conduct the backward-stepwise estimation, two reverse procedures are performed simultaneously: backward selection and forward selection[148]. Specifying the appropriate significance levels for removal (addition) from (to) the model, terms with p-values greater or equal to the specified threshold for removal, are removed from the model and terms with p-values less than the specified significance level for addition, are added to the model (Hosmer *et al.*, 2013). The backward-stepwise estimation starts with fitting the full model containing all the variables; if the least-significant included term is "insignificant", it is removed and the model is re-estimated, and if the most-significant excluded term is "significant", it is added back and the model is re-estimated, and these backward and forward selections are repeated until neither is possible (StataCorp, 2015). In order to improve reliability of the results, we use a 10% significance level threshold for the backward selection of variables and a 0.1% significance level threshold for the forward selection of variables.

[148] While the stepwise estimations are implemented in Stata via the **stepwise** command, the **pr()** and **pe()** options are used to conduct and specify the threshold significance levels for the backward-selection and forward-selection procedures, respectively.

However, the stepwise estimation techniques are only available for pooled models and cannot be applied to panel models. Accordingly, we have no alternative but to perform the stepwise estimation using a pooled logit model (via the **`logit`** option after the **`stepwise`** command) to identify the optimum set of variables in a multivariate model, and use the respective variables to estimate a panel model and its corresponding coefficients, via the **`xtlogit`** command.

Table 4.2 reports the backward-stepwise estimation results of the logit model using the full set of individually significant explanatory variables, as suggested by the univariate logit analysis. We also report a number of post-estimation tests and statistics to evaluate the estimated models' overall fit. Where, *Log Likelihood* denotes the log likelihood of the fitted model. *LR Chi2(k-1)* denotes the likelihood ratio chi-square statistic that with *Prob > Chi2*, which is used as the p-value, test the null hypothesis that all coefficients except the constant are jointly equal to zero and is computed for (*k-1*) degrees of freedom with *k* being the number of parameters. The *pseudo-*R^2 denotes the McFadden's (1974) likelihood-ratio index, which is computed as $(1 - \frac{L_1}{L_0})$ where L_1 and L_0 are the log likelihood value for the fitted model and the null model excluding all explanatory variables, respectively. Although there are no equivalent measures to the conventional R^2 available for binary models indicating the proportion of variation in *y* explained by *x*, the *pseudo-*R^2 is similar to R^2 as it is also on a [0, 1] scale, with 0 indicating that the explanatory variables failed to increase likelihood an 1 indicating the model perfectly predicts each observation[149]. Finally, as suggested by Windmeijer (1995a), $corr(Zombie_{it}, \widehat{Zombie}_{it})^2$, which denotes the squared correlation coefficient between actual and fitted values of the dependent variable, is also included as an alternative measure of the overall fit of the model.

Accordingly, as presented in Table 4.2, the large *LR Chi2* and the associated small *p-value* suggest a strong rejection of the null that the coefficients on all the included explanatory variables are jointly zero[150]. That is, the retained explanatory variables,

[149] It should be noted that, in logit model, unlike linear regressions, increasing the number of explanatory variables does not always result in prefect prediction. In fact, perfect prediction may inadvertently occur because of the perfect correlation between one or more explanatory variable and the binary dependent variable. Perfect correlation is more likely to happen when there is a high proportion of 0s or 1s in the sample and model includes dummy independent variables.

[150] The *log likelihood* value has no meaning in and of itself, however, it is used to obtain measures for goodness-of-fit of the model.

representing different firm characteristics, seem to exert a significant influence on the probability of becoming a zombie. With regards to the goodness-of-fit of the model, the high values 0.82 of 0.81 for *pseudo-R^2* and the squared correlation coefficient between actual and fitted values of the dependent variable respectively, suggest that the fitted model is doing a very good job in predicting the probability of becoming a zombie. It should be noted that, while $corr(y_{it}, \hat{y}_{it})^2$ and $(1 - \frac{L_1}{L_0})$ are equivalent in the case of linear regression models with continuous dependent variables, the two measures do not have the same values for models with qualitative dependent variables. However, they seem to be very close here, which suggests that they are in fact measuring the goodness-of-fit of the model fairly accurately.

Table 4.2 Stepwise Regression Results

Zombie	*Coef.*	*Std. Err.*	*z*	*P* > | *z* |
TDTA	0.097	0.036	2.680	0.007
EBITS	-1.244	0.276	-4.510	0.000
CFOTA	-0.212	0.099	-2.140	0.032
DVDND	3.275	1.134	2.890	0.004
CEOCHNG	2.293	1.147	2.000	0.046
_cons	-0.487	0.841	-0.580	0.563
Obs.				425
Log Likelihood				-20.357
LR Chi2(5)				196.24
Prob > Chi2				0.000
Pseudo-R^2				0.828
$Corr(Zombie_{it}, \widehat{Zombie}_{it})^2$				0.813

Where, the analysis period is 2008-2012; $Zombie = \ln(\frac{\Pr(y_{it}=1)}{\Pr(y_{it}=0)})$ denotes the log of odds ratio of becoming a zombie (i.e., $AICR = \frac{Operating\ Income + Interest\ Income}{Total\ Interest\ Expense} < 1$); $TDTA = \frac{Total\ Debt}{Total\ Assets}$ denotes leverage ratio; $EBITS = \frac{Earnings\ Before\ Inerest\ \&\ Taxes}{Sales}$ denotes profitability; $CFOTA = \frac{Operating\ Cash\ Flow}{Total\ Assets}$ denotes cash-generating ability; *DVDND* is a dummy variable that takes value of 1 if firm does not make dividend payment during the year and 0 otherwise; *CEOCHNG* is a dummy variable that takes value of 1 if CEO (or equivalent) resigned during the year and 0 otherwise; and *Std. Err.* denotes standard errors.

Turning to the reported coefficient estimates on the firm characteristics determining the probability of becoming a zombie, the results suggests that variables measuring size (*SIZE*), activity ratios (*NSTA*), two of the profitability measure (*ROA* and *ROE*), and the dummy variable for the Retail sector (*RTIL*) have not entered into the

multivariate logit model, as they did not meet the specified significance levels thresholds required for retaining in the model[151]. On the other hand, the reported coefficients on all the retained variables are significant at the 5% significance level or better. Furthermore, the directions of the impacts on the retained variables are as expected. That is, an increase in profitability and cash-generating ability of the firm reduces the probability of becoming a zombie, while an increase in the level of indebtedness leads to a higher probability of a firm becoming a zombie. Likewise, firms that do not make dividend payments or have experienced a resignation of the CEO (or equivalent) are more likely to become zombie than those who pay dividends or haven't experienced such drastic changes in their top management.

Having identified the statistically significant determinants of becoming zombie that can be used in a multivariate model, we proceed with the panel estimation of the probability of becoming a zombie.

[151] Given that there has been no direct evidence of high pairwise correlation or multicollinearity among the included variables in the stepwise estimation, the excluded variables may have dropped due to their insignificant incremental information content, due to the presence of other significant variables in the model. That is, they may measure the same effect as some other variables and if these other variables are better measures of that particular effect, when included in the same model, their less significant imitators could become redundant and hence drop out from the model.

4.2.2.3. Panel Model

The stepwise estimation of the pooled logit model has led to identification of statistically significant determinants of zombieness status that can be used in a multivariate model. Thus, in order to estimate their respective impact on the probability of becoming a zombie, while controlling for the panel nature of the data, we must estimate a panel logit model. Accordingly, given the results from the stepwise analysis, our final estimation model for the probability of becoming a zombie is:

$$Zombie_{it} = \alpha_0 + \beta_1 TDTA_{it} + \beta_2 EBITS_{it} + \beta_3 CFOA_{it} + \beta_4 DVDND_{it} + \beta_6 CEOCHNG_{it} + \varepsilon_{it}. \quad (4.3)$$

However, before proceeding with the estimation results, we must first test if our model is correctly specified.

4.2.2.3.1. Model Specification Test

Although the included variables in Eq. (4.3) are obtained through stepwise significance tests of the potential determinants of zombieness, we can still test for the functional form of the model. Recalling the underlying functional form of standard logit models presented in Eq. (3.11) (i.e., $P_{it} = \Pr(y_{it} = 1|X_{it}) = \frac{1}{1+e^{-Z_{it}}} = \frac{e^{Z_{it}}}{1+e^{Z_{it}}}$), Stukel (1988) proposes an alternative model, called the generalized *h*-family logit model, to the standard logit model. The alternative model has the following functional form:

$$\Lambda_\alpha(X'_{it}\beta) = \frac{e^{h_\alpha(X'_{it}\beta)}}{1+e^{h_\alpha(X'_{it}\beta)}}. \quad (4.4)$$

Where, $h_\alpha(X'_{it}\beta)$ is a strictly increasing nonlinear function of $X'_{it}\beta$, indexed by the shape parameters α_1 and α_2 that govern the heaviness of the tails and the symmetry of the $\Lambda(.)$ function, respectively. Stukel (1988) proposes using a Lagrange Multiplier (LM) test to evaluate if the functional form presented in Eq. (4.4) is better than the functional form of the standard logit model presented in Eq. (3.11).

The LM test has the advantage that it requires only the estimation of the null hypothesis model (i.e., Eq. 3.11), rather than the estimation of the alternative hypothesis model in Eq. (4.4). Accordingly, we can implement the LM test by including a generated regressor that is function of $X'_{it}\beta$ as an additional regressor in the model in Eq. (3.11), and then test for the significance of the augmented regressor. Following Cameron and Trivedi (2009), in order to test for departure from the logit model in the direction of an asymmetric *h*-family, we include $(X'_{it}\hat{\beta})^2$, as an additional regressor to the null hypothesis model and test if the model fit is significantly improved. Thus, the re-specified estimation model can be presented as follows:

$$Zombie_{it} = \alpha_0 + \beta_1 TDTA_{it} + \beta_2 EBITS_{it} + \beta_3 CFOA_{it} + \beta_4 DVDND_{it} + \beta_6 CEOCHNG_{it} + \beta_7 (X'_{it}\hat{\beta})^2 + \varepsilon_{it}. \quad (4.5)$$

The estimation results from the re-specified logit model with the additional regressor are presented in Table 4.3. The high *p-value* of the coefficient estimate on $(X'_{it}\hat{\beta})^2$ suggests that the additional regressor is not statistically significant. However, in order to formally test whether the added variable significantly improves the fit of the model, we perform a Wald test on $(X'_{it}\hat{\beta})^2$. The result of the Wald test for the added regressor is presented in the last two rows of Table 4.3. Accordingly, given the small *Wald-statistic* and the high *p-value* of the Wald test of zero coefficient of the added regressor, we fail to reject the null hypothesis of correct model specification, suggesting that the underlying functional form of our estimation model seems to be correctly specified. Having confirmed the specification for our estimation model, we proceed with discussing the regression results.

Table 4.3 Test of Model Specification – Re-specified Functional Form

Zombie	*Coef.*	*Robust Std. Err.*	*z*	*P > | z |*
TDTA	0.096	0.039	2.480	0.013
EBITS	-1.203	0.244	-4.930	0.000
CFOTA	-0.202	0.112	-1.800	0.072
DVDND	3.158	1.245	2.540	0.011
CEOCHNG	2.286	1.017	2.250	0.025
$(X'_{it}\hat{\beta})^2$	-0.007	0.061	-0.110	0.913
_cons	-0.496	1.013	-0.490	0.624
Obs.				425
No. of groups				133
Obs. per group:			*min*	1
			avg	3.2
			max	5
Wald Chi2(5)				34.35
Prob > Chi2				0.000
$Corr(Zombie_{it}, \widehat{Zombie}_{it})^2$				0.812
Test: $(X'_{it}\hat{\beta})^2 = 0$			*Chi2(1)*	0.01
			Prob > Chi2	0.914

Where, the analysis period is 2008-2012; $Zombie = \ln(\frac{\Pr(y_{it}=1)}{\Pr(y_{it}=0)})$ denotes the log of odds ratio of becoming a zombie (i.e., $AICR = \frac{Operating\ Income + Interest\ Income}{Total\ Interest\ Expense} < 1$); $TDTA = \frac{Total\ Debt}{Total\ Assets}$ denotes leverage ratio; $EBITS = \frac{Earnings\ Before\ Inerest\ \&\ Taxes}{Sales}$ denotes profitability; $CFOTA = \frac{Operating\ Cash\ Flow}{Total\ Assets}$ denotes cash-generating ability; *DVDND* is a dummy variable that takes value of 1 if firm does not make dividend payment during the year and 0 otherwise; *CEOCHNG* is a dummy variable that takes value of 1 if CEO (or equivalent) resigned during the year and 0 otherwise; $(X'_{it}\hat{\beta})^2$ denotes the additional generated regressor; and *Robust Std. Err*. denotes the Huber-White heteroskedasticity-robust standard errors.

4.2.2.3.2. Regression Results

Table 4.4 reports the coefficient estimates and the standard test-statistics for the panel estimation of the logit model presented by Eq. (4.3). As can be seen from the table, the tests on coefficients of the explanatory variables in a panel model are performed by the Wald test, testing the null hypothesis is that the coefficients on all the included regressors except for the constant are jointly equal to zero. Accordingly, the large *Wald statistic* and the associated low *p-value* suggest a strong rejection of the null hypothesis, meaning that the included regressors representing different firm characteristics do in fact exert a significant impact on the probability of becoming a zombie. With regards to the goodness-of-fit of the model, the high value of 0.812 for $corr(Zombie_{it}, \widehat{Zombie}_{it})^2$ indicates that the model is doing a very good job in predicting the probability of becoming a zombie.

Turning to the reported coefficient estimates on the firm characteristics determining the probability of becoming a zombie, the positive and significant coefficient on leverage measure suggests that, firms with higher leverage ratios are more likely to become zombies. This finding is consistent with the expectation that, *ceteris paribus*, an increase in the indebtedness level increases the likelihood of firms to fail on their financial obligations, and become technically insolvent.

Furthermore, the negative and highly significant coefficient on profitability suggests that firms with lower profitability are more likely to become zombies. That is, given that *EBITS* measures the profit-generating ability of the firm from its main activities and hence its ability to service its debt and make payments on its financial obligations, firms with lower profitability are more likely to fail on their financial obligations and become technically insolvent than more profitable firms, holding everything else constant.

Similarly, the ability to generate cash from operation is also found to have a negative impact on the probability of becoming a zombie. That is, *ceteris paribus*, firms with a greater ability to generate operating cash flow would have greater resources at their disposal and therefore would be less likely to default on the payments of their financial obligations.

The dummy variable to control for CEO (or equivalent) resignation during the year is used as a proxy to capture the top management's assessments of the firm's viability. Accordingly, the positive coefficient on *CEOCHNG* suggests that, firms whose CEO (or equivalent) resigns during the fiscal year are more likely to become zombies than the more viable firms without such drastic changes in their top management.

Finally, the positive and significant coefficient on the dummy variable to control for dividend payment behaviour of firms indicates that, firms that do not pay dividends, or more specifically, cannot afford to pay dividends, are more likely to become zombie than their non-financially constrained counterpart that can make regular dividend payments.

Summarizing the results from Table 4.4, highly indebted firms with low profitability and cash-generating ability are more likely to become zombies than highly profitable firms with greater cash-generating ability and lower financial leverage. Furthermore, firms whose CEO (or equivalent) resigns during the fiscal year and do not make dividend payments are more likely to become zombies than the more viable and non-financially constrained firms without drastic changes in their top management and regular dividend payments.

Table 4.4 Panel Regression Results

Zombie	*Coef.*	*Robust Std. Err.*	*z*	*P* > | *z* |
TDTA	0.097	0.038	2.580	0.010
EBITS	-1.215	0.272	-4.460	0.000
CFOTA	-0.205	0.105	-1.950	0.051
DVDND	3.190	1.154	2.760	0.006
CEOCHNG	2.317	0.808	2.870	0.004
_cons	-0.519	0.912	-0.570	0.569
Obs.				425
No. of groups				133
Obs. per group:			*min*	1
			avg	3.2
			max	5
Wald Chi2(5)				34.27
Prob > Chi2				0.000
$Corr(Zombie_{it}, \widehat{Zombie}_{it})^2$				0.812

Where, the analysis period is 2008-2012; $Zombie = \ln(\frac{\Pr(y_{it}=1)}{\Pr(y_{it}=0)})$ denotes the log of odds ratio of becoming a zombie (i.e., $AICR = \frac{Operating\ Income + Interest\ Income}{Total\ Interest\ Expense} < 1$); $TDTA = \frac{Total\ Debt}{Total\ Assets}$ denotes leverage ratio; $EBITS = \frac{Earnings\ Before\ Inerest\ \&\ Taxes}{Sales}$ denotes profitability; $CFOTA = \frac{Operating\ Cash\ Flow}{Total\ Assets}$ denotes cash-generating ability; *DVDND* is a dummy variable that takes value of 1 if firm does not make dividend payment during the year and 0 otherwise; *CEOCHNG* is a dummy variable that takes value of 1 if CEO (or equivalent) resigned during the year and 0 otherwise; and *Robust Std. Err*. denotes the Huber-White heteroskedasticity-robust standard errors.

4.2.2.4. Marginal Effects

So far we have only investigated whether the included explanatory variables have a significant impact on the probability of becoming a zombie and whether the impact is positive or negative, and have not discussed the magnitude of this impact, also known as the Marginal Effects (MEs). While MEs and coefficient estimates are the same in traditional linear regressions with continuous dependent variable, the two measures differ significantly in the case of binary regression models. As noted by Cameron and Trivedi (2010: p. 333):

> A marginal effect (ME), or partial effect, most often measures the effect on the conditional mean of *y* of a change in one of the regressors, say, x_j. In the linear regression model, the ME equals the relevant slope coefficient, greatly simplifying analysis. For nonlinear models, this is no longer the case, leading to remarkably many different methods for calculating MEs.

That is, given that the dependent variable in logit models is the log of odds ratio of the event of interest happening (i.e.$\ln\left(\frac{\Pr(y_{it}=1)}{\Pr(y_{it}=0)}\right)$), the reported coefficients in Table 4.4 indicate the change in *the log of odds ratio of becoming a zombie* for a unit change in the value of the respective regressor (holding other regressors constant). Thus, they ought to be different than the MEs, which indicate by how much the *probability of becoming a zombie* (i.e., $\Pr(y_{it}=1)$) changes as a given explanatory variable changes by one unit[152].

Logistic regression enables computation of two main types of MEs; Conditional Marginal Effects (CMEs) and Average Marginal Effects (AMEs). As the name suggests, CMEs measure the marginal effect of each explanatory variable *conditional* on holding all other variables at some specific values such as the mean or any other justifiable values. Accordingly, with CMEs, particular values are specified for each of the independent variables in the model except the variable of interest, and then the

[152] The marginal effect for the dummy variables (i.e., *DVDND* and *CEOCHNG*) indicates the discrete change in $\Pr(y_{it}=1)$ as the dummy variable changes from 0 to 1, controlling for the other variables in the model.

probability of becoming a zombie is calculated for a firm that has the pre-specified values for the respective explanatory variables.

The most common type of CMEs are the Marginal Effects at the Means (MEMs), which, fix the values of the variable of interest, and then use the means for the other variables to compute the predicted probability (Williams, 2012). However, despite the misleading name, the use of mean values in calculation of MEMs does not reflect the characteristics of an "average" or "typical" firm. In fact, MEMs can never present the average firm if there are dummy explanatory variable in the model, as in our case. This is because, unless all the observations values are 1s or 0s, which will lead to perfect collinearity and hence the exclusion of the variable from the estimation model, the mean value for the dummy variable is meaningless[153]. Furthermore, with using only the means or any other specified set of values, the MEMs in particular and CMEs in general do not utilise the information in the data to the full extent.

The second type of MEs are AMEs, which, instead of using the means to compute the predicted probabilities, use the actual observed values for the variables whose values are not otherwise fixed. Essentially, having fixed the values for the variable of interest and using the observed values for all other variables, the AME computes a predicted probability for each firm with the fixed and observed values of variables, and then average the predicted values.

Accordingly, while the CMEs, using mean values, indicate the marginal effects at the average values, the AMEs, using all available observations, indicate the average of marginal effects. However, the marginal effects at the means and the average marginal effects are different quantities and can produce different estimates (Wiggins, 2013) [154].

Given that, AMEs use all the available data without imposing any restrictions on the values of explanatory variables, it would lead to more efficient estimates than the CMEs, which only use means or other specific values (Bartus, 2005; Cameron and

[153] For instance, a mean of 0.15 for *CEOCHNG* would suggest that the firm has experienced a 15% resignation in the CEO (or equivalent), which does not make any sense.

[154] Stata computes the Marginal Effects (MEs) at chosen covariate values via the **margins, dydx** command. However, alternative measures of MEs can be computed by specifying different options for covariate values: **asobserved** (estimate MEs at the observed values of covariates), **atmeans** (estimate MEs at the means of covariates), **at(.)** (estimate MEs at other specified values of covariates).

Trivedi, 2010). Accordingly, we estimate and report the AMEs to quantify the impact of the explanatory variables on the probability of becoming a zombie. Furthermore, since our analysis sample, the constituents of the FTSE 250 Index, is a close representative of the mid-cap firms in the UK, the estimated average marginal effects could be interpreted as the average marginal effects for the population of mid-cap firms in the UK[155].

Table 4.5 reports the AMEs and the associated standard errors for the explanatory variables used in the panel estimation of the logit model presented in Eq. (4.3). Where, *dy/dx* denotes the average marginal effects and *Delta method Std. Err*. denotes the heteroskedasticity-robust standard errors that are estimated using the delta method[156].

As can be seen from Table 4.5, the estimated average marginal effects suggest that, on average, for mid-cap firms in the UK, the probability of becoming a zombie increases by 0.14% for every 1% increase in the leverage ratio (*TDTA)*. In contrast, a 1% increase in the profitability (*EBITS)* and the cash-generating ability *(CFOTA)* of the mid-cap firms tend to lower the probability of becoming a zombie by 1.74% and 0.29%, respectively. Furthermore, mid-cap firms that do not make dividend payments are 4.58% more likely to become zombies than those firms that pay dividends. Finally, the probability of becoming a zombie for firms whose CEO (or equivalent) resigns is, on average, 3.33% higher than it is for more viable firms with no such drastic changes in their top management.

Having identified the significant determinants of the zombieness status and estimated the marginal effects of the respective determinants on the probability of becoming a zombie, we proceed with evaluating the overall fit of the model and assessing its explanatory power.

[155] While FTSE 250 Index is the market index for mid-cap firms, firms in our sample presents an average of 61.65% of the FTSE250 index for each year during 2008-2012.

[156] In Stata the delta-method standard errors are obtained – using the first-order Taylor series expansion - by computing the square root of the diagonal elements of the estimated variance matrix that corresponds with the reported predictive margins. For more details, see Wooldridge (2002, Section 3.5.2) and Pitblado (2014).

Table 4.5 Marginal Effects of Explanatory Variables

Zombie	*dy/dx*	*Delta-method Std Err.*	*z*	*P > | z |*
TDTA	0.0014	0.001	2.310	0.021
EBITS	-0.0174	0.002	-7.510	0.000
CFOTA	-0.0029	0.002	-1.820	0.069
DVDND	0.0458	0.019	2.450	0.014
CEOCHNG	0.0333	0.016	2.030	0.043
Obs.				425

Where, the analysis period is 2008-2012; $Zombie = \ln(\frac{\Pr(y_{it}=1)}{\Pr(y_{it}=0)})$ denotes the log of odds ratio of becoming a zombie (i.e., $AICR = \frac{Operating\ Income+Interest\ Income}{Total\ Interest\ Expense} < 1$); $TDTA = \frac{Total\ Debt}{Total\ Assets}$ denotes leverage ratio; $EBITS = \frac{Earnings\ Before\ Inerest\ \&\ Taxes}{Sales}$ denotes profitability; $CFOTA = \frac{Operating\ Cash\ Flow}{Total\ Assets}$ denotes cash-generating ability; *DVDND* is a dummy variable that takes value of 1 if firm does not make dividend payment during the year and 0 otherwise; *CEOCHNG* is a dummy variable that takes value of 1 if CEO (or equivalent) resigned during the year and 0 otherwise; *dy/dx* denotes the Average Marginal Effects (AMEs); and *Delta-method Std. Err*. denotes the heteroskedasticity-robust standard errors that are estimated using the delta method.

4.2.2.5. Goodness-of-Fit of the Model

In addition to the *pseudo-R^2* measure discussed in Section 4.2.2.2, some other commonly used measures to assess the overall fit of the logistic regression models are the Hosmer-Lemeshow test, the classification matrix and the area under the Receiver Operating Characteristic (ROC) curve. However, similar to the *pseudo-R^2* case, these measures also can only be estimated for pooled models.

Having said that, the logit coefficients on the variables based on the pooled model estimated by the stepwise method (Table 4.2) and the panel estimation results (Table 4.4) are very close, suggesting that the efficiency gain of controlling for the firm-level effect are not significant – which is not surprising, given the population-averaged nature of the panel estimation and the assumed exchangeable within-group correlations. Accordingly, estimating the measures of the goodness-of-fit for the pooled logit model is believed to provide us with a very close approximation about the overall fit of the panel model.

Given that Stata does not allow controlling for heteroskedasticity in the stepwise estimation, we use the heteroskedasticity-robust pooled estimation of Eq. (4.3), which gives us identical coefficients to the stepwise estimation, to assess the overall fit of the model[157].

4.2.2.5.1. Hosmer-Lemeshow Test

The Hosmer-Lemeshow's (1980) specification test evaluates the goodness-of-fit by testing the null hypothesis that the sample frequency of the dependent variable (i.e., the actual values of the dependent variable) is equal to the fitted probability of subgroups of observations (i.e., estimated values of the dependent variable). Table 4.6 reports the results of the Hosmer-Lemeshow test, where the *Chi^2* statistic with $(g - 2)$ degrees of freedom – g denoting the number of groups, is used to test the null hypothesis. Given that the number of subgroups is based on the quantiles of the ordered predicted probabilities, we use the conventional 10 subgroups so that each group corresponds to a decile of the ordered predicted probability.

[157] The pooled regression results of the estimation model presented in Eq. (4.3) with heteroskedasticity-robust standard errors are presented in Table 7.5 in the Appendix.

As can be seen from Table 4.6, given the low *Hosmer-Lemeshow statistic* and the associated high *p-value* we strongly fail to reject the null hypothesis. Accordingly, failure to reject the null that the difference between the actual values and the fitted values are insignificant, suggests that the model is doing a good job in explaining the probability of becoming a zombie.

However, while the Hosmer-Lemeshow test is easy to interpret, the test outcome is very sensitive to the number of groups used in the specification. Furthermore, the test does not indicate how good of a job the firm is doing in explaining the probability of the specific outcomes (i.e., becoming zombie and not becoming zombie)[158].

Table 4.6 Goodness-of-Fit – Hosmer-Lemeshow Test

Number of observations	425
Number of groups	10
Hosmer-Lemeshow:	
Chi2(8)	1.13
Prob > Chi2	0.997

4.2.2.5.2. Classification Matrix

As an alternative to the Hosmer-Lemeshow test, we can assess the goodness-of-fit of the model by evaluating its classification power. That is, determining how many of the actual zombie observations (i.e., $y_{it} = 1$) and the actual non-zombie observations (i.e., $y_{it} = 0$) does the model correctly classify as zombies (i.e., $\hat{y}_{it} = 1$) and non-zombies ($\hat{y}_{it} = 0$), respectively.

Accordingly, to evaluate the classification power of the model, the classification matrix and the percentage of correctly and incorrectly classified observations are presented in Table 4.7. Where, *D* denotes the true zombies, ~*D* denotes true non-zombies, and the default cutoff value of 0.5 is used for determining if an observation has a predicted zombie outcome, such that observations are classified as:

$$+, \text{ if } \Pr(D) \geq 0.5 \quad \text{and} \quad \text{as } -, \text{ if } \Pr(D) < 0.5. \tag{4.6}$$

As can be seen from Table 4.7, there are 2 observations misclassified as zombies

[158] In particular, using a large number of groups in the test causes a divergence between the empirical cumulative distribution function (CDF) and the CDF of the specified chi2 distribution under the null hypothesis (Cameron and Trivedi, 2009).

when the correct classification is non-zombie, while 5 observations are misclassified as non-zombies, when the correct classification is zombie. The remaining 29 + 389 observations are correctly classified.

The *sensitivity* value indicates that, 85.29% of the observations classified as + are in fact zombies, while the *specificity* value indicates that 99.49% of the – classified observations are true non-zombies. Furthermore, the values for *Pr (D | +)* and *Pr (~D | -)* , respectively, indicate that 93.55% of the true zombies are correctly classified as +, while 98.73% of true non-zombies are correctly classified as -. Accordingly, the overall rate of correct classification of the model is 98.35%.

Although the overall classification is sensitive to the relative sizes of each group, and always favors classification into the larger group, the estimated model seems to do a substantially great job in correctly classifying zombies, which are significantly smaller than the non-zombie group.

Table 4.7 Goodness-of-Fit – Classification Matrix

Classified	---------- *True* ----------		*Total*
	D	*~D*	
+	29	2	31
-	5	389	394
Total	34	391	425
Sensitivity: Pr (+ | D)			85.29%
Specificity: Pr (- | ~D)			99.49%
Pr (D | +)			93.55%
Pr (~D | -)			98.73%
Pr (+ | ~D)			0.51%
Pr (- | D)			14.71%
Pr (~D | +)			6.45%
Pr (D | -)			1.27%
Correctly classified			98.35%

Where, True D denotes observations for which the dependent variable is equal to 1 (i.e., zombie); True ~D denotes observation for which the dependent variable is equal to 0 (i.e., non-zombie); Sensitivity denotes the probability of correctly classifying zombies; Specificity denotes the probability of correctly classifying non-zombies; *Pr (D | +)* denotes probability of classify true zombies as +; *Pr (~D | -)* denotes probability of classifying true non-zombies as –; *Pr (D | +)* denotes the false + rate for true ~D; *Pr (- | D)* denotes the false – rate for true D; *Pr (~D | +)* denotes the false + rate for classified +; *Pr (D | -)* denotes the false – rate for classified -; and observations are classified as + if predicted $\Pr(D) \geq 0.5$ and as – if $\Pr(D) < 0.5$.

4.2.2.5.3. Area under the ROC Curve

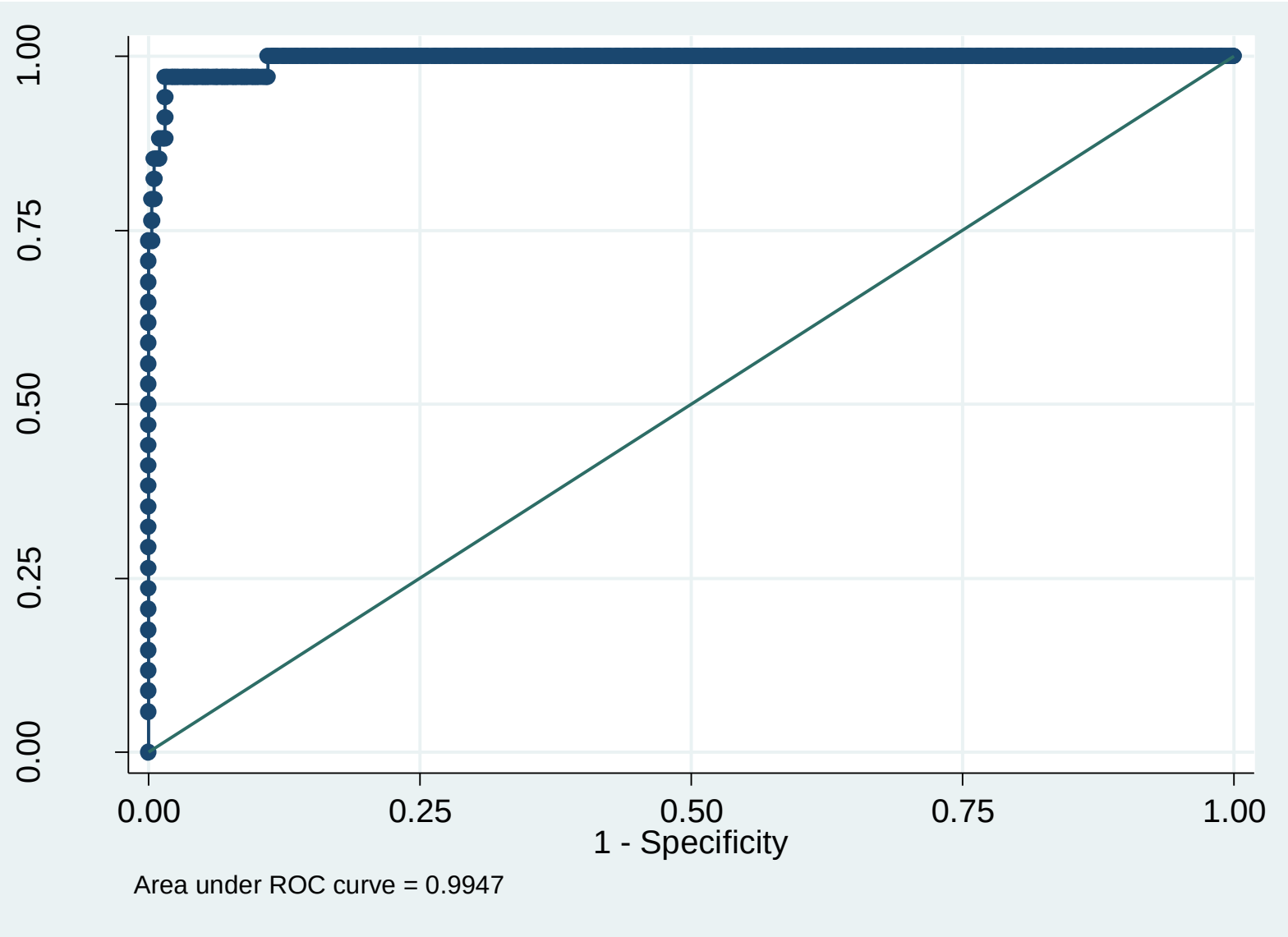
The final measure of the goodness-of-fit of the logit model which is also closely related with the classification matrix is the Receiver Operating Characteristic (ROC) curve. The ROC curve is plotted in the *sensitivity* (the proportion of correctly classified zombies) and the *1 – specificity* (the proportion of misclassified non-zombies) dimension. Accordingly, the area under the ROC curve measures the classification power of the model (Hanley and McNeil, 1982). The ROC curve corresponding to the pooled estimation of the Eq. (4.3) is presented in Figure 4.1.

Given that a model with no predictive power classifies observations into zombies and non-zombies using a 0.5 probability (50% sensitivity, 50% 1-specificitity), its ROC curve takes the form of a 45° line. On the other hand, a model with perfect classification power (i.e., 100% sensitivity, 0% 1-specificity) has a ROC curve that passes through the upper left corner. Accordingly, the greater the classification power of the model, the more convex will be its ROC curve (Zweig and Campbell, 1993).

As can be seen from Figure 4.1, the ROC curve corresponding to the estimated model is just short of perfect classification. That is, consistent with the reported values in the classification matrix, the area under the ROC curve is 99.47%, which indicates the significant classification power of the estimated model.

Overall, the three measures of the goodness-of-fit of the model discussed above suggest that, the pooled model with 5 explanatory variables is doing a significantly good job in explaining the probability of becoming a zombie and correctly classifying the observations. Given the minor differences between the estimated coefficients of the pooled and panel model, the overall fit measures of the pooled model can provide us with a close approximation about the goodness-of-fit of the panel estimation of the model. However, one must keep in mind the high proportion of 0s in the actual values of the dependent variable, when inferring the above measures of model fit.

Figure 4.1 Goodness-of-Fit – Area under the ROC Curve



4.3. Results (Capital Structure)

4.3.1. Descriptive Statistics

Table 4.8, Table 4.9, and Table 4.10 present the descriptive statistics of the analysis variables, which allows for a preliminary assessment of the impact of the recent GFC and the consequent economic recession on firms' leverage ratios. The means of the dependent variable and all the independent variables for each year of the analysis period are reported in Table 4.8, for the pre-crisis and post-crisis periods in Table 4.9, and for non-zombies and zombies in Table 4.10[159]. Where, *Obs.* denotes the number of observations; *Leverage* denotes book leverage ratio and is calculated as $\frac{Total\ Debt}{Total\ Debt+Total\ Equity}$; *GRT* denotes growth opportunities and is calculated as $\frac{Book\ Value\ Total\ Assets-Book\ Value\ Equity+Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$; *SIZ* denotes firm size and is calculated as $\ln(Total\ Assets)$; *TNG* denotes asset tangibility and is calculated as $\frac{Net\ Fixed\ Assets}{Total\ Assets}$; *PRF* denotes profitability and is calculated as $\frac{EBITDA}{Total\ Assets}$; *NDTS* denotes non-debt tax shields and is calculated as $\frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$; and *RSK* denotes business risk and is calculated as $\frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$

The significant changes of corporate capital structure after the recent GFC is easily observable through the changes in the average leverage ratio over the period 2004-2012. As illustrated in Table 4.8, while *LVG* seems to follow a general upward trend before 2008, data indicates a substantial reduction in the average leverage ratio of firms from 2008 onwards, with 2009 exhibiting the largest drop. In fact, the average leverage ratio has consistently decreased over the years after the GFC such that, from the peak of 37.51% in 2007 (the onset of the GFC) it reaches 27.41% in 2012, indicating a substantial decrease of 10% (i.e., 27% in absolute values)[160]. Looking at the changes in the mean values of other firm characteristics over the analysis period

[159] While we do not attempt to define a definitive starting and ending point for the recent Global Financial Crisis (GFC), we simply use the terms "pre-crisis" and "post-crisis" to refer to the years including and before 2007 (i.e., the onset of the GFC) and the years after 2007, respectively.

[160] A word of caution is in order: while annual mean leverage ratios may suggest significant changes in the leverage ratios over the years after the GFC, it does not necessarily mean that the GFC has caused these changes. That is, average leverage ratios could have decreased for different reasons other than the overall macroeconomic conditions.

will help us obtaining a better understanding of the impact of the GFC and the consequent economic recession on sample firms.

Generally, *GRT* illustrates an increasing pattern in the period before the financial crisis. However, as expected, the negative impact of the GFC and the economic recession on market value of the firms is evident by the significant decrease of 66% the average market-to-book ratio in 2008. However, it has started to recover since then, such that in 2012 it almost reaches its pre-crisis peak of 249%. Despite the two occasions of minor decreases in 2006 and 2012, the average firm size (*SIZ*), follows a consistent but very gradual upward trend over the entire analysis period. This may merely reflect the fact that firms generally tend to invest in new assets and expand their operations over time in order to keep in business.

Consistent with the general increase in total assets, the average *TNG*, measured as the proportion of tangible assets to total assets, indicates a general decreasing pattern, reflecting the smaller relative investments in fixed tangible assets. Furthermore, the two minor increases in 2008 and 2009 may be due to substantial write-offs of intangible assets such as goodwill and brand recognitions caused by the financial crisis. Table 4.8 also shows a decreasing pattern for profitability (*PRF*), especially in the early years after the GFC. In fact, except for three instances (i.e., 2006, 2010, and 2011) where it increases marginally, the mean value of return on assets follows a general downward trend over the entire observation period, with the largest drop of 2.3% in 2008.

As expected, *NDTS* follows a similar pattern to *TNG*. That is, except a few minor increases, the average value of depreciation and amortization expenses to total assets follows a general decreasing pattern over the analysis period. Furthermore, the decrease in the non-debt tax shield items may merely reflect smaller acquisition of depreciable assets relative to total assets. However, the changes in the mean values, especially after 2009, are too small to be meaningful. Finally, *RSK* has by far experienced the most drastic changes over the period 2004-2012. The fluctuations in earnings' volatility are in fact too frequent to be reliably interpreted. However, it may be more helpful to look at the changes in absolute values. As can be seen from the last column of Table 4.8, the reported mean value for earnings volatility doubles between years 2007 and 2008 (from 1.9 to 3.8), which may be indicating the

significant impact of financial crisis on earnings' stability. However, *RSK* decreases by more than half from 3.8 in 2008 to 1.2 in 2009 and remain low since then. Thus, we may infer that the possible impact of financial crisis on earnings' volatility, though significant, was only temporary.

While Table 4.8 suggests significant changes in the mean values of *GRT* (decrease), *PRF* (decrease), and *RSK* (increase) between 2007 and 2008, the respective changes in *SIZ* (increase), *TNG* (increase), and *NDTS* (increase) are quite small. However, all changes are in the expected direction. That is, as a consequence of the negative economic and financial shock after the GFC, market value of firms and their ability to generate profit are substantially deteriorated, and understandably their earnings become more volatile. The increase in total assets, proportion of tangible assets relative to total assets, and depreciation and amortization expenses scaled by total assets can be simply a consequence of the sustainable growth policies of businesses where they must increase their asset base in order to stay in business.

Table 4.8 Means of the Dependent and Independent Variables: 2004-2012

Year	*Obs.*	*Leverage*	*GRT*	*SIZ*	*TNG*	*PRF*	*NDTS*	*RSK*
2004	123	33.898	193.919	20.459	31.487	15.402	4.990	1.840
2005	132	37.320	218.682	20.535	28.458	15.053	4.112	1.616
2006	137	35.095	249.724	20.523	26.475	16.582	3.936	2.236
2007	136	37.513	226.964	20.547	26.450	16.013	3.710	1.860
2008	135	36.239	160.253	20.598	27.167	13.724	3.941	3.754
2009	135	31.384	185.425	20.619	27.300	12.765	4.339	1.220
2010	130	28.623	215.372	20.660	26.564	14.501	4.334	1.601
2011	135	26.986	205.912	20.665	25.456	16.077	4.515	1.356
2012	134	27.408	238.402	20.622	25.287	15.772	4.444	0.509

By reporting the average values of the leverage ratio and other explanatory variables over the pre-crisis period (2004-2007) and post-crisis period (2008-2012), Table 4.9 provides a more direct comparison of the average firm in the pre-crisis with an average firm in the post-crisis. The significant reduction in leverage ratio after the GFC is even more noticeable when comparing the pre-crisis period with the post-crisis period. As presented in Table 4.9 the average leverage ratio fell by almost 5.85% (i.e., 16.4% in absolute values) from 35.99% in the pre-crisis period to 30.14% in the post-crisis period. As expected, since the onset of the GFC firms have become less

profitable and have experienced a downward trend in the market value of future growth opportunities and their tangible assets. On the other hand, the average firm size is marginally larger and earnings have become significantly more volatile over the post-crisis period as opposed to the pre-crisis period. Furthermore, non-debt tax shields, although marginally, also increase between the two periods, which may reflect the larger amortization expenses due to impaired intangible assets. All of these factors may have contributed to the lower average leverage ratio in the post-crisis period.

Table 4.9 Means of the Dependent and Independent Variables: Pre-Crisis vs. Post-Crisis

Time Period	*Obs.*	*Leverage*	*GRT*	*SIZ*	*TNG*	*PRF*	*NDTS*	*RSK*
Pre-Crisis	528	35.995	223.101	20.517	28.132	15.778	4.167	1.084
Post-Crisis	669	30.143	200.910	20.633	26.354	14.566	4.314	1.690

Where, Pre-crisis denotes the period 2004–2007; Post-Crisis denotes the period 2008–2012.

Finally, Table 4.10 presents the means of the dependent and the independent variables of zombies and non-zombies in our sample of firms. Consistent with the definition of zombies discussed in Section 2.3.5, Table 4.10 illustrates that, despite their far less profitability, zombies tend to have higher average leverage ratios than non-zombies. In fact, the average leverage ratio of the zombie group is about 4.06% higher (approximately 10% higher in absolute values) than the leverage ratios of non-zombies, despite their 12.53% lower average profitability. While, this finding may suggest that zombies tend to have higher leverage ratios than non-zombies, it should be noted that this does not prove causation. That is, although zombies may have average higher leverage ratios, it does not necessarily imply that being a zombie causes higher leverage ratios.

Table 4.10 Means of the Dependent and Independent Variables: Non-Zombies vs. Zombies

Firm Type	*Obs.*	*Leverage*	*GRT*	*SIZ*	*TNG*	*PRF*	*NDTS*	*RSK*
Non-Zombie	535	37.128	185.543	20.784	28.208	14.242	4.090	1.634
Zombie	42	41.193	153.685	21.158	29.303	1.708	4.303	8.080

Where, *non-zombie* denotes firms with $AICR = \frac{EBIT + Interest\ Income}{Total\ Interest\ Expense} \geq 1$ that are not identified as zombies and *zombie* denotes firms with $AICR = \frac{EBIT + Interest\ Income}{Total\ Interest\ Expense} < 1$ that are identified as zombies.

Accordingly, the mean values of the analysis variables presented in Table 4.10 suggest that, while zombies and non-zombies differ significantly in their measure of leverage ratios, growth opportunities, profitability, and business risk, the difference in the mean values of other variables (i.e., *SIZ*, *TNG*, and *NDTS*) between the two groups are too small to be meaningful. In particular, zombies seem to be, on average, less profitable than non-zombies and tend to have higher leverage ratios, fewer growth opportunities and significantly more volatile earnings. However, one must be cautious of the average nature of these values and the substantially smaller size of zombie group (42 observations) as opposed to the non-zombies group (535 observations) when considering these inferences.

4.3.2. Correlation Matrices

Next, we look at the pairwise correlations of the independent variables to detect the presence of multicollinearity among them[161]. Although it does not lead to biased coefficient estimates, it is important to check for multicollinearity as it may lead to unreliable inferences on the impact of individual variables on firms' leverage ratios (Hair *et al.*, 2010). That is, as correlation between independent variables increases, it becomes more difficult to ascertain the effect of individual independent variables on the dependent variable.

Econometrically speaking, the standard errors associated with the coefficients tend to increase with the degree of multicollinearity. This implies that, as the extent of multicollinearity increases, the variance and the confidence intervals of the coefficients get bigger, and hence making it more difficult for the estimated coefficients to be statistically significant (Belsley *et al.*, 1980; Hair *et al.*, 2010; and Gujarati and Porter, 2010)[162].

Accordingly, the Pearson's correlation coefficient, which is a statistical measure of the strength of a linear relationship between paired data, is used obtain an understanding of the degree of co-movement among our independent variables[163]. Table 4.11, Table 4.12, Table 4.13, Table 4.14, and Table 4.15 present the Pearson correlations between all independent variables: reporting the pairwise coefficient of correlations for the full sample, the pre-crisis period, the post-crisis period, the non-zombie subsample, and the zombie sample, respectively[164].

As can be seen from Table 4.11, all correlations are in expected directions and fairly small in magnitude. The commonly used rule of thumb for interpreting the size of a

[161] Hair *et al.* (2010: p. 104) defines multicollinearity as: "the degree to which any variable's effect can be predicted or accounted for by the other variables in the analysis".

[162] Defining G_x as the set of all independent variables other than x, the standard error of variable x increases by $\sqrt{\frac{1}{(1-correlation_{xGx})}}$, where the term under the square root sign is called the Variance Inflation Factor (VIF). This will be discussed later in this section.

[163] Pearson's correlation is the appropriate correlation measure as all our variables are scaled, (i.e., are intervals or ratios).

[164] The first independent variable, *L.LVG*, is the 1-year lag of the dependent variable, and hence the underlying relation between lagged leverage measure and other independent variables is very similar to their relation with the dependent variable. Accordingly, given that the relation and impact of the independent variables on leverage ratio was extensively discussed in the previous section, we do not comment on the bivariate correlations between *L.LVG* and other independent variables.

correlation coefficient suggests that, values above 0.8 indicate possible "troublesome" correlations between the two variables (Menard, 1995; Evans *et al.*, 1996; Hair *et al.*, 2010). Accordingly, as can be seen from Table 4.11, there are no worryingly high correlations among the independent variables for the full sample. To obtain a better understanding of the co-movements between paired variables, we can use a graphical presentation of the data. The scatterplots with the overlaid quadratic prediction plot is used to see whether there exist any visually observable relationships between the independent variables. As can be seen from Figure 4.2, consistent with the pairwise correlations reported in Tables 5.4, we find that larger firms tend to have lower growth opportunities and lower profitability, while high-growth firms tend to be more profitable. Furthermore, we find no evidence of a discernible relationship between any other two independent variables. However, it would be interesting to see if there are any sign reversions or significant changes in the magnitude of the correlations when sample is broken down based on different criteria.

Table 4.11 Pearson Correlation Matrix – Full Sample

Variable	*L.LVG*	*GRT*	*SIZ*	*TNG*	*PRF*	*NDTS*	*RSK*
L.LVG	1.000						
GRT	-0.088	1.000					
SIZ	0.385	-0.458	1.000				
TNG	0.244	-0.066	0.101	1.000			
PRF	-0.139	0.483	-0.515	0.085	1.000		
NDTS	0.091	-0.002	-0.160	0.417	0.265	1.000	
RSK	0.022	0.005	-0.010	-0.012	-0.035	-0.003	1.000

Figure 4.2 Scatterplots Overlaid with Quadratic Prediction Plot



Comparing the correlation matrices for the pre-crisis and the post-crisis period as presented in Table 4.12 and Table 4.13, respectively, indicates a significant consistency in both sign and magnitude of the correlation coefficients across the two time periods. That is, except for the correlation between *PRF* and *TNG*, which loses half of its strength from pre-crisis to the post-crisis, there are no other significant changes in the magnitude of the correlations between the two periods. The correlation between profitability and the degree of asset tangibility may have weakened because of the expected reduction in the profit-generating ability of fixed assets in the post-crisis environment. Firms may have been unable to optimally utilise their fixed assets due to the excess capacity caused by the asset accumulation and investments occurred in the pre-crisis period with the hope of continuous growth. This is also consistent by the smaller average profitability and asset tangibility of firms in the post-crisis period as opposed to the pre-crisis period (see, Table 4.9).

Table 4.12 Pearson Correlation Matrix – Pre-Crisis

Variable	*L.LVG*	*GRT*	*SIZ*	*TNG*	*PRF*	*NDTS*	*RSK*
L.LVG	1.000						
GRT	-0.138	1.000					
SIZ	0.391	-0.547	1.000				
TNG	0.207	-0.063	0.095	1.000			
PRF	-0.198	0.494	-0.544	0.126	1.000		
NDTS	0.156	-0.023	-0.131	0.465	0.334	1.000	
RSK	0.016	0.011	-0.022	-0.009	-0.016	-0.000	1.000

Table 4.13 Pearson Correlation Matrix – Post-Crisis

Variable	*L.LVG*	*GRT*	*SIZ*	*TNG*	*PRF*	*NDTS*	*RSK*
L.LVG	1.000						
GRT	-0.069	1.000					
SIZ	0.392	-0.413	1.000				
TNG	0.268	-0.074	0.110	1.000			
PRF	-0.116	0.418	-0.503	0.061	1.000		
NDTS	0.043	-0.015	-0.187	0.378	0.235	1.000	
RSK	0.037	0.002	-0.002	-0.016	-0.062	-0.008	1.000

Finally, the most noticeable difference between the correlation matrices for the non-zombie and the zombie subsamples are the reversed directions of the pairwise correlations of *RSK* with the other independent variables. As can be seen from Table 4.14 and Table 4.15, except for the correlation with *PRF*, all pairwise correlations of *RSK* show opposite signs across the two subsamples. The correlation matrix for non-zombies indicate that, while *GRT*, *TNG*, and *NDTS* are positively correlated with the measure of business risk, the correlation coefficient between *SIZ* and *RSK* is negative. On the other hand, the exact opposite pattern holds for the zombies. That is, while the pairwise correlation of *RSK* with *GRT*, *TNG* and *NDTS* are negative, *SIZ* and *RSK* tend to be positively correlated with each other. Furthermore, although profitability is negatively correlated with business risk in both subsamples, the magnitude of the correlation is substantially larger for zombies (-0.599) than non-zombies (-0.004), which may be due to the significantly lower profitability of zombies in comparison to non-zombie. That is, as can be seen from Table 4.10, while the average profitability for non-zombie group is 14.24%, the corresponding value for the zombie group is a significantly lower value of 1.71%. Similarly, the drastic reversion of the signs may have happened because of the substantial differences in the business risk of the two groups. Going back at Table 4.10, we can see that zombies, on average, tend to be substantially riskier than non-zombies with an average earnings' volatility of 8.08, which is almost 5 times greater than the corresponding value of 1.63 for the non-zombie group.

Table 4.14 Pearson Correlation Matrix – Non-Zombies

Variable	*L.LVG*	*GRT*	*SIZ*	*TNG*	*PRF*	*NDTS*	*RSK*
L.LVG	1.000						
GRT	0.162	1.000					
SIZ	0.232	-0.543	1.000				
TNG	0.285	0.022	0.089	1.000			
PRF	0.049	0.485	-0.548	0.139	1.000		
NDTS	0.136	-0.075	-0.161	0.449	0.471	1.000	
RSK	0.046	0.021	-0.033	0.023	-0.004	0.042	1.000

Table 4.15 Pearson Correlation Matrix – Zombies

Variable	*L.LVG*	*GRT*	*SIZ*	*TNG*	*PRF*	*NDTS*	*RSK*
L.LVG	1.000						
GRT	-0.047	1.000					
SIZ	0.561	-0.483	1.000				
TNG	0.385	0.246	0.078	1.000			
PRF	0.119	0.272	-0.162	0.271	1.000		
NDTS	-0.115	-0.241	-0.432	0.118	0.595	1.000	
RSK	0.053	-0.184	0.070	-0.315	-0.599	-0.387	1.000

Having discussed the correlations among independent variables, one must note that, pairwise correlation is merely a standardised measure of the covariance between two variables, and a high correlation with one variable may not necessarily imply the presence of *multi*collinearity. Furthermore, Pearson correlation matrices can only identify linear correlations, and thus do not provide any information about possible non-linear correlations among the independent variables.

As an alternative to Pearson correlations, one can use more formal econometric statistics such as the Variance Inflation Factor (VIF) and the Tolerance measure to test for the presence of multicollinearity[165]. The VIF and the Tolerance can be obtained by running a linear regression of each independent variable on all the other independent variables. Accordingly, VIF_x is calculated as $\frac{1}{Tolerance_x}$ and Tolerance is calculated as $1 - {r_x}^2$, where r_x denotes the correlation coefficient of variable x with all other independent variables and measures the speed at which variances and covariances increase (Greene, 2008)[166]. Thus, the larger (smaller) the value of VIF (Tolerance), the greater is the degree of multicollinearity.

However, multicollinearity is a matter of degree. The general consensus in the empirical literature to cause concern about multicollinearity is for cases with $VIF > 10$ (Kleinbaum *et al.*, 1988; Kennedy, 1992; Mendard, 1995; Hair *et al.*, 2010; Chatterjee and Hadi, 2012). In fact, Stata manual (StataCorp, 2015: p. 2157) notes: "*there is evidence of multicollinearity if: 1. The largest VIF is greater than 10 (some choose a more conservative threshold value of 30) 2. The mean of all the VIFs is*

[165] See, Belsley *et al.* (1980) and Hill and Adkins (2001) for alternative collinearity diagnostics.
[166] For example, the VIF of 1.9 indicates that the variance of the variable of interest is 90% larger than it would be if that variable was completely uncorrelated with all other independent variables.

considerably larger than 1". Table 4.16 reports the VIF, the Tolerance and the mean VIF for all the independent variables. As can be seen, on the basis of both the VIF and the mean VIF criteria, there is no evidence to suggest the presence of multicollinearity among the independent variables.

Table 4.16 Test of Multicollinearity

Variable	*VIF*	*1/VIF*
PRF	3.49	0.287
GRT	3.18	0.315
YR12	1.80	0.555
YR11	1.80	0.557
YR09	1.79	0.560
YR08	1.79	0.560
YR06	1.78	0.561
YR05	1.76	0.568
YR10	1.76	0.569
YR04	1.73	0.578
SIZ	1.70	0.590
NDTS	1.49	0.670
L.LVG	1.32	0.759
TNG	1.31	0.762
RSK	1.01	0.989
Mean VIF	1.85	

4.3.3. Estimation Results – Static Models

Although our two main estimation models, the base model and the zombie model (presented in Eq. (3.34) and Eq. (3.35), respectively), are dynamic, in order to demonstrate the empirical procedure of choosing the final estimator and model specification, we start our analysis by estimating static versions of the base model and the zombie model and then move on to dynamic models.

The static version of the base model is as follows:

$$Leverage_{it} = \alpha_0 + \beta_1 GRT_{it} + \beta_2 PRF_{it} + \beta_3 TNG_{it} + \beta_4 SIZ_{it} + \beta_5 NDTS_{it} + \beta_6 RSK_{it} + \gamma_1 YR_{2004} + \gamma_2 YR_{2005} + \gamma_3 YR_{2006} + \gamma_4 YR_{2008} + \gamma_5 YR_{2009} + \gamma_6 YR_{2010} + \gamma_7 YR_{2011} + \gamma_8 YR_{2012} + \mu_i + \lambda_t + \varepsilon_{it}. \quad (4.7)$$

Where, $Leverage_{\mathrm{it}}$ is the book leverage ratio of firm i in year t; GRT_{it}, PRF_{it}, TNG_{it}, SIZ_{it}, $NDTS_{\mathrm{it}}$, and RSK_{it} represent the measures of growth opportunities, profitability, tangibility, size, non-debt tax shields and earnings' volatility of firm i in year t; YRs are the annual time dummies, α_0 is the constant; μ_i represents time-invariant unobservable firm-specific effects; λ_t represents firm-invariant unobservable time-specific effects which are common to all firms and can change through time; ε_{it} is the idiosyncratic error term; and βs and γs are the unknown parameters to be estimated.

The static version of the zombie model is as follows:

$$Leverage_{it} = \alpha_0 + \beta_1 GRT_{it} + \beta_2 PRF_{it} + \beta_3 TNG_{it} + \beta_4 SIZ_{it} + \beta_5 NDTS_{it} + \beta_6 RSK_{it} + \beta_7 ZMB_{i,t-1} + \gamma_1 YR_{2008} + \gamma_2 YR_{2009} + \gamma_3 YR_{2010} + \gamma_4 YR_{2011} + \gamma_5 YR_{2012} + \mu_i + \lambda_t + \varepsilon_{it}. \quad (4.8)$$

Where, $ZMB_{\mathrm{i,t-1}}$ denotes a dummy variable that takes a value of 1 if a firm is identified as zombie at the beginning of a given year, and 0 otherwise.

4.3.3.1. Tests of OLS Assumptions

We assume the following main assumption of the classical Least Squares linear regression to hold for both of our static estimation models (Greene, 2008):

1. **Linearity:** model is linear in parameters, α, βs, γs, μ_i, λ_t, and ε_{it}.
2. **Full rank:** no exact linear relationship (i.e., correlation of 1) among any of the independent variables. It is also referred to as the no-perfect-collinearity assumption[167].
3. **Strict exogeneity of the independent variables:** independent variables do not carry useful information for prediction of the residuals, which is also known as the zero-conditional-mean assumption (i.e., $E(\varepsilon_{it} \forall X_{it}) = 0\ ,\ t = 1, \dots, T$)[168]. This assumption also implies that residuals are Identically and Independently Distributed (*i.i.d*).
4. **No-auto correlation of the residuals:** residuals are uncorrelated with each other (i.e., $Cov(\varepsilon_{it}, \varepsilon_{i,t-k}) = 0\ ,\ k = 1, \dots, T-1$).
5. **Homoscedasticity of the residuals:** the variance of the residuals is constant conditional on all the independent variables (i.e., $Var(\varepsilon_{it} \forall X_{it}) = \sigma^2\ ,\ t = 1, \dots, T$).
6. **Normal distribution of the residuals:** residuals follow a normal distribution with mean 0 and variance σ^2 (i.e., $\varepsilon_{it} \sim N(0, \sigma^2)$).

Following the common practice and to avoid unnecessary complications in a static context, the first four assumptions are assumed to hold valid. However, given that the last two assumptions limit the generality of the model, we must test for their validity before proceeding with the estimation results[169].

After estimating the pooled OLS model, in the process of testing for normality and homoscedasticity of the residuals, we detect that, the residuals do not follow a normally distribution and, as expected, there is strong evidence for existence of

[167] The validity of the no perfect collinearity assumption has been already tested in Section 4.3.2.
[168] Residuals or errors refer to the difference between the actual value of the dependent variable and its predicted value.
[169] However, the assumption of exogeneity and no-autocorrelation are relaxed and tested for in the context of dynamic model.

heteroskedastic errors. Accordingly, we must address these two concerns before reporting the estimation results obtained using the pooled OLS.

4.3.3.1.1. Test of Normality

Although, non-normality of the residuals does not lead to biased or even inefficient coefficient estimates, the normality assumption assures the validity of the *p-values* for significance testing, and hence obtaining reliable inferences of the coefficients (Weisberg, 2005; Tabachnick and Fidell, 2006; Hair *et al.*, 2010)[170]. This motivates us to first check and test whether the residuals follow a normal distribution and then test for possible heteroskedasticity.

We employ both numerical and graphical tests to detect normality of the residuals. We use two alternative numerical tests and three alternative graphical tests. The numerical tests are the Skewness and Kurtosis (SK) test and the Shapiro-Wilk (SW) test for normality, which for the base model are presented in Table 4.17 and Table 4.21, respectively, and for the zombie model are presented in Table 4.19 and Table 4.22, respectively.

The SK test, developed by D'Agostino *et al.* (1990), evaluates the normality of residuals based on the skewness and kurtosis and then combines the two into an overall test-statistics, with the null hypothesis that the skewness and kurtosis of the residuals' distribution is not significantly different to that of the normal distribution.

The Shapiro-Wilk's *W-statistic*, developed by Shapiro and Wilk (1965), is a test-statistic calculated as the ratio of the best estimator of the variance to the usual corrected sum of squares estimator of the variance, which is 1 for normal distribution. Thus, the closer the value of the SW's *W* to 1, the closer is the distribution of the residuals to normality[171]. The SW test also reports a value for *V*, which is an index transformed measure of W that shows the deviation from normality. That is, a median value of 1 indicates the normality of the residuals and thus, the larger the reported values of *V*, the greater is the degree of non-normality of the residuals.

[170] Using conservative *p-values* such as 1% rather than 5% or 10% routinely, can be a non-statistical remedy for possible violations of the normality assumption. See Tabachnick and Fidell (2006) and Hair *et al.* (2010) for detailed discussion of the remedies to non-normal residuals.

[171] While the original test developed by Shapiro and Wilk (1965) is only valid for sample with 3< N <50, Royston (1992) developed an extended version of the test that can be applied to samples with 4< N <2000.

As can be seen from Table 4.17, the small joint significance *p-value* for the skewness and kurtosis following a normal distribution suggests a rejection of the null, meaning that residuals are not normally distributed. However, the *p*-value of 0.047 for the kurtosis indicates that, based on the kurtosis measure we cannot reject the hypothesis that residuals are normally distributed at the 1% significance level. In fact, as can be seen from Table 4.18, the kurtosis of residuals is 3.3, which is very close to the kurtosis value of the normal distribution, 3.

Table 4.17 Test for Normality (Skewness and Kurtosis) – Base Model

Variable	*Obs.*	*Pr(Skewness)*	*Pr(Kurtosis)*	---------- *joint* ----------	
				chi2(2)	*Prob > chi2*
residuals	1197	0.000	0.047	32.81	0.000

Table 4.18 OLS Residuals – Base Model

Percentiles		*Smallest*	*Obs.*	1197
1%	-39.882	-69.607	*Sum of Weights*	1197
5%	-29.695	-52.951		
10%	-24.256	-47.765		
25%	-14.592	-47.030		
			Mean	4.52e-09
50%	-1.396		*Std. Dev.*	19.881
		Largest		
75%	12.758	66.198		
90%	24.769	67.671	*Variance*	395.265
95%	33.818	67.714	*Skewness*	0.392
99%	54.041	68.292	***Kurtosis***	**3.302**

Looking at the Table 4.19, we also reject the joint null that skewness and kurtosis of the residuals for the zombie model are significantly different from skewness and kurtosis of the normal distribution at the 1% level, suggesting that residuals are not normally distributed. Interestingly, the reverse conditions of the base model hold true for the Zombie model. That is, unlike the base model, where residuals' kurtosis is similar to that of normal distribution, the *p*-value of 0.947 for skewness indicates that the skewness of the residuals in the zombie model is not significantly different to that

of the normal distribution. In fact, as shown in Table 4.20, the skewness of residuals is 0.007, which is very close to zero, the skewness of the normal distribution.

Table 4.19 Test for Normality (Skewness and Kurtosis) – Zombie Model

Variable	*Obs.*	*Pr(Skewness)*	*Pr(Kurtosis)*	---------- *joint* ----------	
				chi2(2)	*Prob > chi2*
residuals	572	0.947	0.000	18.04	0.000

Table 4.20 OLS Residuals – Zombie Model

Percentiles		*Smallest*	*Obs.*	572
1%	-43.915	-91.164	*Sum of Weights*	572
5%	-28.252	-68.830		
10%	-22.488	-49.680		
25%	-13.052	-46.587		
			Mean	-1.81e-08
50%	0.328		*Std. Dev.*	18.716
		Largest		
75%	11.919	57.847		
90%	20.839	57.869	*Variance*	350.278
95%	31.220	57.926	***Skewness***	**0.007**
99%	53.000	59.722	*Kurtosis*	4.304

Furthermore, as can be seen from Table 4.21 and Table 4.22, the corresponding *low p-values* for the SW tests suggest the rejection of the null of normal distribution for both models. However, the *W* statistics of close to 1 suggests that the residuals for both models are actually very close to being normal.

Table 4.21 Test for Normality (Shapiro-Wilk) – Base Model

Variable	*Obs.*	*W*	*V*	*z*	*Prob > z*
residuals	1197	0.989	8.047	5.202	0.000

Table 4.22 Test for Normality (Shapiro-Wilk) – Zombie Model

Variable	*Obs.*	*W*	*V*	*z*	*Prob > z*
residuals	572	0.987	5.119	3.949	0.000

In sum, even though the results from the SK tests and the SW tests suggest that residuals are not normally distributed in either of our estimation models, the degree of non-normality seem to be at a very moderate level, given the individual *p-value* for the skewness (for zombie model) and kurtosis (for base model) in the SK test and the close to 1 values of W in the SW tests.

Thus, although the numerical tests can tell us whether or not residuals are normally distributed, they do not specify the degree and non-normality. To make a better judgment on the severity of the non-normality and to decide if any correction is needed, we combine the statistical tests with a number of diagnostic plots, as it is easier to look at a graphical presentation of the residuals' distribution and see how it compares to a normal distribution. The graphical tests for normality are the Kernel Density (KD) plot, the Standardised Normal Probability (SNP) plot, and the Quantiles on Quantiles (QQ) plot, which are combined and presented in Figure 4.3 and Figure 4.4 for the base model and the zombie model, respectively.

Similar to simple histograms, Kernel density estimators merely approximate the density $f(x)$ from observations on x, x being the residuals in this case[172]. The KD plot essentially graphs the kernel density of the residuals overlaid by a normal density plot. By looking at the KD plot, we can obtain an understanding of the distance of the residuals' distribution from normality[173]. The SNP plot estimates the probability of normal distribution by comparing the distribution of the residuals against the normal distribution, which is presented by a 45-degree line. The QQ graph, or what Miller (1997) refers to as the "probit plotting", is used to plot the quantiles of residuals against the quantiles of a normal distribution, using the same procedure as the SNP. In a way, the SNP and the QQ plot complement each other. That is, while the SNP is sensitive to non-normality in the middle range and emphasizes the centre of the distribution, the QQ plot is sensitive to non-normality near the end points and focuses on the tails of the distribution. Accordingly, considering the two plots together should provide us with a more coherent and better understanding of the degree of non-normality.

[172] Kernel density estimates are typically preferred over histograms because of the smoother shape and their independence to the choice of origin. See, Salgado-Ugarte *et al.* (1993) for more details.
[173] The bandwidth size is decided following the test the graph method suggested by Silverman (1978).

Although we present all three graphical measures, following the strong recommendation of Miller (1997: pp. 13-14): "*if a deviation from normality cannot be spotted by eye on probit paper, it is not worth worrying about*", we assign a greater weight to the QQ plot. As can be seen from Figure 4.3 and Figure 4.4, the KD plots suggest only very minor deviations in the distribution of the residual from the normal distribution density. Furthermore, the SNP plots show no indication of non-normality, as the residual values fall along the diagonal with no substantial or systematic departures. Finally, except for the slight deviations at the upper tails, the QQ plots suggest that the distribution of residuals and the normal distributions seem highly matched, quantiles on quantiles.

Figure 4.3 Test for Normality (KD, SNP, and QQ Plots) – Base Model

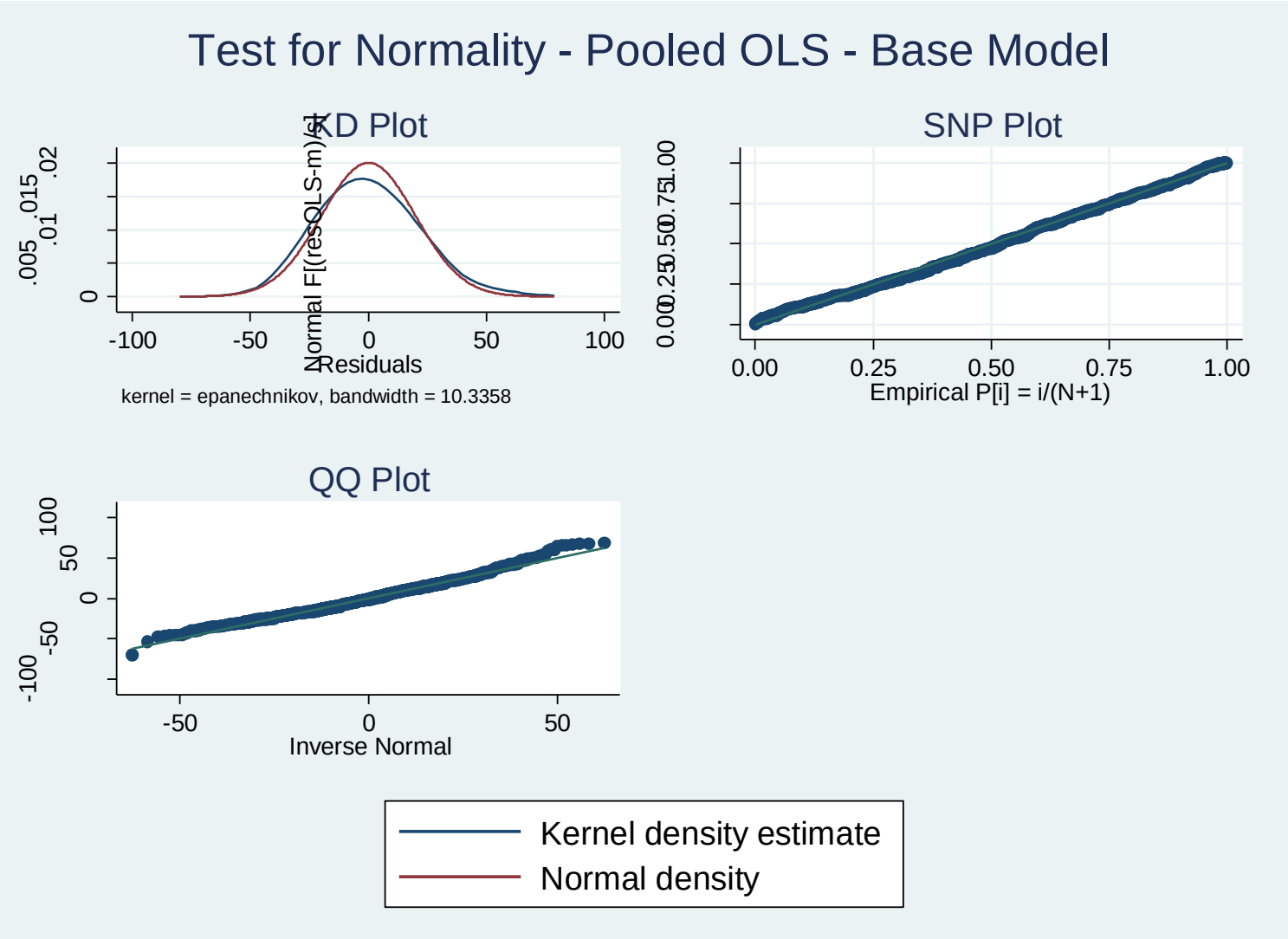
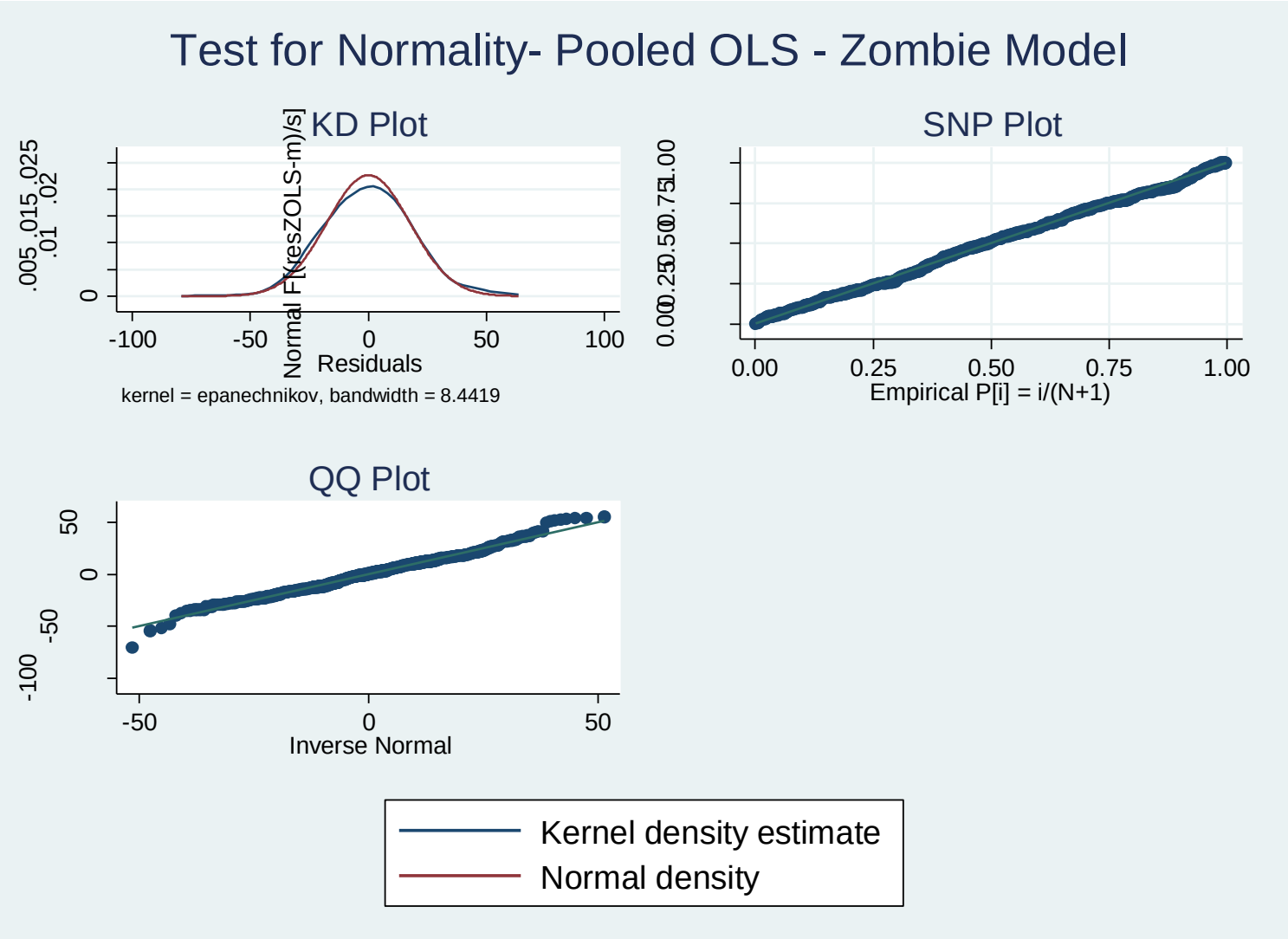


Figure 4.4 Test for Normality (KD, SNP, and QQ Plots) – Zombie Model



In sum, the results of the numerical and graphical tests suggest that the distribution of residuals only marginally deviate from the *perfect* normal distribution. However, given the moderately large sample, we do not expect our significance tests and coefficient inferences to be significantly affected, if at all, by the violation of the normality assumption.

That is, despite the marginal non-normality of the residuals, as the sample size increases, standard errors for both skewness and kurtosis decrease and hence the significance tests and inferences about coefficients become more reliable (Gujarati, 2004; Tabachnick and Fidell, 2006; Greene, 2008; Hair *et al.*, 2010; and Williams *et al.*, 2013). The proof is based on the Central Limit Theorem (CLT), which implies that, assuming some reasonably minimal preconditions, the distribution of the arithmetic mean of the independent random variables approaches a normal distribution as the number of variables approaches infinity (Fischer, 2011). Consistent with this argument, William Green (2010: p. 69) also notes that: "*if the regressors are well behaved and observations are independent, the* ***asymptotic normality*** *of the least squares estimator does not depend on normality of the disturbances; it is a consequence of the central limit theorem*". Accordingly, although we acknowledge the minor degree of non-normality in the residuals of the static models, it is not going to be a significant concern for our analysis[174].

4.3.3.1.2. Test of Homoscedasticity

We next test for homoscedasticity of the residuals; more specifically, we are interested to know if there is evidence of heteroskedasticity (i.e., lack of homoscedasticity) in the residuals. Given that homoscedasticity refers to constant variance of the residuals, the presence of heteroskedasticity implies that variance of the residuals is not constant across observations (Greene, 2008). Heteroskedasticity may occurs due to many different reasons, such as existence of outlier, model misspecification, incorrect data transformation, skewness in the distribution of independent variables, which are also common causes for non-normality of the residuals[175]. Accordingly, given the detected non-normality of the residuals, we would also expect to find some degrees of

[174] For the purpose of illustration, the graphical diagnostics for normality for the RE and FE estimation of both the base model and the zombie model are presented in Figures 8.1 to 8.4 in the Appendix.
[175] For a great discussion of the possible sources of heteroskedasticity see Chapter 11 in Gujarati (2004).

heteroskedasticity in the residuals (Tabachnick and Fidell, 2006). Although heteroskedasticity does not cause the parameter estimates to be biased or inconsistent, it may lead to inefficient and unreliable coefficient inferences (Weisberg, 2005; Greene 2008). That is, while the coefficient estimates themselves are unaffected, the presence of heteroskedasticity of residuals leads to biased standard errors, which in turn may result in inaccurate confidence intervals and biased p-values for the significance tests.

Since OLS assumes constant residual variances, by construction it gives equal weight to all observations. However, in the presence of heteroskedasticity, residual variances vary across observations and observations with larger variance of residuals tend to contain less information than observations with smaller residuals' variance. Accordingly, by allocating equal weights to all observations, OLS effectively gives larger weights than it should to observations containing small information and vice versa, hence leading to biased t-statistics and confidence intervals (Gujarati 2004; Greene 2008). Consistent with this argument, Wooldridge (2002: p. 125) notes that: "*heteroskedasticity does not affect the consistency of the estimators, and [rather] it is only a minor nuisance for inference*". Accordingly, to assure reliable coefficient inferences, we must test for the presence of heteroskedastic residuals in our regression models. The two commonly used statistical tests for detecting heteroskedasticity in OLS regressions are the Breusch-Pagan (1979) and Crook-Weisberg's (1983) test and the White's (1980) test. We perform both tests, to ensure reliability of the results.

The Breusch-Pagan/Crook-Weisberg (BP/CW) test for heteroskedasticity is designed to detect any linear form of heteroskedasticity and tests the null hypothesis that variances of the error are homoscedastic against the alternative that they are not.

The standard form of the BP/CW test in Stata, performed through **`hettest`** command, assumes residuals' normality and uses fitted values of the dependent variable to check for heteroskedasticity, hence detect heteroskedasticity by modelling the variance as a function of the fitted values only. However, given that the assumption of homoscedasticity requires the variance of the residuals *conditional on the values of the explanatory variables* to be constant, we proceed with testing for

heteroskedasticity of residuals as a function of the right-hand side variables, by specifying the option **`rhs`**[176].

We also conduct the White's (1980) general heteroskedasticity test, which is designed to detect heteroskedasticity as a function of an auxiliary set of variables by regressing the squared residuals on all unique terms in the product and cross-product of the independent variables. However, it should be noted that while the White test allows detecting non-linear heteroskedasticity, it may be less powerful than the BP/CW test because of the significantly greater degrees of freedom caused by the inclusion of the cross-product and interaction terms of the independent variables (Greene, 2000)[177].That is, the addition of all these additional terms may make the test less likely to produce a significant result than a less general test would.

Nonetheless, we include both tests to obtain more reliable results regarding the presences of heteroskedasticity, as BP/CW test is more appropriate for testing linear heteroskedasticity and the White test is more appropriate for testing non-linear heteroskedasticity. The results of the heteroskedasticity tests for the base model and the zombie model are reported in Table 4.23 and Table 4.24, respectively.

Table 4.23 Tests for Heteroskedasticity – Base Model

Test	*Chi2*	*D.O.F.*	*Prob > Chi2*
Breusch-Pagan/Cook-Weisberg	31.33	14	0.005
White's general	127.31	83	0.001

Table 4.24 Tests for Heteroskedasticity – Zombie Model

Test	*Chi2*	*D.O.F.*	*Prob > Chi2*
Breusch-Pagan/Cook-Weisberg	121.07	12	0.000
White's general	209.95	74	0.000

[176] Furthermore, given the detected non-normality of the residuals, the **iid** option is used to relax the test's default assumption of normality.

[177] Greene (2000) proposes an alternative version of the White test, where the squared residuals are regressed against the fitted values and their squares. However, as discussed before, despite its higher degrees of freedom, the standard general white test is preferred to the modified version as it tests for heteroskedasticity by modelling the variance of residuals as function of the *independent variables* which is merely what the OLS assumption implies.

As can be seen from both tables, both tests produce small *p-values*, suggesting the rejection of the null hypothesis. The difference in the degrees of freedom (D.O.F.) for the chi-squared statistics stems from the number of regressors included in the auxiliary regression. For BP/CW test the degrees of freedom of 14 and 12 for the base model and zombie model, respectively, indicate the number of the independent variables. Whereas, the degrees of freedom for the White test come from adding an auxiliary variable list containing the squared and cross-product of the all the independent variables, 83 and 74 for the base model and the zombie model, respectively. Given that both tests of heteroskedasticity test the null hypothesis that residuals are homoscedastic, the rejection of the null due to low *p-values*, provide strong evidence for the presence of heteroskedasticity.

The standard econometric remedy for dealing with heteroskedasticity is to use the Huber-White (HW) estimator, which produces heteroskedasticity-robust standard errors (Greene, 2000; Baltagi, 2005; Cameron and Trivedi, 2010)[178]. While the OLS estimators assume the error terms to be Identically and Independently Distributed (*i.i.d*) and thus become biased in the presence of heteroskedasticity, the HW's robust standard errors estimators are more reliable in such events as they relax the identical distribution assumption (Greene, 2000)[179]. Accordingly, using the robust standard error estimator does not affect the coefficient estimates, but merely changes the standard errors, which will lead to more accurate and unbiased p-values and significance tests. Consistent with this argument, Wooldridge (2002: p. 57) notes that: "*these [robust] standard errors are asymptotically valid in the presence of any kind of heteroskedasticity, including homoscedasticity*". Accordingly, given that heteroskedasticity is a common occurrence in panel data with independent panel units, researchers tend to routinely use heteroskedasticity-robust standard errors in their OLS

[178] While the robust variance matrices were introduced by Huber (1967), White (1980) was the first to develop the heteroskedasticity-robust variance matrix estimator.

[179] Other remedies include transformation of the variables (i.e., model re-specification) and use of Weighted Least Squares (WLS). However, re-specifying the model to capture non-linear or quadratic relations and transformation of the commonly used scaled variables is expected to significantly affect the nature of our estimation model, distorting the basis of our analysis relevance to the existing theoretical and empirical predictions of the capital structure literature. Furthermore, given that in order to use the WLS estimator, one must know all the weights (i.e., as x increase (decrease) by how much the residuals increase (decrease)) or a plausible theory for what the weights should be, it is very rarely used. Accordingly, the above concerns motivate us to follow the common practice and use the robust standard errors to control for the heteroskedasticity of residuals.

regressions, including pooled OLS, Random Effect or Fixed Effect models (Cameron and Trivedi, 2009)[180].

Stata allows using heteroskedasticity-robust standard errors for all OLS estimators via the **robust** option. Thus, following the same approach, we use robust standard errors in all estimations of the static models, and given that the coefficients are exactly the same as in ordinary OLS, we only report and comment on the heteroskedasticity-robust regression results[181]. Having addressed the non-normality and heteroskedasticity concerns, we proceed to the estimation results.

4.3.3.2. Pooled OLS

The first and simplest approach to estimate Eq. (4.7) is to ignore the panel structure of the data and apply pooled Ordinary Least Squares (OLS) estimator. The pooled OLS estimator assumes independence within firms and ignores the possible time-specific effects that are common across all firms. Accordingly, the pooled OLS estimator estimates the following regressions for the base model and the zombie model, respectively:

$$Leverage_{it} = \alpha_0 + \beta_1 GRT_{it} + \beta_2 PRF_{it} + \beta_3 TNG_{it} + \beta_4 SIZ_{it} + \beta_5 NDTS_{it} + \beta_6 RSK_{it} + \gamma_1 YR_{2004} + \gamma_2 YR_{2005} + \gamma_3 YR_{2006} + \gamma_4 YR_{2008} + \gamma_5 YR_{2009} + \gamma_6 YR_{2010} + \gamma_7 YR_{2011} + \gamma_8 YR_{2012} + \varepsilon_{it}. \quad (4.9)$$

$$Leverage_{it} = \alpha_0 + \beta_1 GRT_{it} + \beta_2 PRF_{it} + \beta_3 TNG_{it} + \beta_4 SIZ_{it} + \beta_5 NDTS_{it} + \beta_6 RSK_{it} + \beta_7 ZMB_{i,t-1} + \gamma_1 YR_{2008} + \gamma_2 YR_{2009} + \gamma_3 YR_{2010} + \gamma_4 YR_{2011} + \gamma_5 YR_{2012} + \varepsilon_{it}. \quad (4.10)$$

Table 4.25 and Table 4.26 report the coefficient estimates and the standard test-statistics for the pooled OLS estimation of the base model and the zombie model,

[180] For the purpose of illustration, the tests of heteroskedasticity for the random and fixed effect estimations of the static base model and the static zombie model are presented in Tables 8.6 and 8.7 in the Appendix, respectively.

[181] In fact, comparing the results of Table 4.25 and Table 4.26 with the results obtained without the robust standard errors indicates that, while none of the coefficient estimates have changed, the standard errors and hence the t values and p-values are slightly different between estimators with robust standard errors and those with non-robust standard errors. Had there been greater degree of heteroskedasticity in residuals, the difference would have been more significant. The non- heteroskedasticity-robust estimation results obtained from the pooled OLS estimation of the base model and the zombie model are presented in Tables 8.8 and 8.9 in the Appendix, respectively.

respectively; where, the coefficients indicate estimated impact of the respective variables on leverage ratio, the robust standard errors are the Huber-White heteroskedasticity standard errors associated with the coefficients, and the t and $p > |t|$ are the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively. We also report a number of post-estimation tests and statistics to evaluate the estimated models' overall fit. Where, Obs. denotes the (N) number of observations; the F-statistic ($k, N-k$) tests the joint null hypothesis that all coefficients except the constant are zero, and is computed for ($k-1$) parameters and ($N-k$) degrees of freedom, and $P > F$ is used as the p-value to test the null. Furthermore, we report the R^2 and the adjusted-R^2, which indicate the proportion of the variation in the dependent variable explained by the model, as a relative measures of goodness-of-fit of the model[182]; and finally the Root Mean Square Residuals ($RMSE$), which indicates the standard deviation of the error term, is included as an absolute measure of the goodness-of-fit (i.e., the same unit as the dependent variable).

Accordingly, the *F-statistics* and the associated small *p-values* for both models suggest a strong rejection of the null that all coefficients are zero. That is, the included explanatory variables in the models are indeed able to explain the leverage ratios. While the R^2 values of 0.28 (base model) and 0.27 (zombie model) are within the reasonable range, the minor differences between the values for R^2 and *adjusted-*R^2 and the negligible loss in the explanatory power, further indicate a lack of overfitting in both models. Finally, the values for the *RMSE* show that the average distance of the estimator from the mean in estimating leverage ratios is 19.99% for the base model and 18.91% for the zombie model. To make better sense of the *RMSE* measure, we can calculate the Normalised *RMSE (NRMSE)*, which measures how big the standard deviation of the error in estimating the leverage ratios is relative to the range of values for leverage ratio[183]. Accordingly, given that the leverage ratio (*LVG*) is restricted in the range of 0% and 100%, the *NRMSE* of 19.99% and 18.91% seem fairly reasonable. Accordingly, overall, both models seem to do a decent job in explaining the leverage ratios.

[182] While R^2 increases with the number of regressors, irrespective of their explanatory power, the adjusted-R^2, computed as $1 - \frac{(1-R^2)(N-1)}{(N-k-1)}$, is the R^2 which is adjusted for the number of parameters in the model and that penalises inclusion of irrelevant explanatory variables.

[183] The *NRMSE* is calculated as: $\frac{RMSE}{(Maximum\ Value\ Dependent\ Variable - Minimum\ Value\ Dependnet\ Variable)}$.

As presented in Table 4.25 and Table 4.26, the coefficient estimates on the firm-specific determinants of capital structure show a great degree of consistency in the sign and statistical significance across the two models. In fact, except for the *RSK* coefficient that is insignificant in the base model but becomes significant in the zombie model, all firm-specific determinants of capital structure have been found to have a significant impact on leverage with the direction of their respective impact being consistent across both models.

Furthermore, the directions of the effects for all firm-specific variables are in line with the predictions of the theories of capital structure[184]. More precisely, the positive coefficients on *GRT*, *NDTS* and *RSK* and the negative coefficient on *PRF* can be explained via the pecking order theory. However, the positive coefficient on *SIZ* is only justified under the trade-off and the agency theories of capital structure. Finally, there has been a mutual agreement among the three theories on the positive impact of asset tangibility on the amount of debt employed in firms' capital structure, and hence the positive coefficient on *TNG*.

The pecking order theory suggests that, due to the information asymmetries between new investors and managers about the firms' true values, firms would prefer to finance new investment by using their internal funds rather than raising external finance. Likewise, if external financing is required, debt is always preferred to equity, because of the smaller associated adverse selection problem. Finally, equity would only be issued as a last resort, when the risk of bankruptcy due to large amounts of debt is sufficiently high. Accordingly, with regard to the possible determinants of capital structure, the pecking order theory suggests that firm-specific characteristics that may imply greater information asymmetries or smaller internal sources of finance are expected to be correlated with higher leverage ratios. In the same way, firm characteristics that may suggest greater sources of funds to internally finance investment activities or less severe adverse selection problem associated with equity issues, are expected to be negatively correlated with leverage ratio.

[184] Since the final estimation model for our analysis is of dynamic nature and is estimated using system GMM estimator, and given that the static models are potentially misspecified in the sense they ignore the theoretical and empirical evidence for the dynamic nature of capital structures, we do not comment on the coefficients' magnitudes and empirical interpretation and only briefly discuss the theoretical prediction for each coefficient. The detailed discussion of the coefficients in the context of both theoretical predictions and the empirical expectations, for the final models are provided in Sections 4.3.4.2. and 4.3.4.3.

Accordingly, assuming constant profitability and internal sources of finance, an increase in growth and investment opportunities, would imply a greater need for external financing and a higher leverage ratio, considering the smaller information asymmetries associated with debt issues than equity issues. Furthermore, given that retained earnings are the main source of internal financing, income statement items that contribute to the reduction in retained earnings are expected to increase the probability of firms' internal funds falling short of its financing needs, and thus lead to larger debt component in their capital structure, *ceteris paribus*. Accordingly, as depreciations and amortizations expenses, which are the main components of the non-debt tax shields, are expense items and thus counted against the retained earnings, the reported positive impact of *NDTS* on leverage ratio is in line with the prediction of the pecking order theory. Similarly, highly unstable earnings are also expected to impair the ability of the firm to finance its investments internally, and thus increase the likelihood of the firm requiring external funds issuing additional debt. This in turn, implies a positive relation between the measure of earnings' volatility (*RSK*) and leverage ratio, which we only find supporting evidence for, in the estimation of the zombie model. However, the theory suggests that the inverse must also hold true. That is, as profitability increases, the ability of the firm to internally finance its investment activities improves, suggesting that the need for external financing via debt issues is expected to decrease. Consistent with this prediction, we also find a negative relation between *PRF* and leverage ratio.

The positive impact of firm size on the debt component of capital structure has been predicted by the trade-off and the agency theory. They propose that, since large firms are typically more diversified with greater assets-in-place than small firms, they are less prone to bankruptcy and hence face lower costs of bankruptcy and agency costs of debt, suggesting a greater incentive for debt financing. Furthermore, to the extent that lager firms have greater free cash flows, debt becomes valuable as a disciplinary tool to mitigate the agency costs of free cash flows. Thus, both theories predict that, larger firms have the incentive to employ greater debt components in their capital structure, implying a positive relationship between *SIZ* and leverage ratio.

Finally, the trade-off and the agency theory imply that unlike intangible assets, tangible assets, which are often used as collaterals against which firms tend to borrow,

are expected to reduce bankruptcy and agency costs of debt. That is, while the value of intangible assets such as goodwill or brand recognition are extremely sensitive to the financial health of the firm and almost wipes out in the event of bankruptcy, tangible assets are less likely to suffer from substantial loss in value, should the firm default. Furthermore, tangible assets are more difficult to manipulate and be replaced with riskier assets (i.e., excessive risk taking), thus firms with high degrees of tangible assets are less prone to the risk-shifting problem, and hence are expected to face lower agency costs of debt. Finally, the pecking order theory implies that, given that tangible assets are easy to value, the information asymmetries about their true value and hence the adverse selection problem associated with issuing equity is less likely to be substantial for firms with high level of tangible assets. Accordingly, all three theories suggest a positive relation between tangible assets and the debt component of the capital structure, and thus predict a positive impact of asset tangibility on leverage ratios, hence the positive coefficient on *TNG*.

As can be seen from Table 4.26, the zombie model contains *ZMB* as an additional variable that is included to capture the impact of being zombie on the leverage ratios. Since *ZMB* is a dummy variable that takes a value 1 if firm is identified as zombie and 0 otherwise, a statistically significant coefficient suggests significant differences in the leverage ratios of zombies compared to non-zombies. As discussed in Section 2.3.5.4, due to lack of theoretical and empirical evidence on the subject of zombies and the determination of their capital structure, there are no *a priori* expectations regarding the impact of being zombie on leverage ratios. Having said that, recalling the discussion regarding the possible causes of the emergence of zombies, to the extent that the banks' loan forbearances and the rescue packages offered by the government had involved additional lending to the zombies and significantly increased their leverage ratios, we would expect to find a positive coefficient on *ZMB*, suggesting that zombies tend to have higher leverage ratios than non-zombies. However, as suggested by its high *p-value* we find that the difference between the leverage ratios of zombies and non-zombies is not statistically different than zero, suggesting no strong evidence for the positive impact of being zombie on leverage ratio.

Recalling Section 2.3.4.2, we include a set of annual time dummy variables for the period 2004-2012, with 2007 (the onset of the Global Financial Crisis (GFC)) as the

base year, to capture the impact of the recent GFC on firm's leverage ratio, while controlling for the firm-specific determinants of capital structure[185]. The significant coefficients on the year dummies indicate that, controlling for all other factors, the overall economic condition tend to have a significant impact on the leverage ratios, especially in the years after the GFC.

As presented in Table 4.25 and Table 4.26, the coefficient estimates on the annual time dummies show a great degree of consistency across the two models. That is, although the base model is estimated over the full sample period 2004–2012 and the zombie model is estimated over the period 2008–2012, the coefficients on the common annual time dummies (i.e., *YR08*, *YR09*, *YR10*, *YR11* and *YR12*) show consistency in both sign and magnitude across both models[186].

Furthermore, Table 4.25 shows that, except for 2004 which indicate a positive and significant coefficient, all annual time dummies with statistically significant coefficients have a negative sign. However, it should be noted that since 2007 is the base year, the negative coefficients on the annual time dummies refer to opposite leverage ratios trends depending on whether they are before or after the base year. That is, for years before 2007 the negative coefficients suggest an increasing trend in leverage ratios, whereas and the negative coefficients on the annul time dummies for years after 2007 are actually an indication of a decreasing trend in leverage ratios.

Accordingly, the negative estimated coefficients for the years after 2007 suggest that, firms tend to have significantly lower leverage ratios, compared to the year the GFC started[187]. However, the reverse pattern holds for the years towards the crisis, as the negative coefficients on the annual time dummies for 2004, 2005 and 2006, suggests an increasing trend in the leverage ratios over time. Nevertheless, the relative change in leverage ratios seems to be statistically significant only for 2004, and not significantly different than zero for 2005 and 2006, as suggested by their high *p-values*.

[185] Each annual time dummy acts as an aggregate measure containing all macroeconomic variables external factors in the respective year.
[186] The small differences in magnitude may be due to the exclusion of the firm-year observations for which the zombie indictor cannot be computed or the measure is not meaningful for example firms with missing values for total interest expense, or firms with negative AICR.
[187] It should be noted that even though leverage ratios indicate a minor increase in 2008, the difference is not statistically different than zero, and hence the insignificant positive coefficient

Recalling the generic expectations of capital structure theories about the impact of macroeconomic conditions on leverage ratios (see, Section 2.3.4.1), we find the reported negative coefficient estimates for the annual time dummies consistent with the predictions of the trade-off theory, as it implies that firms are more likely to operate at higher leverage ratios in expansionary economic environments (i.e., 2004-2007), where tax benefits of debt financing are expected to be higher while bankruptcy costs associated with debt are expected to be low. With the same logic, firms are expected to reduce their level of indebtedness in a recessionary economic environment expected after financial crises, where the conditions reverse.

Table 4.25 Static – OLS – Base Model

Leverage	*Coef.*	*Robust Std. Err.*	*t*	*P > | t |*
GRT	0.043	0.008	5.140	0.000
SIZ	10.611	0.762	13.920	0.000
TNG	0.190	0.027	6.980	0.000
PRF	-0.596	0.119	-5.000	0.000
NDTS	1.204	0.222	5.420	0.000
RSK	0.001	0.039	0.020	0.986
YR04	-4.109	2.472	-1.660	0.097
YR05	-1.140	2.554	-0.450	0.656
YR06	-3.086	2.484	-1.240	0.214
YR08	0.707	2.536	0.280	0.781
YR09	-7.951	2.531	-3.140	0.002
YR10	-11.264	2.459	-4.580	0.000
YR11	-11.571	2.515	-4.600	0.000
YR12	-12.238	2.635	-4.640	0.000
_cons	-190.254	16.314	-11.660	0.000
Obs.				1197
F (14, 1182)				38.19
Prob > F				0.000
R^2				0.282
Adjusted-R^2				0.274
RMSE				19.999

Where, the analysis period is 2004–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; $YR04–YR12$ are the annual time dummies with 2007 used as the base year; *Robust Std. Err*. denotes the Huber-White heteroskedasticity standard errors; and t and $p > |t|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 4.26 Static – OLS – Zombie Model

Leverage	*Coef.*	*Robust Std. Err.*	*t*	*P > | t |*
GRT	0.097	0.032	3.030	0.003
SIZ	8.803	1.629	5.400	0.000
TNG	0.190	0.039	4.800	0.000
PRF	-0.640	0.162	-3.950	0.000
NDTS	1.412	0.366	3.850	0.000
RSK	0.083	0.034	2.420	0.016
ZMB	4.123	3.143	1.310	0.190
YR08	0.720	2.951	0.240	0.807
YR09	-8.981	2.872	-3.130	0.002
YR10	-12.732	2.795	-4.550	0.000
YR11	-9.807	2.757	-3.560	0.000
YR12	-12.401	2.874	-4.320	0.000
_cons	-159.287	39.348	-4.050	0.000
Obs.				572
F (12, 559)				18.45
Prob > F				0.000
R^2				0.273
Adjusted-R^2				0.257
RMSE				18.916

Where, the analysis period is 2008–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; ZMB denotes a dummy variable takes a value of 1 if firm is identified as zombie and 0 otherwise; $YR08$–$YR12$ are the annual time dummies with 2007 used as the base year; *Robust Std. Err*. denotes the Huber-White heteroskedasticity standard errors; and t and $p > |t|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

4.3.3.3. Panel Estimators

Since panel data relate to individual units over time, there is bound to be heterogeneity in these units (Greene, 2008). For instance, firms may differ in their management competence and quality, reputation, political influence, geographical locations, capital intensity, etc., which generally do not change over time. Similarly, there may be time-specific factors such as macroeconomic shocks or events in a particular year that affect all the firms; for instance, availability of credit, implementation of expansionary or contractionary monetary and fiscal policies, etc. Accordingly, as long as these unobserved factors are slowly changing (if not strictly time-invariant) or they affect most firms (if not strictly firm-invariant), their impact on capital structure is absorbed by the firm- and time-specific effects, respectively (Lemmon *et al.*, 2008)[188]. Thus, an appropriate estimation method for models with firm- and time-heterogeneity must allow controlling for such effects.

However, the pooled OLS estimator assumes independence within firms and ignores the possible time-specific effects that are common across all firms. Consequently, the possible unobserved firm- and time-specific effects are captured via the time-varying disturbance term, ε_{it}, hence leading to an omitted variable bias (Hsiao, 2003). Thus, we must use alternative and more appropriate estimators for panel data that allow controlling for unobserved heterogeneity. The two commonly used alternative panel data approaches that allow for firm and time heterogeneity are the Random-Effect (RE) and the Fixed-Effect (FE) estimation methods. Recalling, Eq. (4.7) and Eq. (4.8), while both the RE and the FE models assume that the unobserved specific effects (μ_i and λ_t) are uncorrelated with the time-varying error term, they differ in their assumption about the correlation between the unobserved heterogeneity and the included regressors, X_{it} (Greene, 2008). The FE model controls for the unobserved firm-heterogeneity by allowing each firm to have its own intercept value that does not vary over time and assumes μ_i and λ_t are correlated with the included regressors. The RE model, on the other hand, controls for individual differences in the error term by regarding them as random disturbances and assuming μ_i and λ_t to be uncorrelated with the included regressors (Gujarati and Porter, 2010). Having discussed the

[188] In microeconometric applications, the term firm-specific (time-specific) effects are also referred to as many other names, such as unobserved firm (time) heterogeneity, individual (time) effects. As such, we use these terms interchangeably in this Thesis.

econometric arguments on the appropriateness of using panel estimation models in Chapter 3, in this section we will only present the test for heterogeneity and comment on the estimation results for RE and FE models.

4.3.3.4. Random Effects

The RE models use the Generalized Least Square (GLS) estimation procedure and they effectively treat the individual-level effects, μ_i, as an additional random disturbance, hence the term Random Effects. Accordingly, the RE versions of the base model and the zombie model can be written as Eq. (4.11) and Eq. (4.12), respectively:

$$Leverage_{it} = \alpha_0 + \beta_1 GRT_{it} + \beta_2 PRF_{it} + \beta_3 TNG_{it} + \beta_4 SIZ_{it} + \beta_5 NDTS_{it} + \beta_6 RSK_{it} + \gamma_1 YR_{2004} + \gamma_2 YR_{2005} + \gamma_3 YR_{2006} + \gamma_4 YR_{2008} + \gamma_5 YR_{2009} + \gamma_6 YR_{2010} + \gamma_7 YR_{2011} + \gamma_8 YR_{2012} + \varepsilon_{it}. \quad (4.11)$$

$$Leverage_{it} = \alpha_0 + \beta_1 GRT_{it} + \beta_2 PRF_{it} + \beta_3 TNG_{it} + \beta_4 SIZ_{it} + \beta_5 NDTS_{it} + \beta_6 RSK_{it} + \beta_7 ZMB_{i,t-1} + \gamma_1 YR_{2008} + \gamma_2 YR_{2009} + \gamma_3 YR_{2010} + \gamma_4 YR_{2011} + \gamma_5 YR_{2012} + \varepsilon_{it}. \quad (4.12)$$

Where, $\varepsilon_{it} = \mu_i + \nu_{it}$ and is called the "composite-error term". It should be noted that while the RE model controls for time-invariant individual effects via inclusion of an additional error component, the firm-invariant time effects are controlled via inclusion of annual time dummies[189].

Table 4.27 and Table 4.28 report the coefficient estimates and the standard test-statistics for Eq. (4.11) and Eq. (4.12), respectively[190]. Where, *Obs.* is the total number of observations; *No. of groups* denotes the total number of unique firms; *min*, *avg*, and *max* denote the minimum, average and maximum number of observations for unique firms; the *Wald Chi2* tests the joint null hypothesis that all coefficients except

[189] We will formally test for the existence of time effects in Section 4.3.3.4.2.

[190] Given that the results are significantly similar to those observed from the OLS, and to avoid repeating previous explanations, we will only comment on the changes of coefficient estimation between the two estimators.

the constant are zero, and *Prob > Chi2* is used as the p-value to test the null[191]. Furthermore, we report three measures of R^2: the R^2-*between*, which measures the proportion of the variation in the dependent variable between separate panel units explained by the model; the R^2-*within*, which measures the proportion of the variation in the dependent variable within the panel unites explained by the model; and the R^2-*overall*, which is the weighted average of the R^2-*between* and the R^2-*within*. Two measures of the error term are also included as additional measures of the goodness-of-fit of the model: *sigma_u* and *sigma_e*, which measure the standard deviation of the residuals within groups and the standard deviation of the overall residuals, respectively. Finally, *rho (*also known as the measure of interclass correlation), which is calculated as $\frac{(sigma\_u)^2}{(sigma\_u)^2+(sigma\_e)^2}$, is reported to measure the fraction of variance which is due to differences across panels (i.e., individual effects).

As can be seen from Table 4.27 and Table 4.28, the base model is estimated on 1197 observations from 263 separate firms, while the zombie model is estimated on 572 observations from 187 panel units. Furthermore, the *Wald statistics* and the associated small *p-values* suggest a strong rejection of the null that all coefficients are zero for both models. That is, the included explanatory variables are indeed able to explain the firms' leverage ratios. Although the R^2 measures are slightly lower than the pooled OLS, they are still at a reasonable level. Consistent with the pooled OLS estimation, the base model seems to do a slightly better job in explaining the observed leverage ratios than the zombie model. The values for *sigma_e*, which is the equivalent of *RMSE*, indicates significantly better goodness-of-fit in absolute measures as *sigma_e* values for both models are lower than their corresponding *RMSE* values. Furthermore, the values for *sigma_u* suggest moderate degrees of variation in leverage ratios of the firms across time for both models. Finally, the large interclass variation measure (*rho*) indicates that a significant fraction of the variance is actually due to individual differences across firms (i.e., 72.4% and 78.2% for the base model and the zombie model, respectively). The high values of *rho* can be also seen as strong evidence for the presence of firm-specific heterogeneity.

[191] Since the GLS assumes chi-squared distribution, the Wald statistic and the respective *Prob > Chi2* are reported, which are the equivalent of F-statistics and *Prob > F*, respectively, if predicted values are assumed to follow an F distribution.

Turning to the determinants of leverage ratios, the estimated coefficients reported in Table 4.27 and Table 4.28 suggest that, except for the coefficient on *TNG* in the zombie model which becomes marginally insignificant at the 10% level, all firm-specific determinates of leverage are consistent in both sign and significance across the two estimators. There are also no significant differences in the magnitude of the coefficients. Similar to the OLS estimation of the zombie model, the coefficient on *ZMB* remains as positive and insignificant for the RE model, however it decreases by half in size. This suggests that, the estimated impact of being zombie on the leverage ratio was overestimated due to the impact of unobserved heterogeneity effects.

We can see a similar general consistency for the coefficients on the annual time dummy variables. In fact, the reported coefficients for the years after 2007 indicate similar sign and significance across both estimators, with no significant changes in the magnitudes. However, the coefficients on two of the annual time dummies for the years before 2007 seem to have changed. First, the coefficient on *YR04* has changed from negative and significant to negative and insignificant. However, it should be noted that the coefficient ton *YR04* is only marginally significant based on the pooled OLS with *p-value* of 0.097, and thus becoming insignificant when the panel nature of data is accounted for should not be a surprise. Second, the coefficient on *YR05* changes from negative and insignificant to positive and insignificant. However, given that it is not statistically significant in both cases, we do not consider it as a critical change.

Table 4.27 Static – RE – Base Model

Leverage	*Coef.*	*Robust Std. Err.*	*z*	*P > | z |*
GRT	0.039	0.013	3.000	0.003
SIZ	11.776	1.302	9.040	0.000
TNG	0.110	0.056	1.950	0.051
PRF	-0.408	0.101	-4.050	0.000
NDTS	1.032	0.330	3.130	0.002
RSK	0.004	0.008	0.530	0.599
YR04	-1.977	1.878	-1.050	0.292
YR05	0.575	1.637	0.350	0.725
YR06	-2.144	1.314	-1.630	0.103
YR08	0.666	1.538	0.430	0.665
YR09	-5.625	1.658	-3.390	0.001
YR10	-9.012	1.699	-5.300	0.000
YR11	-9.596	1.793	-5.350	0.000
YR12	-10.689	1.947	-5.490	0.000
_cons	-214.166	26.981	-7.940	0.000
Obs.				1197
No. of groups:				263
Obs. per group:			*min*	1
			avg	4.6
			max	9
Wald chi2 (14)				232.08
Prob > Chi2				0.000
R^2*:*			*within*	0.158
			between	0.238
			overall	0.273
sigma_u				17.811
sigma_e				11.000
rho				0.724

Where, the analysis period is 2004–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; $YR04$–$YR12$ are the annual time dummies with 2007 used as the base year; *Robust Std. Err*. denotes the Huber-White heteroskedasticity standard errors; and z and $p > |z|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 4.28 Static – RE – Zombie Model

Leverage	*Coef.*	*Robust Std. Err.*	*z*	*P > | z |*
GRT	0.058	0.021	2.810	0.005
SIZ	11.193	1.894	5.910	0.000
TNG	0.114	0.070	1.630	0.103
PRF	-0.374	0.158	-2.370	0.018
NDTS	0.873	0.474	1.840	0.065
RSK	0.071	0.023	3.140	0.002
ZMB	2.162	2.031	1.060	0.287
YR08	1.789	1.768	1.010	0.312
YR09	-6.648	1.923	-3.460	0.001
YR10	-10.696	1.935	-5.530	0.000
YR11	-10.761	2.048	-5.260	0.000
YR12	-11.487	2.216	-5.180	0.000
_cons	-202.064	41.033	-4.920	0.000
Obs.				572
No. of groups:				187
Obs. per group:			*min*	1
			avg	3.1
			max	6
Wald chi2 (12)				172.21
Prob > Chi2				0.000
R^2*:*			*within*	0.226
			between	0.223
			overall	0.224
sigma_u				18.133
sigma_e				9.585
rho				0.782

Where, the analysis period is 2008–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; ZMB denotes a dummy variable takes a value of 1 if firm is identified as zombie and 0 otherwise; $YR08$–$YR12$ are the annual time dummies with 2007 used as the base year; *Robust Std. Err*. denotes the Huber-White heteroskedasticity standard errors; and z and $p > |z|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

4.3.3.4.1. Test of Heterogeneity

The differences, although small, between the estimated coefficients based on RE and pooled OLS, as well as the high values for *rho* and non-zero values for *sigma_u*, suggest evidence for the presence of heterogeneity across panel units. However, the statistical significance of these individual effects can be formally tested. Accordingly, as an additional post-estimation test, we run the Breusch and Pagan's (1980) Lagrange Multiplier (BPLM) test to formally test for the existence of unobserved individual heterogeneity (u_i) in the data. The BPLM test essentially tells us whether or not pooled OLS can be used to explain the dependent variable. In particular, it tests the null that individual effects are non-existent (i.e., $Var(u_i) = 0$) against the alternative that they do exist. Accordingly, given that the pooled OLS fails to account for the individual differences across panel units, the rejection of the null would suggest that individual heterogeneity is present and hence the pooled OLS is not an appropriate estimator to model the dependent variable.

Table 4.29 reports the results of the BPLM test for both the base model and the zombie model. As can be seen from the table, the small *p-values* for both models suggest a strong rejection of the null, meaning that there is indeed strong evidence of the presence of individual heterogeneity. Thus, the pooled OLS is not an appropriate estimator to estimate either of the models.

Table 4.29 Test for Individual Heterogeneity

Model	*Test: Var(u)=0*	
	chibar2(01)[*]	*Prob > chibar2*
Base Model	1179.77	0.000
Zombie Model	243.59	0.000

[*]chibar2(01) is the test-statistic for the likelihood-ratio (LR) test, evaluating if the variance of the two models are different from zero.

4.3.3.4.2. Test of Time-Effects

As discussed in Section 3.4.7, annual time dummies are included in both of our estimation models to capture the impact of the GFC on leverage ratios, acting as an aggregate measure of all the time-specific factors that have affected all firms. However, econometrically speaking, the inclusion of time dummy variables also controls for the unobservable time heterogeneity (i.e., firm-invariant time effects).

We can also test for the presence of time effects by simply estimating a regression of the leverage ratio with only the annual time dummy variables as explanatory variables, and then perform a Wald test, testing the null that the coefficients on the time dummies are jointly equal to zero. Table 4.30 and Table 4.31 present the results for the auxiliary regression and the corresponding Wald test for the joint significance of the time specific effects for the base model and the zombie model, respectively. Accordingly, given the low *p-values* of the *Wald statistics*, we strongly reject the null hypothesis for both models, suggesting the existence of time effects. Accordingly, the inclusion of the time dummies to capture the aggregate impact of the crisis is indeed justified as they seem to exert a significant influence on borrowing decisions of firms.

Table 4.30 Test for Time Heterogeneity – Base Model

Leverage	*Coef.*	*Robust Std. Err.*	*z*	*P* > | *z* |
YR04	-4.129	1.931	-2.140	0.032
YR05	-0.785	1.814	-0.430	0.665
YR06	-2.647	1.338	-1.980	0.048
YR08	1.313	1.359	0.970	0.334
YR09	-3.352	1.581	-2.120	0.034
YR10	-6.107	1.629	-3.750	0.000
YR11	-6.914	1.767	-3.910	0.000
YR12	-6.143	1.944	-3.160	0.002
_cons	35.992	1.783	20.190	0.000
Wald chi2 (8)				51.07
Prob > χ2				0.000

Table 4.31 Test for Time Heterogeneity – Zombie Model

Leverage	*Coef.*	*Robust Std. Err.*	*z*	*P* > | *z* |
YR08	1.814	1.358	1.340	0.182
YR09	-2.833	1.602	-1.770	0.077
YR10	-5.504	1.704	-3.230	0.001
YR11	-6.322	1.786	-3.540	0.000
YR12	-5.610	1.986	-2.820	0.005
_cons	35.743	1.905	18.770	0.000
Wald chi2 (5)				42.85
Prob > χ2				0.000

4.3.3.5. Fixed Effects

The alternative approach to control for unobserved heterogeneity is the FE model, where unlike the RE, the individual effects are assumed to be correlated with the included regressors. Unlike the RE model that assumes orthogonality between individual effects and regressors, the FE estimator assumes arbitrary correlation between μ_i, which are called individual Fixed Effects, and the observed regressors included in the model. That is, the FE estimator acknowledges that since fixed effects reflect the unobserved heterogeneity among individual firms and are constant over time, they are likely to be correlated with other firm-specific characteristics that vary over time (Baltagi, 2005).

The FE models use the OLS estimation procedure, however, the assumed correlation between the individual fixed effects and the included regressors violates the strict exogeneity assumption of the OLS, and hence lead to inconsistent coefficient estimates. Consequently, as discussed in Section 3.4.3, the FE estimator removes the individual fixed effects from the estimation process by subtracting the individual's mean value of the dependent variable and each regressor from the respective variable. Accordingly, the FE versions of the base model and the zombie model can be written as Eq. (4.13) and Eq. (4.14), respectively:

$$\left(Leverage_{it} - \overline{Leverage_i}\right) = \beta_1\left(GRT_{it} - \overline{GRT_i}\right) + \beta_2\left(SIZ_{it} - \overline{SIZ_i}\right) + \beta_3\left(TNG_{it} - \overline{TNG_i}\right) + \beta_4\left(PRF_{it} - \overline{PRF_i}\right) + \beta_5\left(NDTS_{it} - \overline{NDTS_i}\right) + \beta_6\left(RSK_{it} - \overline{RSK_i}\right) + \gamma_1 YR_{2004} + \gamma_2 YR_{2005} + \gamma_3 YR_{2006} + \gamma_4 YR_{2008} + \gamma_5 YR_{2009} + \gamma_6 YR_{2010} + \gamma_7 YR_{2011} + \gamma_8 YR_{2012} + (\varepsilon_{it} - \overline{\varepsilon}_i). \quad (4.13)$$

$$\left(Leverage_{it} - \overline{Leverage_i}\right) = \beta_1\left(GRT_{it} - \overline{GRT_i}\right) + \beta_2\left(SIZ_{it} - \overline{SIZ_i}\right) + \beta_3\left(TNG_{it} - \overline{TNG_i}\right) + \beta_4\left(PRF_{it} - \overline{PRF_i}\right) + \beta_5\left(NDTS_{it} - \overline{NDTS_i}\right) + \beta_6\left(RSK_{it} - \overline{RSK_i}\right) + \beta_7\left(ZMB_{it} - \overline{ZMB_i}\right) + \gamma_1 YR_{2008} + \gamma_2 YR_{2009} + \gamma_3 YR_{2010} + \gamma_4 YR_{2011} + \gamma_5 YR_{2012} + (\varepsilon_{it} - \overline{\varepsilon}_i). \quad (4.14)$$

Where, $\overline{Leverage_i} = \frac{1}{T}\sum_{t=1}^{T} Leverage_{it}$, $\overline{GRT_i} = \frac{1}{T}\sum_{t=1}^{T} GRT_{it}$, $\overline{SIZ_i} = \frac{1}{T}\sum_{t=1}^{T} SIZ_{it}$, $\overline{TNG_i} = \frac{1}{T}\sum_{t=1}^{T} TNG_{it}$, $\overline{PRF_i} = \frac{1}{T}\sum_{t=1}^{T} PRF_{it}$, $\overline{NDTS_i} = \frac{1}{T}\sum_{t=1}^{T} NDTS_{it}$, $\overline{RSK_i} =$

$\frac{1}{T}\sum_{t=1}^{T} RSK_{it}$, $\overline{ZMB}_i = \frac{1}{T}\sum_{t=1}^{T} ZMB_{it}$, and $\bar{\varepsilon}_i = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_{it}$. The Eq. (4.13) and Eq. (4.14) are also known as the "within-unit estimator" or simply the "within estimator" and remove both the constant term and the individual-effect from the regression[192].

Table 4.32 and Table 4.33 report the coefficient estimates and the standard test-statistics for the within estimator of Eq. (4.9) and Eq. (4.10), respectively. Where, the *F-statistic* tests the joint null hypothesis that all coefficients except the constant are zero, and *Prob > F* is used as the p-value to test the null. In addition, we report the estimated correlation between the individual effects and the included regressors, *Corr(μ_i , Xb)*, to evaluate the arbitrary correlation assumption of the FE model. Recalling the demeaning process of the FE estimator, it should be noted that R^2 value reported after the FE estimator is also obtained by only fitting a mean deviated model, where the individual effects are assumed to be constant and thus are removed from the model with no attempt being made to quantify their overall effect on the fit of the model[193]. Accordingly, given that in Least Squares Dummy Variables (LSDV) estimator lead to virtually the same coefficients estimates and standard errors as th4e FE estimator, while actually estimating the individual effects (through individual dummy variables) and therefore incorporate their effect on the total sum of squares of the model, we report the adjusted R^2 obtained from the LSDV estimation of the model as a measure of the goodness-of-fit of the fixed effect model.

Accordingly, the *F-statistics* and the associated small *p-value* suggest a strong rejection of the null that all coefficients are zero for both models. Furthermore, while, RE by construction assumes the correlation between the individual effects and the included regressors to be zero, the estimated *Corr(μ_i , Xb)* values of -0.089 and -0.392 for the base model and the zombie model, respectively, suggest that fixed effects are moderately correlated with the included regressors in the zombie model, and to a lesser extent for the base model. The adjusted R^2 obtained from the LSDV estimator is significantly higher than the OLS and the RE estimators, indicating a better goodness-of-fit of the model. In addition, contrary to the RE estimator, the higher

[192] As α_0 and μ_i are assumed to be fixed, we have $\alpha_0 = \bar{\alpha}_0$ and $\mu_i = \bar{\mu}_i$, respectively, hence removing $(\alpha_0 - \bar{\alpha}_0)$ and $(\mu_i - \bar{\mu}_i)$ from the equation. However, it should be noted that, the annual time dummy variables are not affected by the demeaning process as they do not vary across firms and hence cannot be averaged.

[193] Similarly, the coefficient on the *_cons* variable reported for the FE model is a coefficient on the average of constant variables, and not the constant for individual firms.

value of *adjusted-R^2* for the FE estimation of zombie model as opposed to that of the base model, suggests that the zombie model seems to do a slightly better job in explaining the observed leverage ratios than the base model.

As expected, the values for *sigma_e*, which indicates the standard deviation of the residuals is the same as for the RE model and lower than those from the pooled OLS, indicating significantly better goodness-of-fit than the pooled OLS model. The values of *sigma_u* also suggest moderate degrees of variation in leverage ratios of the firms across time for both models, although they both are higher than their corresponding values for RE estimation. Finally, the higher values of *rho* (75.7% and 84.2% for the base model and the zombie model, respectively) for both the base model and the zombie model than their corresponding values based on the RE estimator suggest that the FE estimator is able to explain more of the *within* variations that are due to the individual differences across firms, especially for the zombie model where the difference is bigger (6%).

With regards to the firm-specific determinants of leverage in the base model, except for the coefficient on *TNG* in the base model which becomes insignificant at the 10% level, all firm-specific determinates of leverage show consistency in both sign and significance across the two estimators. However, the differences between zombie models are more substantial. As can be seen from Table 4.33, in contrast to the pooled OLS and RE estimations, where the reported coefficients on *ZMB* are positive but insignificant, the FE estimator leads to a positive and statistically significant coefficient on *ZMB*. In fact, the results suggest that, controlling for all other factors, becoming a zombie increases firms' leverage ratios by 3.57%. Recalling the discussion in Section 3.4.7, the positive and significant coefficient on *ZMB* suggest the existence of some additional factors specific to zombies that leads to a significant increase in their leverage ratios. Accordingly, a possible explanation may be that, as part of the government-sponsored support schemes and banks' forbearance on non-performing loans, zombies have been able to obtain additional borrowing, despite their deteriorated ability to repay their existing financial obligations. Finally, as expected the coefficients on the annual time dummies also show great consistency in sign and significance for both models across the two estimators.

Table 4.32 Static – FE – Base Model

Leverage	*Coef.*	*Robust Std. Err.*	*t*	*P > | t |*
GRT	0.040	0.013	3.130	0.002
SIZ	14.387	2.658	5.410	0.000
TNG	0.050	0.133	0.370	0.709
PRF	-0.384	0.105	-3.660	0.000
NDTS	0.956	0.497	1.920	0.055
RSK	0.007	0.009	0.710	0.480
YR04	-0.527	2.134	-0.250	0.805
YR05	1.676	1.659	1.010	0.313
YR06	-1.474	1.348	-1.090	0.275
YR08	0.439	1.690	0.260	0.795
YR09	-5.623	1.838	-3.060	0.002
YR10	-9.110	1.952	-4.670	0.000
YR11	-9.843	2.102	-4.680	0.000
YR12	-11.323	2.339	-4.840	0.000
_cons	-267.369	54.220	-4.930	0.000
Obs.				1197
No. of groups:				263
Obs. per group:			*min*	1
			avg	4.6
			max	9
F (14 , 262)				7.91
Prob > F				0.000
Corr(u_i , Xb)				-0.089
Adjusted-R^2				0.780
sigma_u				19.442
sigma_e				11.000
rho				0.757

Where, the analysis period is 2004–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; $YR04–YR12$ are the annual time dummies with 2007 used as the base year; *Robust Std. Err.* denotes the Huber-White heteroskedasticity standard errors; and t and $p > |t|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 4.33 Static – FE – Zombie Model

Leverage	*Coef.*	*Robust Std. Err.*	*t*	*P > | t |*
GRT	0.057	0.026	2.170	0.031
SIZ	17.237	5.589	3.080	0.002
TNG	0.092	0.178	0.520	0.606
PRF	-0.366	0.177	-2.070	0.040
NDTS	0.215	0.692	0.310	0.075
RSK	0.064	0.020	3.130	0.002
ZMB	3.674	1.993	1.840	0.067
YR08	1.773	2.207	0.800	0.423
YR09	-6.171	2.314	-2.670	0.008
YR10	-10.857	2.286	-4.750	0.000
YR11	-11.674	2.612	-4.470	0.000
YR12	-12.636	2.942	-4.290	0.000
_cons	-319.279	118.088	-2.700	0.007
Obs.				572
No. of groups:				187
Obs. per group:			*min*	1
			avg	3.1
			max	6
F (12 , 186)				13.19
Prob > F				0.000
Corr(u_i , Xb)				-0.392
Adjusted-R^{2*}				0.809
sigma_u				22.151
sigma_e				9.585
rho				0.842

Where, the analysis period is 2008–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; ZMB denotes a dummy variable takes a value of 1 if firm is identified as zombie and 0 otherwise; $YR08$–$YR12$ are the annual time dummies with 2007 used as the base year; *Robust Std. Err*. denotes the Huber-White heteroskedasticity standard errors; and t and $p > |t|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

4.3.3.5.1. Random vs. Fixed Effects

Given the strong evidence supporting the presence of individual effects in our data, as suggested by the rejection of the heterogeneity test conducted in Section 4.3.3.4, and the differences in the ability of the RE and the FE estimators in explaining the within variations that are due to the individual differences across firms (*sigma_u*), we must determine which of the two estimators better models the individual heterogeneity's structure and thus is more appropriate to be used.

While the FE estimator uses the orthogonality conditions that the regressors are uncorrelated with the error term, the RE estimator uses additional orthogonality conditions that the included regressors are uncorrelated with the individual effects. Given that these additional orthogonality conditions are overidentifying restrictions, the test of FE versus RE can be also seen as a test of overidentifying restrictions (StataCorp, 2015). Accordingly, given that the standard Hausman (1978) test requires the homoscedasticity assumption of the residuals to hold and cannot be applied to robust RE and FE estimators, we conduct the Schaffer and Stillman's (2010) test of overidentifying restrictions, which is the asymptotical equivalent of Hausman test under conditional homoscedasticity, to determine which of the two models is better able to explain the data[194].

Table 4.34 reports the results of the test of overidentifying restrictions for both the base model and the zombie model. As indicated by the high *p-value* of the Hansen statistic for the base model, we fail to reject the null hypothesis that the overidentifying restrictions are valid, which implies that the RE estimator is the appropriate estimator to be used for estimating the base model. However, the low *p-value* and large Hansen statistic for the zombie model suggests a strong rejection of the null, meaning that FE estimator is the more appropriate choice to estimate the zombie model.

Furthermore, the choice of appropriate estimator is also consistent with the reported values for the correlation between the individual effects and the included regressors, -0.0893 and -0.392 for the base model and the zombie model, respectively. That is, given that RE assumes zero correlation between the individual effects and included

[194] The robust-Hausman test can be performed through **xtoverid** command in Stata.

regressors, it is a more appropriate estimator than the FE for the base model. However, the strong correlation found between fixed effect and the included regressors for the zombie model suggests that FE is the more appropriate estimator.

Table 4.34 Test of Overidentifying Restrictions – FE vs. RE

Model	*Hansen statistic*	*Prob > Chi2*
Base Model	13.600	0.480
Zombie Model	32.382	0.001

4.3.3.5.2. Test of Time-Effects

As for the RE model, we can also test for the presence of time effects in the FE model. Table 4.35 and Table 4.36 present the results for the auxiliary regression and the corresponding F test for the joint significance of the time specific effects for the base model and the zombie model, respectively. Accordingly, given the low *p-values* of the *F-statistics*, we strongly reject the null hypothesis that the coefficients on the set of annual time dummies are jointly equal to zero, suggesting the existence of time-specific effects and supporting the significant impact of the GFC on firms' leverage ratios in both models.

Table 4.35 Test for Time Heterogeneity – Base Model

Leverage	*Coef.*	*Robust Std. Err.*	*t*	*P > | t |*
YR04	-4.238	2.004	-2.120	0.035
YR05	-0.793	1.841	-0.430	0.667
YR06	-2.580	1.350	-1.910	0.057
YR08	1.562	1.364	1.150	0.253
YR09	-3.046	1.595	-1.910	0.057
YR10	-5.717	1.669	-3.430	0.001
YR11	-6.347	1.823	-3.480	0.001
YR12	-5.564	2.008	-2.770	0.006
_cons	35.6698	1.15804	30.8	0.000
F (8 , 262)				6.11
Prob > F				0.000

Table 4.36 Test for Time Heterogeneity – Zombie Model

Leverage	*Coef.*	*Robust Std. Err.*	*t*	*P > | t |*
YR08	2.270	1.375	1.650	0.100
YR09	-2.322	1.632	-1.420	0.156
YR10	-4.975	1.757	-2.830	0.005
YR11	-5.661	1.855	-3.050	0.003
YR12	-4.916	2.061	-2.390	0.018
_cons	33.968	1.293	26.260	0.000
F (5 , 218)				8.41
Prob > F				0.000

4.3.3.6. Summary

In sum, the strong evidence supporting existence of firm-specific and time-specific heterogeneity and the results of the robust Hausman tests suggest that, RE is the appropriate estimator to estimate the static version of the base model and FE is the appropriate estimator to estimate the static version of the zombie. Table 4.37 present the summary of the estimation results for the base model and the zombie model obtained from the Pooled OLS, the RE and FE estimator.

Accordingly, the reported coefficient estimates under the RE estimator column for the base model suggest that, leverage increases with growth opportunities, firm size, degree of asset tangibility, and the amount of non-debt tax shields, and decreases with profitability. Similarly, with regards for the zombie model, the estimated coefficient on the zombie dummy variable from the FE estimator suggests that, zombies tend to have higher leverage ratios than non-zombies. Furthermore, over the post-crisis period, leverage seems to increase with growth opportunities, firm size and earnings' volatility and decrease with profitability.

Table 4.37 Summary of the Static Models

Variable	*Base Model*[a]			*Zombie Model*[b]		
	Pooled OLS	***RE***	*FE*	*Pooled OLS*	*RE*	***FE***
GRT	0.043***	**0.039*** **	0.040***	0.097***	0.058***	**0.057** **
SIZ	10.611***	**11.776*** **	14.387***	8.803***	11.193***	**17.237*** **
TNG	0.190***	**0.110***	0.050	0.190***	0.114	**0.092**
PRF	-0.596***	**-0.408*** **	-0.384***	-0.640***	-0.374**	**-0.366** **
NDTS	1.204***	**1.032*** **	0.956*	1.412***	0.873*	**0.215**
RSK	0.001	**0.004**	0.007	0.083**	0.071***	**0.064*** **
ZMB				4.123	2.162	**3.674***
YR04	-4.109*	**-1.977**	-0.527			
YR05	-1.140	**0.575**	1.676			
YR06	-3.086	**-2.144**	-1.474			
YR08	0.707	**0.666**	0.439	0.720	1.789	**1.773**
YR09	-7.951***	**-5.625*** **	-5.623***	-8.981***	-6.648***	**-6.171*** **
YR10	-11.264***	**-9.012*** **	-9.110***	-12.732***	-10.696***	**-10.857*** **
YR11	-11.571***	**-9.596*** **	-9.843***	-9.807***	-10.761***	**-11.674*** **
YR12	-12.238***	**-10.689*** **	-11.323***	-12.401***	-11.487***	**-12.636*** **
_cons	-190.254***	**-214.166*** **	-267.369***	-159.287***	-202.064***	**-319.279*** **
Obs.	1197	**1197**	1197	572	572	**572**

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[a] The analysis period for all estimations are 2004-2012.

[b] The analysis period for all estimations are 2008-2012.

Where, $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; ZMB denotes a dummy variable takes a value of 1 if firm is identified as zombie and 0 otherwise; $YR04$–$YR12$ are the annual time dummies with 2007 used as the base year.

4.3.4. Estimation Results - Dynamic Models

So far with the static models and their estimations, as the name suggests, we have ignored the strong theoretical arguments and the empirical support for the dynamic nature of capital structure decisions[195].

However, as for the test of time effects, we can easily test for the presence of dynamic effect and check whether the alternative estimations of the static models (i.e., pooled OLS, RE and FE) suffer from an omitted variable problem.

To do so, we simply estimate a regression of the leverage ratio with only the lagged leverage ratio (*L.LVG*) as explanatory variables, and then perform an F test or a Wald test, depending on the estimator, to test the null that the coefficient on the lagged leverage ratio is not significantly different than zero. Table 4.38 and Table 4.39 present the results for the auxiliary regression and the corresponding F tests and Wald tests for the statistical significance of the 1-year lagged leverage ratio for the base model and the zombie model, respectively.

Accordingly, given the low *p-values* of the *F-statistics* and the *Wald-statistics*, we strongly reject the null hypothesis that the coefficients on the lagged leverage ratio is equal to zero for both models across all estimation alternatives, suggesting the existence of a significant dynamic effect. Thus, the static model is misspecified and hence we proceed with the dynamic models, estimating Eq. (4.15) and Eq. (4.16) for the base model and the zombie model, respectively:

$$Leverage_{it} = \alpha_0 + \beta_1 L.LVG_{it} + \beta_2 GRT_{it} + \beta_3 PRF_{it} + \beta_4 TNG_{it} + \beta_5 SIZ_{it} + \beta_6 NDTS_{it} + \beta_7 RSK_{it} + \gamma_1 YR_{2004} + \gamma_2 YR_{2005} + \gamma_3 YR_{2006} + \gamma_4 YR_{2008} + \gamma_5 YR_{2009} + \gamma_6 YR_{2010} + \gamma_7 YR_{2011} + \gamma_8 YR_{2012} + \mu_i + \lambda_t + \varepsilon_{it}. \quad (4.15)$$

$$Leverage_{it} = \alpha_0 + \beta_1 L.LVG_{it} + \beta_2 GRT_{it} + \beta_3 PRF_{it} + \beta_4 TNG_{it} + \beta_5 SIZ_{it} + \beta_6 NDTS_{it} + \beta_7 RSK_{it} + \beta_8 ZMB_{i,t-1} + \gamma_1 YR_{2008} + \gamma_2 YR_{2009} + \gamma_3 YR_{2010} + \gamma_4 YR_{2011} + \gamma_5 YR_{2012} + \mu_i + \lambda_t + \varepsilon_{it}. \quad (4.16)$$

[195] For more details, see Section 2.3.2.

Where, $L.LVG_{\mathrm{it}}$ is the 1-year lagged leverage ratio and is calculated as $\frac{Total\ Debt_{t-1}}{Total\ Debt_{t-1}+Total\ Equity_{t-1}}$. Following the detailed discussion in Section 3.4, regarding the biased and inconsistent estimates of the pooled OLS, RE and FE estimation methods caused by the violation of strict exogeneity assumption, the 2-step System Generalized Method of Moments (SYSGMM) is used as the most efficient estimator to estimate the above dynamic models.

Table 4.38 Test for the Dynamic Effect – Base Model

Leverage	*Base Model*					
	Pooled OLS		*RE*		*FE*	
	Coef.	*P > | t |*	*Coef.*	*P > | z |*	*Coef.*	*P > | t |*
L.LVG	0.823	0.000	0.727	0.000	0.336	0.000
_cons	5.745	0.000	8.994	0.000	21.709	0.000
F (1 , 1195)		2068.64				
Prob > F		0.000				
Wald Chi2 (1)				742.02		
Prob > Chi2				0.000		
F (1 , 262)						49.92
Prob > F						0.000

Table 4.39 Test for Dynamic Effect – Zombie Model

Leverage	*Zombie Model*					
	Pooled OLS		*RE*		*FE*	
	Coef.	*P > | t |*	*Coef.*	*P > | z |*	*Coef.*	*P > | t |*
L.LVG	0.850	0.000	0.732	0.000	0.333	0.000
_cons	4.407	0.000	8.566	0.000	20.809	0.000
F (1 , 803)		1815.01				
Prob > F		0.000				
Wald Chi2 (1)				407.93		
Prob > Chi2				0.000		
F (1 , 218)						23.16
Prob > F						0.000

4.3.4.1. Model Specification Tests

As noted by Baum (2006), any model misspecifications that violate the underlying assumptions of the estimation method such as serial correlation in the error terms or using inappropriate instruments to account for the endogeneity problem, may render all inferences suspect at best, and completely invalid at worse. Thus, before we proceed to discussing the regression results, we must first ensure that the estimation models used to derive the results are correctly specified. There are two standard specification tests for GMM estimators that are commonly used to ensure estimation models are correctly specified. The first test relates to the serial correlation in the original error terms of the original model, and the second test relates to the validity of the instruments used by the estimator.

It should be noted that, although the lagged dependent regressor (L.LVG) is treated as a predetermined variable and thus can be instrumented using its own lags, choosing different number of lags would imply different model specifications and performances. Accordingly, we examine different specifications for each of the estimation models according to the number of the lagged values of *L.LVG* that are used as instruments. Given that the analysis period for the base model and the zombie model are 2004-2012 and 2008-2012, respectively, we can use up to 8 lags of the *L.LVG* as instruments for the base model and up to 4 lags for the zombie model. Consequently, 8 alternative specifications are tested for the base model and 4 alternative specifications are tested for the zombie model. Table 4.40 and Table 4.41 report the specification tests for alternative GMM specifications of the base model and the zombie model, respectively, based on the number of lags of the predetermined variable used as instruments[196].

4.3.4.1.1. Test of No Serial Correlation in the Error Term

Recalling the discussion in Section 3.4, we know that GMM estimators will only lead to consistent estimates so long as the original error term. ε_{it}, is serially uncorrelated. As noted by Arellano and Bond (1991: p. 278): "*an estimator that uses lags as instruments under the assumption of white noise errors would lose its consistency if in*

[196] The detailed estimation results for each of the alternative specifications are presented in Section B of the Appendix (Tables 7.11 to 7.22).

fact the errors were serially correlated". It is therefore essential to test for the lack of serial correlation of error term.

If the original error term, ε_{it}, is serially uncorrelated, then the First-differenced (FD) error term, $\Delta\varepsilon_{it}$, follows an $MA(1)$ process (i.e., correlated with $\varepsilon_{i,t-1}$), because $Cov(\Delta\varepsilon_{it}, \Delta\varepsilon_{i,t-1}) \neq 0$. Accordingly, if $\Delta\varepsilon_{it}$ follows an $MA(2)$ process, it would then imply that, ε_{it} follows $AR(1)$ process and is no longer serially uncorrelated. Therefore, if ε_{it} is serially uncorrelated, $\Delta\varepsilon_{i,t-1}$ must be uncorrelated with $\Delta\varepsilon_{i,t-k}$ for $k \geq 2$). This can be easily tested after the GMM estimator using the correlation of the fitted residuals, $\Delta\hat{\varepsilon}_{it}$.

In fact, Stata reports the results of the test for no autocorrelation in error terms at the end of the SYSGMM estimation results[197]. The null hypothesis of the no autocorrelation test is that $Cov(\Delta\varepsilon_{it}, \Delta\varepsilon_{i,t-k}) = 0$ for $k = 1, 2$. Accordingly, we expect to reject the null hypothesis of zero autocorrelation at order 1. However, serial correlation in $\Delta\varepsilon_{it}$ at an order > 1 implies that the moment conditions (i.e., instruments) used by the SYSGMM are not valid, and hence the model is misspecified. Thus, we expect not to reject the null hypothesis of no autocorrelation at order 2, if our model is correctly specified.

As can be seen from Table 4.40 and Table 4.41, the low *p-values* for *Arellano-Bond AR(1)* and the high *p-values* for *Arellano-Bond AR(2)* suggest that, the null hypothesis of no autocorrelation at order 1 is strongly rejected, while there are no evidence of serial correlation at order 2 across alternative specifications of both the base model and the zombie model. Thus, there is no evidence of serial correlation in the original error term for either of the estimation models, as desired.

4.3.4.1.2. Test of Overidentifying Restrictions

The second specification test is a test of overidentifying restrictions. A model is said to be overidentified, if the number of instruments are greater than the number of endogenous and predetermined variables. As can be seen from Table 4.40 and Table 4.41, this condition is met for both estimation models. That is, the minimum number

[197] The test of autocorrelation for linear GMM panel regressions was developed by Arellano and Bond (1991). Stata automatically report the Arellano-Bond's no autocorrelation test results after the **xtabond2** command.

of instruments among the base model specifications is 47, which are used to estimate 16 parameters, and hence implies that there are at least 31 overidentifying restrictions for the base model. Similarly, for the zombie model, the minimum number of instruments among the zombie model specifications to estimate the 14 model parameters is 22, which implies that there are at least 8 overidentifying restrictions for the zombie model.

The difference-in-Hansen test (also known as the Hansen test) test is the formal test for overidentifying restrictions and the validity of the instruments, which is automatically reported after the SYSGMM[198]. While we have already tested for the validity of the instruments of the individual endogenous regressors in Section 3.5, given the addition of the instruments for the predetermined variable to the instrument set, we must test if the combined set of instruments is also valid. Similar to the case for individual variables, the null hypothesis is that instruments are valid. As can be seen from Table 4.40 and Table 4.41, we fail to reject the null hypothesis across all alternative specifications for both models. Furthermore, the *p-values* for Hansen test for both estimation models are within the reliable range of $[0.25\ ,1)$, as suggested by Roodman (2009a).

Having confirmed that all the estimation models are correctly specified, we must choose the final specifications for each of the base model and the zombie model from the available alternatives.

4.3.4.1.3. Measures of Relative Goodness-of-Fit

The most common approach to choose among competing model specifications is on the basis of goodness-of fit. Given that there is no single best measure to assess the relative goodness-of-fit among competing models and also to improve reliability of the results, we manually calculate and use 3 alternative measures of model fit to determine the optimal model specification: The Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the Residual Sum of Squares (RSS).

[198] As Sargan test requires the errors to be *i.i.d*, it becomes invalid for SYSGMM estimator with heteroskedasticity-robust standard errors, and thus Hansen test which is the equivalent of Sargan test for robust estimators is used instead (Baum *et al.*, 2003). For detailed discussion of the test of overidentifying restrictions, see Section 3.5.3.

The AIC is calculated as $-2ln(L)+2k$ where $ln(L)$ is the maximised log-likelihood of the model and k is the number of parameters. While the first part of the formula captures model fit, the second component captures complexity as measured by the number of parameters. The constants -2 and 2 indicate the weight to model fit and complexity, respectively, which suggest that while the AIC rewards greater fit, it punishes for the number of parameters. The BIC is also very similar to AIC, except it also controls for the sample size and is calculated as $-2ln(L)+ln(N)k$, where N is the total number of observations[199]. Accordingly, since the model fit component is measured negatively and the complexity component is measured positively, the model with the smaller AIC and BIC values is considered to be better (Bonate, 2006). Furthermore, since RSS measures the proportion of the variation in the dependent variable that is *unexplained* by the model, a lower value of RSS also suggests higher explanatory power and better model fit.

As presented in Table 4.40 and Table 4.41, the lowest values of AIC, BIC and RSS for the base model are reported for the model specification where only the first lag of *L.LVG* is used as instrument, while the lowest value of AIC, BIC and RSS for the zombie model are reported for the model specification with lags 1-4 of the *L.LVG*, meaning that these two model specifications leads to the smallest loss of information and the smallest unexplained variation in leverage ratios. Accordingly, lag 1 of *L.LVG* and lags 3 and 4 of *RSK* are used as instruments for the base model, while lags 1–4 of *L.LVG* are used as instruments in the zombie model. Having determined the final specifications for both of our estimation models, we proceed with discussing the regression results.

[199] Going into details about the underlying theoretical arguments and mechanism of the information criterion measures is beyond the scope of this Thesis, however, more details can be found in Akaike (1974); Schwarz (1978); Kass and Raftery (1995); and Bonate (2006).

Table 4.40 SYSGMM Specification Tests – Base Model

	Alternative Specifications (lag limits) *							
Assessment criteria	*lag (1 1)*	*lags (1 2)*	*lags (1 3)*	*lags (1 4)*	*lags (1 5)*	*lags (1 6)*	*lags (1 7)*	*lag (1 8)*
Wald Chi2(15)	1024.58	1055.87	995.53	981.42	985.19	982.08	968.58	968.69
Prob > Chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
No. of instruments	47	54	60	65	69	72	74	75
Arellano-Bond AR(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Arellano-Bond AR(2)	0.949	0.968	0.994	0.980	0.990	0.996	0.998	0.996
Hansen	0.488	0.326	0.253	0.260	0.308	0.320	0.327	0.358
AIC	6220.707	6241.923	6287.694	6267.422	6301.403	6311.539	6309.081	6307.450
BIC	6302.107	6323.325	6369.095	6348.823	6382.804	6392.940	6390.482	6388.851
RSS	210608.1	214374.5	222730.4	218990.1	225295.9	227211.7	226745.8	226437.0

*The analysis period for all estimation models are 2004-2012.

Table 4.41 SYSGMM Specification Tests – Zombie Model

	*Alternative Specifications (lag limits)**			
Assessment criteria	*lag (1 1)*	*lags (1 2)*	*lags (1 3)*	*lags (1 4)*
Wald Chi2(13)	249.10	274.90	294.58	310.20
Prob > Chi2	0.000	0.000	0.000	0.000
No. of instruments	22	26	29	31
Arellano-Bond AR(1)	0.010	0.039	0.029	0.015
Arellano-Bond AR(2)	0.603	0.181	0.430	0.102
Hansen	0.422	0.184	0.342	0.292
AIC	2989.575	2985.612	3027.719	2954.366
BIC	3050.463	3046.500	3088.607	3015.254
RSS	101388.8	100688.8	108380.4	95336.0

*The analysis period for all estimation models are 2008-2012.

4.3.4.2. Regression Results – Base Model

Recalling the discussion in Section 3.4, given that the pooled OLS estimate of the lagged dependent regressor is biased upward while the FE estimator leads to downward biased estimate of the lagged dependent regressor, their respective coefficients can be used as the upper limit and lower limit of the unbiased and consistent estimate obtained from the SYSGMM, respectively (Bond, 2002; Roodman, 2009b). Accordingly, although we only report and comment on the estimation results obtained using SYSGMM, the OLS and FE estimation of the dynamic models are also presented to provide the approximate upper and the lower bound for the coefficient on the lagged dependent regressor, respectively. Table 4.42 reports the estimation results of the dynamic base model estimated by the pooled OLS and the FE estimators[200]. Accordingly, as can be seen from the table, we expect the coefficient on *L.LVG* based on the SYSGMM estimator to be somewhere in between 0.31 (the lower bound obtained from the FE estimator) and 0.76 (the upper-limit value obtained from the pooled OLS estimator).

Table 4.43 reports the coefficient estimates and the standard test-statistics for the 2-step SYSGMM estimation of the base model as presented by Eq. (4.15); where, the reported coefficients indicate estimated impact of the respective variables on leverage ratio, the corrected robust standard errors are the Windmeijer's (2005) heteroskedasticity-robust standard errors corrected for the finite sample bias; and the z and $p > |z|$ are the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

We also report a few post-estimation tests and statistics to evaluate the estimated models' performance and overall fit. Where, the *Wald Chi2* statistic tests the joint null hypothesis that all coefficients except the constant are zero and *Prob > Chi2* is used as the *p-value* for testing the null. Furthermore, given that Stata does not generate any absolute measure of the goodness-of-the fit of the model after the 2-step SYSGMM estimation, following Windmeijer (1995b) and Bloom *et al.* (2007), we compute the squared correlation coefficient between actual and predicted levels of the dependent variable (i.e., $Corr(LVG_{it}, \widehat{LVG}_{it})^2$) as the measure of assessing the overall

[200] Detailed regression results and post-estimation tests for the pooled OLS and FE estimation of the base model and the zombie model are presented in Section C of the Appendix (Tables 7.23 to 7.26).

fit of the model. *AR(1)* and *AR(2)* are the Arellano-Bond tests for zero autocorrelation in first-difference errors at order 1 and 2, respectively. Finally, the *Hansen J statistic* tests the null hypothesis that the overidentifying restrictions are valid.

Accordingly, as presented in Table 4.43, the large *Wald statistic* and the associated small *p-value* suggest a strong rejection of the null that all coefficients are zero. That is, the included firm-specific determinants of capital structure and the overall economic conditions proxied by the time dummies seem to exert a significant influence on the determination of the firms' leverage ratios. With regards to the goodness-of-fit of the model, the high value of 0.692 for $Corr(LVG_{it}, \widehat{LVG}_{it})^2$ indicates that the model is doing a very good job in explaining the dependent variable. As expected, we have no evidence suggesting the presence of serial correlation in the original error term, as *AR(2)* is failed to be rejected. Finally, failure to reject the null hypothesis of the *Hansen* test indicates that the instruments used in the SYSGMM estimation are valid and not correlated with the error term, with the *Prob > Chi2* of being in the acceptable value range of $[0.25\ ,1)$ as suggested by Roodman (2009a).

4.3.4.2.1. Firm-specific Determinants of Leverage Ratios

Turning to the reported coefficient estimates on the firm-specific determinants of capital structure, all the coefficients' signs seem consistent with the theoretical predictions and empirical expectations. Furthermore, all the reported coefficient estimates are significant at 5% significance level or better.

L.LVG

Consistent with the prediction of the dynamic trade-off and the agency theory and the existence of a target (optimal) leverage ratio, the coefficient on the 1-year lagged leverage ratio (*L.LVG*) is found to be positive and statistically significant. This primarily confirms the existence of dynamism in the capital structure decision, in the sense that firms gradually adjust their leverage ratios in order to achieve their target.

Consistent with the strong empirical evidence for the positive (less than unity) and significant coefficient on the lagged leverage ratio (e.g., Jalilvand and Harris, 1984; Ozkan, 2001; Maghyreh, 2004; Leary and Roberts, 2005; Flannery and Rangan, 2006; Lemmon *et al.*, 2008; Antoniou *et al.*, 2008; and Getzmann *et al.*, 2014), we also

report a coefficient of 0.53, which indicates that about 53% of the current leverage ratio can be explained by the previous period leverage ratio, and hence suggesting that leverage ratios are relatively persistent over time. Furthermore, recalling that the speed of adjustment is computed as (*1- the coefficient on the lagged leverag*e), the fairly fast speed of adjustment (0.47) suggests relatively higher costs of being off-target compared to the associated adjustment costs (see, Byoun, 2008).

In addition, as expected, the reported coefficient estimate on *L.LVG* based on SYSGMM is indeed halfway between the lower bound (0.31) and the upper bound (0.76) values as suggested by the FE and the pooled OLS estimator, respectively.

Growth Opportunities

Consistent with the prediction of the pecking order theory, we also find a positive and statistically significant coefficient on *GRT*, the proxy variable used to measure firm's growth opportunities. Assuming constant profitability and internal sources of finance, the pecking order theory suggests that, an increase in growth and investment opportunities would imply a greater need for external financing and a larger debt component in the capital structure, considering the smaller information asymmetries and adverse selection problem associated with debt issues than equity issues.

As discussed in Section 2.3.3, although the empirical studies of capital structure predominantly have found a negative relationship between measure of growth opportunities and leverage ratio, a positive relation between the two has also received some empirical supports (e.g., Chittenden *et al.*, 1996; Jordan *et al.*, 1998; Michaelas *et al.* 1999; Bevan and Danbolt, 2002; and Iqbal and Kume, 2014). Consistent with the prediction of the pecking order theory, researchers that report a positive relation between growth opportunities and leverage ratios attribute their finding to the amplified needs of high growth firms for external finance. That is, the greater are the growth and investment opportunities, the more likely are the retained earnings and other internal sources of finance to fall short of the investment needs. Accordingly, given that high growth firms have relatively small assets-in-place as most of their value stems from future investments, they are expected to suffer more from the information asymmetries associated with equity issues, and thus they tend to cover their financing gap by raising additional debt, hence the higher leverage ratios.

Our finding regarding the measure of growth opportunities, which is calculated as $\frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$, gives support to the above argument. We find that, firms with greater growth opportunities tend to employ more debt in their capital structure. In fact, the reported coefficient on *GRT* indicates that a 1% increase in the measure of growth opportunities will increase the leverage ratio by approximately 0.027%.

Size

The trade-off and the agency theory predict a positive relation between firm size and the debt component of capital structure. They propose that, since large firms typically are more diversified with greater assets-in-place, they are less prone to bankruptcy and hence face lower costs of bankruptcy and agency costs of debt than small firms, suggesting a greater incentive for debt financing. Furthermore, to the extent that lager firms have greater free cash flows, debt becomes valuable as a disciplinary tool used to mitigate the agency costs of free cash flows. Thus, both theories predict that, larger firms have the incentive to employ greater debt components in their capital structure.

Empirical studies of capital structure have also found strong support for the predicted positive relation between firm size and leverage ratio, and suggest that to the extent that size acts as an inverse proxy for the probability of default, a positive relation with leverage ratio is expected (e.g., Rajan and Zingales, 1995; Hovakimian *et al.*, 2001; Fama and French, 2002; Flannery and Rangan, 2006; and Antoniou *et al.*, 2008). Consistent with the with predictions of the trade-off and the agency theory and the empirical findings on the impact of firm size on leverage ratio, we also find a positive and significant coefficient estimate for the proxy variable used to measure firm size, SIZ. That is, larger firms have been found to operate at higher leverage ratios than small firms. In fact, since *SIZ* is calculated as $ln(Total\ Assets)$, the positive and significant coefficient of 5.454 indicates that a 1% increase in *Total Assets* will increase leverage ratio by 0.054%.

Tangibility

There has been a mutual agreement among the main theories of capital structure regarding the predicted relation between firms' capital structures and the degrees of

asset tangibility. The trade-off and the agency theory implies that unlike intangible assets, tangible assets, which are often used as collaterals against which firms tend to borrow, are expected to reduce bankruptcy and agency costs of debt. That is, while the value of intangible assets such as goodwill or brand recognition is extremely sensitive to the financial health of the firm and almost wipes out in the event of bankruptcy, tangible assets are less likely to suffer from substantial loss in value, should the firm default. Furthermore, tangible assets are more difficult to manipulate and to be replaced with riskier assets (i.e., excessive risk taking), thus firms with high degrees of tangible assets are less prone to the risk-shifting problem, and hence are expected to face lower agency costs of debt. Finally, the pecking order theory implies that given that tangible assets are easy to value, the information asymmetries about their true value, and the adverse selection problem associated with issuing equity is less likely to be substantial for firms with high level of tangible assets. Accordingly, all three theories imply a positive relation between the amount of tangible assets and the debt component of the capital structure, suggesting a positive impact of the degrees of asset tangibility on leverage ratio.

The predicted positive relation between leverage and the measure of tangibility has been confirmed by the overwhelming majority of the empirical studies of capital structure (e.g., Frank and Goyal, 2003; Bevan and Danbolt, 2004; Drobetz and Wanzenried, 2006; and Frank and Goyal, 2009). Using *TNG*, which is calculated as $\frac{Net\ Fixed\ Assets}{Total\ Assets}$, as the proxy variable to measure asset tangibility, we also find a positive and significant relation between tangibility and leverage ratio. In fact, the reported coefficient estimate of 0.108 for *TNG* in Table 4.43 indicates that, for every 1% increase in the relative proportion of tangible assets to total assets, there will be a 0.108% increase in the leverage ratio.

Profitability

Profitability and ability of the firm to internally finance its operations and investments are the cornerstones of the pecking order theory. The theory argues that, *ceteris paribus*, profitable firms with high levels of retained earnings and free cash flows are less likely to require external funds to finance their activities, and thus are more likely

to employ small amount of debt in their capital structures. This implies a negative relation between PRF and leverage ratio.

The predicted negative relation between measure of profitability and leverage ratio has been also extensively documented in the empirical literature of capital structure (e.g., Ozkan, 2001; Deesomsak *et al.*, 2004; Flannery and Rangan, 2006; and De Jong *et al.*, 2008). Consistent with the prediction of the pecking order theory and the empirical findings on the relation between profitability and leverage ratio, we also find a negative and significant coefficient estimate for the proxy variable used to measure profitability, *PRF* which is defined as $\frac{EBITDA}{Total\ Assets}$. That is, as profitability increases, the ability of the firm to fund finance its investment activities improves, suggesting that the need for external financing via debt issues is expected to decrease. In fact, the estimated coefficient of -0.397 for *PRF* indicates that, for every 1% increase return on assets, leverage ratio decreases by 0.397%.

Non-Debt Tax Shields

The positive coefficient on the measure *NDTS* can be explained by the general premises of the pecking order theory. The theory states that, in the event of insufficient internal sources of finance, firms opt for external financing, and given the more severe information asymmetries associated with equity issues, firms have a preference to issue additional debt and exhaust this option before raising funds via equity issuance. This in turn implies that, *ceteris paribus*, an increase in the income statement items (expenses) that reduce firms' retained earnings (i.e., the main source of internal funds), effectively increases the need for external financing, and hence may lead to larger debt component of the capital structure. Accordingly, to the extent that non-debt tax shields lead to a reduction in the available sources of internal financing, they are expected to have a positive impact on leverage ratios.

Although the negative relation between non-debt tax shields and leverage as predicted by the trade-off theory has been widely supported in the empirical literature, a positive coefficient on non-debt tax shields has also been documented by a number of empirical studies such as: Boquist and Moore (1984), Bradley *et al.* (1984), MacKie-Mason (1990), Chaplinsky and Niehaus (1993), Homaifar *et al.* (1994), and more

recently, Antoniou *et al.* (2008) and Frank and Goyal (2009)[201]. Although these studies acknowledge the unconventional positive impact of *NDTS* on leverage ratio, they attribute their findings to variable construction and model misspecification issues. For instance, Bradley *et al.* (1984) argue that the positive relation between non-debt tax shields and leverage is due to important variables missing from the estimation model. That is, non-debt tax shields, measured as the sum of depreciation expenses and investment credits, may actually be a proxy for the degree of asset tangibility, and hence act as an instrumental variable for the ability of firm to obtain secured debt. Thus, with the variable for the securibility of the firm's assets missing from the model, the positive coefficient on non-debt tax shield does actually reflect the relation between the ability of firm to issue secured debt and leverage ratio rather than the relation between non-debt tax shields and leverage per se[202].

Similarly, Antoniou *et al.* (2008) propose two possible reasons for the positive and significant relation found between *NDTS* and leverage ratio in their comparative study: 1) depreciation expenses, as the major component of non-debt tax shields, may actually be a proxy for firm's ability to provide collateralisable asset and issue secured debts. Accordingly, firms with higher depreciation expenses tend to have relatively more tangible assets, and hence are likely to borrow more. 2) Non-debt tax shield, which is a function of investment decision, may be mistreated as an exogenous variable, whereas it may actually be endogenously determined. Thus, the positive coefficient on *NDTS* may be biased and inconsistent due to model misspecification and not properly accounting for the endogeneity of *NDTS*[203]. Furthermore, consistent with the missing value argument, Barclay and Smith (1995) and Ozkan (2001) argue that, large depreciation expenses may reflect high proportion of tangible assets (i.e., large assets-in-place) or may similarly reflect low level of growth opportunities.

However, we believe our results do not suffer from such distortions, for two reasons. First, our estimation model includes two separate and more closely related proxy

[201] See Graham (2003) for an extensive review on the impact of taxes on firms' financing decisions.
[202] This is also consistent with the secured debt hypothesis of Scott (1977), which proposes that the higher is the firm's degree of asset tangibility, the easier is to provide collateral and issue secured debt, and hence the higher will be the firm's leverage ratio.
[203] Antoniou *et al.* (2008) attempt to test for possible endogeneity of *NDTS* by estimating three alternative specifications where *NDTS* and effective tax rate (i.e., variable causing the endogeneity of *NDTS*), together and one at a time, are excluded, and find that their results remain qualitatively similar to the base model with both variables included.

variables than *NDTS* to simultaneously control for firm's asset structure (i.e., *TNG*) and future growth opportunities (i.e., *GRT*), and their estimated coefficients are in the expected directions. Thus, we have no reason to suspect that the positive coefficient on *NDTS* is due to a missing variable problem. In addition, the absence of multicollinearity and high correlation is also evident by the low correlation coefficients between *NDTS* and other included firm-specific regressors (see, Table 4.11). Second, having conducted rigid statistical tests to detect endogenous variables in our estimation models, the endogeneity test of *NDTS* suggests strong evidence against its endogeneity, meaning that it is in fact exogenous and thus must be treated as such (see, Table 3.3). Furthermore, different specification tests have been employed to ensure that the estimation model is correctly specified. Thus, model misspecification is not a valid explanation for our finding either.

Instead, we believe that the reported positive coefficient on *NDTS* may be explained under the pecking order theory and through the impact of depreciation expenses on retained earnings. Given that firms depreciate their existing assets in order to invest in newer and more advanced assets, depreciation and amortization are treated as expense items in income statements, and hence reduce the firm's net income and retained earnings. Thus, to the extent that non-debt tax shields act as a substitute for interest tax shields in reducing effective tax rate by lowering taxable income, a negative coefficient is expected. However, if non-debt tax shields are large enough that the negative impact on firm's retained earnings and the accelerated need to raise external fund (primarily in the form of debt) outweigh the tax advantage due to reduction in taxable income, then instead of acting as a substitute, non-debt tax shields may actually act as a compliment to debt related tax shields and lead to higher leverage ratios[204]. In fact, the estimated coefficient of 0.531 on *NDTS*, which is calculated as $\frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$, indicates that if the measure of non-debt tax shields increases by 1%, the leverage ratio would increase by 0.531%.

[204] Consistent with this argument, comparing the mean annual total interest expenses with mean depreciation and amortization expense indicates that, the latter is at least 1.5 times and at most 3 times larger than the former. For details, see Table 7.10 in the Appendix.

Business Risk

Under the pecking order theory, business risk is expected to have a positive relation with the debt component of capital structure. That is, to the extent that earnings' volatility exacerbates the adverse selection problem associated with the equity issues due to the increased uncertainty of outside investors about the firms' financial health and true value, firms with greater volatility in their earnings are expected to have higher leverage ratios. In addition, the pecking order theory also implies that, firms with volatile earnings, which is the main source of internal financing, are more likely to need periodically access the external funds in order to finance their investments, as their internal sources of finance are more likely to fall short of their investment needs. Accordingly, given the smaller information asymmetries and adverse selection problem associated with debt issues as opposed to the equity issues, firms with unstable earnings are more likely to issue debt capital, and hence tend to have larger debt components in their capital structure.

While the majority of the empirical studies in the capital structure literature have found a negative relationship between measure of risk and leverage ratio, there have been a limited support for a positive relation between the two variables, most of which relate to the 1980s and the 1990s (e.g., Castanias, 1983; Long and Malitz, 1985; Kim and Sorensen, 1986; Jaffe and Westerfield, 1987; Jordan *et al.*, 1998; and Michaelas *et al.*, 1999). However, interestingly, all of these studies propose that, the estimated positive relation between earnings' volatility (as the measure of business risk) and leverage ratio may be due to the lower agency costs of debt of firms with large business risk. That is, firms with highly volatile earnings are less likely to exploit debt holders' wealth by taking excessively risky investments, which in turn, implies lower agency costs of debt, and hence the ability to employ more debt in their capital structure. For instance, Michaelas *et al.* (1999) relate the documented significant and positive coefficient on the earnings volatility in their study, to the lower agency costs of debt faced by their analysis sample, and note that: "*bankruptcy costs are not significant enough to ensure a negative relationship between risk and gearing*" (p. 121). The same argument is made by Castanias (1983); they argue that, it is only when earnings are normally distributed and default costs are sufficiently high that business risk (measured by earnings' volatility) is inversely related to leverage ratio.

We, on the other hand, believe that the argument for smaller risk-shifting problem and the consequent lower agency costs of debt argument proposed by the previous empirical studies is best applicable to small firms with relatively smaller investment needs. However, given that our analysis sample includes the constituents of the FTSE 250 Index which are among the largest 350 firms by market capitalization listed on London Stock Exchange, implying greater investment expenditures and needs, the pecking order argument seems more relevant. That is, highly unstable earnings are expected to impair the ability of the firm to finance its investments internally, and thus increase the likelihood of the firm requiring external funds and issuing additional debt.

Consistent with the pecking order prediction, we find a positive and statistically significant coefficient on the proxy variable used to measure business risk, *RSK*, which is calculated as $\frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$. In fact, the coefficient of 0.089 indicates that, for every 1% increase in the measure of the earnings' volatility, the leverage ratio increases by 0.089%.

Although it is not our objective to evaluate the performance or empirical relevance of alternative theories of capital structure, our findings are better explained under the premises of the pecking order theory. That is, except for the positive impact of size on leverage (predicted by the trade-off and the agency theory), the direction of the impact of all firm-specific determinants of capital structure are in line with the general predictions of the pecking order theory. Having said that, the positive and significant coefficient on the 1-year lagged leverage ratio provides support for the existence of an optimal leverage ratio for individual firms, which is in line with the predictions of the trade-off and the agency theory but in contrast to pecking order theory. Accordingly, as noted by Myers (2003: p. 217): "*there is no universal theory of the debt-equity choice, and no reason to expect one*", we also find that different theories tend to capture different factors affecting the financing decisions of firms.

4.3.4.2.2. Leverage Ratio Impact of the GFC

Turning to the impact of the recent GFC on firm's leverage ratio, the results indicate a general increase in leverage ratios in the years before the crisis and a substantially steeper downward trend of leverage ratios for the period after the GFC.

Recalling Section 2.3.4, we include a set of annual time dummy variables for the period 2004-2012, with 2007 (the onset of the GFC) as the base year, to capture the impact of the recent GFC on firm's leverage ratio, while controlling for the firm-specific determinants of capital structure[205]. Accordingly, the coefficients on the year dummies, which we refer to as the impact of the GFC on leverage ratios, indicate the relative change in the leverage ratios in the respective years compared with 2007 which is due to the time-specific overall economic conditions in a given year.

As presented in Table 4.43, except for *YR05* and *YR08,* which show positive and insignificant coefficients, the coefficient estimates on all annual time dummies are both negative and statistically significant. However, it should be noted that since 2007 is the base year, the negative coefficients on the annual time dummies refer to opposite leverage ratios trends depending on whether they are before or after the base year. That is, for years before 2007 the negative coefficients suggest an increasing trend in leverage ratios, whereas and the negative coefficients on the annul time dummies for years after 2007 are actually an indication of a decreasing trend in leverage ratios.

Accordingly, the negative and significant coefficients for the years before 2007 suggests that, firms tend to have increasingly higher leverage ratios over the years before the onset of the GFC, with the exception of 2005 where the coefficient is positive and insignificant. However, the increasing trend reverses over the period following the crisis. That is, the negative estimated coefficients for the years after 2007 suggest that, firms tend to have significantly lower leverage ratios, compared to the year the GFC initiated.

Recalling the discussion in Section 2.3.4.1, the reported negative coefficient estimates for the annual time dummies seem to be consistent with the predictions of the trade-off theory, as it implies that firms are more likely to operate at higher leverage ratios in expansionary economic environments (i.e., 2004-2007), where tax benefits of debt financing are expected to be large (due to higher taxable income) while bankruptcy costs associated with debt are expected to be small (due to lower probability of default). Likewise, firms are expected to reduce their level of indebtedness in a

[205] Each annual time dummy acts as an aggregate measure containing all macroeconomic variables and external factors in the respective years.

recessionary economic environment expected after financial crises, where the conditions reverse.

Our findings regarding the negative impact of the GFC on leverage ratio are also consistent with the empirical studies of Fosberg (2012) and Akbar *et al.* (2013), where they report a negative coefficient estimate on the dummy variables for year 2009 and year 2010, and the period 2007-2009, respectively. Furthermore, the decreasing trend of leverage after the GFC is also consistent with the findings of Graham *et al.* (2015), where they argue that, during periods of economic downturn and increased uncertainty, viable investment opportunities are rare to find and hence the need for external financing is weak, leading to a reduction in firms' leverage ratios. However, as can be seen from Table 4.43, the reported coefficients for the annual time dummies in the post-crisis are substantially larger than those for the pre-crisis time dummies. In fact, while compared to the 2007, leverage ratios in 2004 and 2006 are only 3.42% and 3.09% less, respectively, the difference is much larger for 2009, 2010, 2011 and 2012: 6.65%, 8.27%, 5.97% and 6.43%, respectively. This may be inferred as an indication of the stronger negative impact of financial crises on leverage ratios than the positive impact of economic booms on leverage ratios.

Table 4.42 The Upper- and the Lower-Limit Values for L.LVG – Base Model

	Pooled OLS Estimator		*Fixed Effects Estimator*	
Leverage	*Coef.*	*P > | t |*	*Coef.*	*P > | t |*
L.LVG	**0.757**	0.000	**0.312**	0.000
GRT	0.018	0.000	0.040	0.000
SIZ	2.246	0.000	12.612	0.000
TNG	0.064	0.000	0.029	0.786
PRF	-0.337	0.000	-0.378	0.000
NDTS	0.405	0.002	0.661	0.136
RSK	-0.016	0.440	-0.002	0.693
YR04	-4.106	0.008	-0.236	0.900
YR05	-0.425	0.825	2.001	0.228
YR06	-4.302	0.010	-1.978	0.169
YR08	-0.650	0.696	0.243	0.888
YR09	-8.347	0.000	-6.652	0.000
YR10	-8.610	0.000	-9.144	0.000
YR11	-5.751	0.000	-8.312	0.000
YR12	-4.910	0.001	-9.568	0.000
_cons	-36.365	0.001	-239.661	0.000
Obs.		1197		1197
F (15, 1181)		202.46		
Prob > F		0.000		
F (15 , 262)				16.64
Prob > F				0.000

Where, the analysis period is 2004–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; $YR04$–$YR12$ are the annual time dummies with 2007 used as the base year; and t and $p > |t|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 4.43 Dynamic – SYSGMM – Base Model

Leverage	*Coef.*	*Corrected Std. Err.*	*z*	*P > | z |*
L.LVG	0.530	0.082	6.440	0.000
GRT	0.027	0.007	3.810	0.000
SIZ	5.454	1.165	4.680	0.000
TNG	0.108	0.034	3.170	0.002
PRF	-0.397	0.079	-5.050	0.000
NDTS	0.531	0.241	2.210	0.027
RSK	0.089	0.017	5.330	0.000
YR04	-3.420	1.473	-2.320	0.020
YR05	0.631	1.571	0.400	0.688
YR06	-3.096	1.398	-2.210	0.027
YR08	0.053	1.395	0.040	0.970
YR09	-6.658	1.396	-4.770	0.000
YR10	-8.273	1.228	-6.740	0.000
YR11	-5.976	1.235	-4.840	0.000
YR12	-6.439	1.415	-4.550	0.000
_cons	-98.240	22.371	-4.390	0.000
Obs.				1197
No. of groups:				263
Obs. per group:			*min*	1
			avg	4.55
			max	9
No. of instruments				47
Wald Chi2 (15)				1024.58
Prob > Chi2				0.000
$Corr(LVG_{it}, \widehat{LVG}_{it})^2$				0.692
Arellano-Bond AR(1)			*z*	-3.67
			Prob > z	0.000
Arellano-Bond AR(2)			*z*	0.06
			Prob > z	0.949
Hansen J statistic			*Chi2(31)*	30.57
			Prob > chi2	0.488

Where, the analysis period is 2004–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; $YR04$–$YR12$ are the annual time dummies with 2007 used as the base year; *Corrected Std. Err.* denotes the Windmeijer standard errors which are the heteroskedasticity-robust standard errors that are also corrected for finite sample bias; and z and $p > |z|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

4.3.4.3. Regression Results – Zombie Model

As for the base model, the pooled OLS and the FE estimation of Eq. (4.16) are presented to provide a guideline on the upper- and the lower-limit values of the lagged dependent regressor in the zombie model. As shown in Table 4.44, the *L.LVG* coefficients obtained from the pooled OLS and FE estimator are 0.797 and 0.276, respectively, suggesting that the respective estimated coefficient based on SYSGMM estimator should be somewhere in between 0.276 and 0.797.

Table 4.45 reports the estimation results for the zombie model. As discussed in Section 3.4.7, the zombie model is aimed to examine whether the leverage ratios of zombies are determined any differently than non-zombies. It includes an additional dummy regressor, *ZMB*, which is aimed to capture the impact of being zombie on firms' leverage ratios. Accordingly, a significant positive or negative coefficient would suggest the existence of some additional factors specific to zombies that exert a significant impact on their leverage ratios.

Furthermore, given that the analysis period of the zombie model is limited to the years after the GFC (2008-2012), it can also be used to assess the empirical relevance of the commonly used firm-specific determinants of capital structure in a post-crisis environment. That is, since the same firm-specific determinants of capital structure are used in both the base model (covering both the pre-crisis and the post-crisis periods) and the zombie model (covering only the post-crisis period), changes in the signs or statistical significance of their respective coefficients in the zombie model as opposed to the base model can be inferred as certain firm-specific determinants of capital structure losing their empirical relevance or reversing in their impact in a post-crisis environment.

As can be seen from Table 4.45, the zombie model seems to satisfy all post-estimation tests. While the low *p-value* of the Wald test suggests joint significance of the regressors, the squared correlation coefficient between actual and predicted values of the leverage ratio of 0.672 also indicates a very promising model fit. Furthermore, the no serial correlation test of the differenced error term is rejected at order 1 and failed to be rejected at order 2, suggesting no evidence of serial correlation in the original

error term. Finally, the *Hansen* test is also failed to be rejected with a *Prob > Chi2* of 0.292 which is in the Roodman's (2009a) recommended value range of $[0.25, 1)$.

Comparing the reported coefficient estimates on the firm-specific determinants of capital structure in Table 4.45 with those reported in Table 4.43, we can see that, except for *GRT* and *RSK* which become statistically insignificant, all variables show consistency in their coefficient signs and statistical significance. While the magnitude of the impact changes depending on the analysis sample and period, the direction of the impact of firm-specific determinants of capital structure remains generally unaffected by the economic environment they are applied to.

The coefficient on *GRT* may be insignificant because in the post-crisis environment, investment opportunities are rare to find, and even if they are available, the priority is with survival of the business rather than growth opportunities. Thus, firms may either not need external financing as fewer eligible growth opportunities are available or they may prefer to use the available internal sources on their core business activities and reserve the remaining in anticipation of a rainy day. This is consistent with the findings of Graham *et al.* (2015), where, using historical data, they show that the scarcity of investment opportunities during periods of economic downturn and increased uncertainty leads to weaker needs for external financing, and hence a reduction in firms' lower leverage ratios. The reported insignificant coefficient on *RSK* can be also explained under the same premise. That is, although firms with highly volatile earnings are expected to have greater needs for external funds to finance their investment activities, given the low level of investment activities in the post-crisis period, they do not seem to have a strong incentive to raise additional borrowing. Furthermore, the smaller coefficient on *PRF* for the zombie model as opposed to the base model is also in line with the scarcity of investment opportunities and hence the weaker need for external financing.

Turning to the aggregate impact of the crisis, the coefficient estimate on all annual time dummies are negative and significant, suggesting a significant reduction in the leverage ratios due to commonly experienced year-specific shocks and firm-invariant factors (i.e., the overall economic conditions and general shocks that were commonly experienced by all the firms in the analysis sample). It should be noted that, while the positive and insignificant coefficient on *YR08* for the base model suggests no

significant differences between the leverage of firms in 2008 and 2007, the reported negative and significant coefficient on *YR08* for the zombie model suggests a statistically significant reduction in firms' leverage ratios in the year after the onset of the GFC. Furthermore, although we do not expect the coefficients on the common time dummies (i.e., *YR08*, *YR09*, *YR10*, *YR11*, and *YR12*) to be different across the two models, the minor differences in the coefficients on time dummies is most likely due to the exclusion of 233 firm-year observations (29% of the total post-crisis firm-year observations) with missing values for *ZMB*[206].

Finally, the *ZMB* dummy variable is included to capture the differences between the leverage ratios of zombies and non-zombies, when controlling for all other variables. Since *ZMB* is a dummy variable that takes a value 1 if firm is identified as zombie and 0 otherwise, a statistically significant coefficient suggests significant differences in the leverage ratios of zombies compared to non-zombies. Accordingly, a significant positive (negative) coefficient suggests that, *ceteris paribus*, zombies tend to have higher (lower) leverage ratios than non-zombies.

Due to lack of theoretical and empirical evidence on the subject of zombies and the determination of their capital structure, there are no *a priori* expectations regarding the impact of being zombie on leverage ratios. However, recalling the discussion in Section 2.3.5 regarding the possible causes of the emergence of zombies, to the extent that the banks' loan forbearances and the rescue packages offered by the government had involved additional lending to the zombies and significantly increased their leverage ratios, we would expect to find a positive coefficient on *ZMB*, suggesting that zombies tend to have higher leverage ratios than non-zombies.

However, as indicated by the high p-value reported in Table 4.45, the estimated coefficient on *ZMB* is insignificant at the 10% level, suggesting that, controlling for all other firm-specific and time-specific factors, being zombie does not actually affect firms' leverage ratios[207]. In other words, despite zombies' significantly deteriorated

[206] Firm-year observations are excluded if the underlying zombie indicator (i.e., *AICR*) cannot be computed and/or is meaningless. This includes observations with missing values for Total Interest Expenses and observations with negative Net Interest Expenses, where Interest Income is greater than Interest Expense

[207] It should be noted that, given that the *ZMB* coefficient is statistically insignificant with *p-value* of 0.305, we cannot determine whether the coefficient is actually negative or positive as it is well outside the 10% coefficient's confidence interval, and hence the estimated sign becomes irrelevant.

ability to meet financial obligations relative to non-zombies, their leverage ratios do not seem to be determined any differently. This finding becomes even more interesting, when considering the introduction of different government-sponsored support schemes and the banks' forbearances on non-performing loans that have been documented after the recent GFC.

The reported insignificant coefficient on *ZMB* may be due to the significantly smaller zombie group (36 observations) relative to non-zombie group (536 observations). However, having re-estimated the zombie model for a large number of randomly selected subsamples with equal group sizes we find that, although in most cases the coefficient on *ZMB* is positive, it remains statistically insignificant across all subsamples[208]. Thus, the insignificant coefficient is not due to the differences in the relative group sizes.

Accordingly, one possibility for this finding is that, the zombies in our sample simply have not been subject to any additional support from the government or their lenders and these factors certainly have not contributed to their survival, and hence no significant difference in their leverage ratios in comparison with non-zombies.

Alternatively, we propose that, the reported insignificant coefficient on the zombie variable may be due to the type of support and loan forbearances received by the zombies. That is, while zombies have been subject to the external supports, these supports have been mostly in different forms than additional lending or refinancing packages. So that, the additional borrowings, if any, have not been large enough to cause a significant difference in the leverage ratios of the recipients and non-recipients. This is also consistent with the ample evidence in the financial news regarding the renegotiations of the zombies with their creditors, which have been mostly in the form of granting waivers to breach of pre-agreed loan covenants, switching to an interest-only loan, offering payment holidays, and loan restructurings such as lowering the interest rate and extending the maturity (see, Section 4.2.1).

Furthermore, the insignificant difference between the leverage ratios of zombies and non-zombies, is consistent with the estimated Average Marginal Effects (AMEs) of

[208] The construction of random sample is performed by the **sample** command in Stata. In all cases, 36 randomly selected non-zombie firm-year observations were pooled with the 36 zombie firm-year observations to construct a random analysis sample.

the determinants of zombieness status (see, Section 4.2.2.4). That is, the degree of leverage ratio is found to have the smallest impact on the probability of becoming a zombie in comparison with other determinants of the zombieness status such as: viability of business (as perceived by its top management), profitability, cash-generating ability and the ability to pay dividends. In other words, having high leverage ratio, while common among zombies, is the least strong differentiating zombieistic characteristic!

Table 4.44 The Upper- and the Lower-Limit Values for L.LVG – Zombie Model

	Pooled OLS Estimator		*Fixed Effects Estimator*	
Leverage	*Coef.*	*P > | t |*	*Coef.*	*P > | t |*
L.LVG	**0.797**	0.000	**0.276**	0.006
GRT	0.012	0.557	0.049	0.032
SIZ	0.847	0.482	14.172	0.007
TNG	0.051	0.082	-0.055	0.744
PRF	-0.364	0.000	-0.304	0.062
NDTS	0.511	0.029	0.037	0.957
RSK	0.025	0.500	0.046	0.089
ZMB	-3.251	0.085	1.919	0.329
YR08	-2.011	0.331	1.281	0.600
YR09	-10.159	0.000	-6.763	0.005
YR10	-9.226	0.000	-9.727	0.000
YR11	-5.096	0.006	-9.184	0.000
YR12	-4.369	0.010	-9.969	0.000
_cons	-6.804	0.805	-266.527	0.015
Obs.		572		572
F (13, 558)		111.54		
Prob > F		0.000		
F (13 , 186)				12.36
Prob > F				0.000

Where, the analysis period is 2008–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; ZMB denotes a dummy variable takes a value of 1 if firm is identified as zombie and 0 otherwise; $YR08$–$YR12$ are the annual time dummies with 2007 used as the base year; and t and $p > |t|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 4.45 Dynamic – SYSGMM – Zombie Model

LVG	*Coef.*	*Corrected Std. Err.*	*z*	*P > | z |*
L.LVG	0.488	0.188	2.600	0.009
GRT	0.024	0.028	0.850	0.398
SIZ	4.199	2.502	1.680	0.093
TNG	0.134	0.059	2.250	0.024
PRF	-0.276	0.146	-1.890	0.058
NDTS	0.691	0.396	1.740	0.081
RSK	0.195	0.207	0.940	0.345
ZMB	-1.988	1.937	-1.030	0.305
YR08	-3.447	2.030	-1.700	0.090
YR09	-9.785	1.773	-5.520	0.000
YR10	-9.680	1.800	-5.380	0.000
YR11	-8.393	2.189	-3.830	0.000
YR12	-7.709	2.889	-2.670	0.008
_cons	-71.033	52.223	-1.360	0.174
Obs.				572
No. of groups:				187
Obs. per group:			*min*	1
			avg	3.06
			max	6
No. of instruments				31
Wald Chi2 (13)				310.20
Prob > Chi2				0.000
$Corr(LVG_{it}, \widehat{LVG}_{it})^2$				0.672
Arellano-Bond AR(1)			*z*	-2.43
			Prob > z	0.015
Arellano-Bond AR(2)			*z*	1.64
			Prob > z	0.102
Hansen J statistic			*Chi2(17)*	19.65
			Prob > chi2	0.292

Where, the analysis period is 2008–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; ZMB denotes a dummy variable takes a value of 1 if firm is identified as zombie and 0 otherwise; $YR08$–$YR12$ are the annual time dummies with 2007 used as the base year; *Corrected Std. Err. denotes* the Windmeijer standard errors which are the heteroskedasticity-robust standard errors that are also corrected for finite sample bias; and z and $p > |z|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

4.3.5. Robustness Check

Recalling the discussion in Section 2.3.1, we use the market leverage ratio is used as an alternative measure of capital structure to examine the robustness of our results. Market leverage is essentially the book leverage with the total *market* value of equity instead of book value of equity in the denominator (i.e., $\frac{Total\ Debt}{Total\ Debt+Total\ Market\ Value}$). Accordingly, the 2-step SYSGMM is used to estimate the following versions of the base and the zombie model, respectively:

$$MVLeverage_{it} = \alpha_0 + \beta_1 L.MVLVG_{it} + \beta_2 GRT_{it} + \beta_3 PRF_{it} + \beta_4 TNG_{it} + \beta_5 SIZ_{it} + \beta_6 NDTS_{it} + \beta_7 RSK_{it} + \gamma_1 YR_{2004} + \gamma_2 YR_{2005} + \gamma_3 YR_{2006} + \gamma_4 YR_{2008} + \gamma_5 YR_{2009} + \gamma_6 YR_{2010} + \gamma_7 YR_{2011} + \gamma_8 YR_{2012} + \mu_i + \lambda_t + \varepsilon_{it}. \quad (4.17)$$

$$MVLeverage_{it} = \alpha_0 + \beta_1 L.MVLVG_{it} + \beta_2 GRT_{it} + \beta_3 PRF_{it} + \beta_4 TNG_{it} + \beta_5 SIZ_{it} + \beta_6 NDTS_{it} + \beta_7 RSK_{it} + \beta_8 ZMB_{i,t-1} + \gamma_1 YR_{2008} + \gamma_2 YR_{2009} + \gamma_3 YR_{2010} + \gamma_4 YR_{2011} + \gamma_5 YR_{2012} + \mu_i + \lambda_t + \varepsilon_{it}. \quad (4.18)$$

Where, *MVLeverage* denotes the market leverage ratio, and *L.MVLVG* denotes the 1-year lagged market leverage ratio.

Having performed the same tests for identifying endogenous regressors and appropriate instruments as conducted for the main analysis, *GRT*, *SIZ*, *TNG*, and *NDTS* are identified as endogenous variables in the base model and are instrumentalised by (lags 3 and lag 5), (lags 2 and lag 3), (lags 3 and lag 4), and (lags 2 to 5), respectively. Furthermore, variables *GRT* and *PRF* have been identified as endogenous in the zombie model and both are instrumentalised by (lags 2 to 4). Finally, *L.MVLVG* is treated as predetermined in both models and is instrumented by its first lag.

Table 4.46 and Table 4.47 report the SYSGMM estimation results of the Eq. (4.17) and Eq. (4.18) respectively. As can be seen from the tables, all the post-estimation tests are satisfied for both models. That is, the high *p-values* of *AR(2)* suggest no evidence of serial correlation in the original error term. Furthermore, high *p-values* for the *Hansen J statistics* confirm the validity of the instruments used for the endogenous variables. Finally, the high values reported for *Corr(LVG , $\widehat{LVG}$)^2* suggest

that both models are doing a very good job in explaining the variation in the observed market leverage ratios.

Turning to the estimation results, except for *TNG* and *RSK* in the base model and *NDTS* in the zombie model, which become insignificant, the coefficient estimates on all other firm-specific determinants of capital structure show consistency in both sign and magnitude across the two alternative measures of leverage. Furthermore, the coefficient on *GRT* in the zombie model becomes significant when using the market leverage ratio as the dependent variable. However, we believe the changes in the significance of the firm-specific determinants of capital structure are more of a mechanical reason associated with the way the market leverage ratio is constructed, rather than fundamental differences in the impact, or the empirical irrelevance of the respective variables. That is, given that market value of equity is much more sensitive and responsive to changes in firm characteristics than the book value of equity, certain firm characteristics may have an impact on both the numerator (i.e., Total Debt) and the denominator of the market leverage ratio (i.e., market value of equity), which may have caused the changes in the significance level of their respective coefficients.

For instance, higher level of tangible assets would imply greater ability to offer collaterals, lower information asymmetries about the true value of the assets, and lower agency costs of debt, all of which are expected to lead to larger debt component in the capital structure. However, these same qualities are also likely to lead to higher market values of the firms. Therefore, to the extent that the increase in market value of equity and the increase in debt levels offset each other or lead to insignificant differences in leverage ratios, the coefficient on *TNG* is not expected to be significant. Accordingly, given that higher non-debt tax shields values would imply greater depreciable tangible assets, the insignificant coefficient on *NDTS* in the zombie model can also be due to the same mechanical effects.

Furthermore, the change in the significance of *GRT* in the zombie model may be due to the opposite impact of growth opportunities on the numerator and the denominator of the market leverage ratio. Recalling the discussion in Section 4.3.4.2, high-growth firms are expected to have greater need for additional debt financing. However, given the scarcity of investment opportunities and the increased uncertainty prevalent in the post-crisis period, the measure of growth opportunities does not seem to affect the

debt component of the capital structure. Accordingly, having substantially larger future growth opportunities relative to assets-in-place may not be perceived positively by the market. This in turn will be reflected in the lower market value of high-growth firms in the post-crisis, which would imply smaller market leverage ratio, even if debt levels remain unchanged. Finally, with regards to the impact of the GFC on market leverage ratios, the results remain qualitatively the same as those found in the main analysis. That is, we find an increasing trend in leverage ratios over the years towards the GFC, and a general decreasing pattern in leverage ratios over the years after the GFC. However, two important differences must be noted between the two estimation results. The first difference is that, in contrast to the finding of the main analysis, the coefficients on *YR08* are positive and significant for both models when estimated using the alternative measure of leverage. The second difference is the relatively smaller coefficient estimates of the other annual time dummies, when estimated using market leverage ratio.

The general negative financial shocks after the GFC were directly translated into lower market valuation of firms, especially for firms with high leverage ratios. Accordingly, the positive coefficient on *YR08* may actually capture a mechanical effect rather than an actual change in the financing behaviour of firms. That is, a larger decrease in firm value (denominator) relative to the decrease in the level of indebtedness (numerator) would imply an increase in the ratio. Thus, to the extent that, the reduction in firms' market value in 2008 from their peak in 2007 was greater than the reduction in their financial obligations, we can expect an overall increase in the market leverage ratio. Accordingly, the smaller coefficients on time dummies can be also inferred in the same. That is, part of the impact of the reduction in debt level (numerator) on leverage ratio may be offset by the smaller firm value relative to their peak in 2007 (denominator), and hence may lead to smaller overall reduction in leverage ratios.

Overall, the results of the robustness analysis suggest that the relationship between relationship between leverage and firms-specific determinants of capital structure and the impact of the GFC on firms' leverage ratios is not likely to be driven by the measure of leverage, however, the magnitude and significance of the impact is likely to depend on the way the leverage ratio is constructed.

Table 4.46 Dynamic – SYSGMM – Base Model – MVLeverage

MVLeverage	*Coef.*	*Corrected Std. Err.*	*z*	*P > | z |*
L.MVLVG	0.424	0.074	5.770	0.000
GRT	0.023	0.010	2.340	0.019
SIZ	5.247	1.462	3.590	0.000
TNG	0.074	0.053	1.390	0.164
PRF	-0.279	0.087	-3.200	0.001
NDTS	0.852	0.311	2.740	0.006
RSK	0.004	0.007	0.560	0.574
YR04	-2.707	1.012	-2.670	0.007
YR05	-2.755	0.922	-2.990	0.003
YR06	-3.276	0.829	-3.950	0.000
YR08	3.391	1.029	3.300	0.001
YR09	-4.614	1.026	-4.500	0.000
YR10	-4.540	0.909	-5.000	0.000
YR11	-3.386	1.057	-3.200	0.001
YR12	-5.415	1.016	-5.330	0.000
_cons	-103.161	31.250	-3.300	0.001
Obs.				891
No. of groups:				203
Obs. per group:			*min*	1
			avg	4.39
			max	9
No. of instruments				114
Wald Chi2 (15)				418.03
Prob > Chi2				0.000
$Corr(LVG_{it}, \widehat{LVG}_{it})^2$				0.618
Arellano-Bond AR(1)			*z*	-3.93
			Prob > z	0.000
Arellano-Bond AR(2)			*z*	-1.52
			Prob > z	0.128
Hansen J statistic			*Chi2(98)*	96.58
			Prob > chi2	0.522

Where, the analysis period is 2004–2012; $MVLeverage = \frac{Total\ Debt}{Total\ Debt+Total\ Market\ Value}$ denotes market leverage ratio; $L.MVLVG$ denotes the 1-year lagged market leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets-Book\ Value\ Equity+Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; $YR04$–$YR12$ are the annual time dummies with 2007 used as the base year; *Corrected Std. Err.* denotes the Windmeijer standard errors which are the heteroskedasticity-robust standard errors that are also corrected for finite sample bias; and z and $p > |z|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 4.47 Dynamic – SYSGMM – Zombie Model – MVLeverage

MVLeverage	*Coef.*	*Corrected Std. Err.*	*z*	*P > | z |*
L.MVLVG	0.546	0.141	3.870	0.000
GRT	0.017	0.007	2.550	0.011
SIZ	2.661	0.896	2.970	0.003
TNG	0.068	0.022	3.040	0.002
PRF	-0.267	0.127	-2.090	0.036
NDTS	0.258	0.210	1.230	0.219
RSK	-0.001	0.007	-0.170	0.869
ZMB	0.750	1.044	0.720	0.472
YR08	2.877	1.062	2.710	0.007
YR09	-6.442	1.382	-4.660	0.000
YR10	-5.469	0.934	-5.850	0.000
YR11	-2.854	0.964	-2.960	0.003
YR12	-5.698	0.963	-5.920	0.000
_cons	-46.519	17.563	-2.650	0.008
Obs.				611
No. of groups:				189
Obs. per group:			*min*	1
			avg	3.23
			max	6
No. of instruments				48
Wald Chi2 (13)				575.50
Prob > Chi2				0.000
Corr (LVG , $\widehat{LVG}$)^2				0.691
Arellano-Bond AR(1)			*z*	-3.63
			Prob > z	0.000
Arellano-Bond AR(2)			*z*	1.18
			Prob > z	0.240
Hansen J statistic			*Chi2(34)*	35.31
			Prob > chi2	0.406

Where, the analysis period is 2008–2012; $MVLeverage = \frac{Total\ Debt}{Total\ Debt+Total\ Market\ Value}$ denotes market leverage ratio; $L.MVLVG$ denotes the 1-year lagged market leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets-Book\ Value\ Equity+Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; ZMB denotes a dummy variable takes a value of 1 if firm is identified as zombie and 0 otherwise; $YR08$–$YR12$ are the annual time dummies with 2007 used as the base year; *Corrected Std. Err.* denotes the Windmeijer standard errors which are the heteroskedasticity-robust standard errors that are also corrected for finite sample bias; and z and $p > |z|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

4.4. Concluding Remarks

This chapter aims to present the main empirical findings of the Thesis and discuss the estimation results. Based on the zombie identification criteria discussed in chapter 3, a total of 42 firm-year zombie observations are identified in our analysis sample, representing 29 firms from 10 industries. Using logit regression analysis we develop an empirical model to identify the possible determinants of the zombieness status and estimate the probability of becoming a zombie.

In the first stage of our modelling strategy, we construct an initial list of 50 commonly used variables in insolvency prediction models. Next, in order to evaluate the individual explanatory power of these variables, univariate logit models are estimated for each of the 50 variables, which have led to identifying 11 variables with statistically significant impact on the probability of becoming a zombie. The individually significant variables include: *TDTA*, *EBITS*, *ROA*, *ROE*, *NSTA*, *CFOTA*, *SIZE*, *CEOCHNG*, *DVDND*, *RTIL*, and *GDP*. In the next step, a stepwise estimation procedure is applied to identify the significant determinants of zombieness status in a multivariate model. Accordingly, using 10% and 0.1% as the significance level thresholds for backward selection and forward selection, respectively, *TDTA*, *EBITS*, *CFOTA*, *DVDND* and *CEOCHNG* are retained as the final set of explanatory variables to be included in the panel logit model.

In the final step, we estimate a population-averaged panel logit model with the 5 significant variables obtained from the stepwise estimation to identify the determinants of the zombieness status. The results suggest that, highly indebted firms with low profitability and cash-generating ability are more likely to become zombies than highly profitable firms with greater cash-generating ability and lower financial leverage. In addition, we find evidence that, firms whose CEO (or equivalent) resigns during the fiscal year and do not make dividend payments are more likely to become zombies than the more viable and non-financially constrained firms without drastic changes in their top management and regular dividend payments. As for the goodness of fit the model, the results of the Hosmer-Lemeshow test (failure to reject), overall rate of correct classification (98.35%) and the area under the ROC curve (99.47%) have collectively suggested that the estimation model with 5 explanatory variables is

doing a significantly good job in explaining the probability of becoming a zombie and correctly classifying the observations

Furthermore, the average marginal effects are computed to estimate the magnitude of the impact of each variable on the probability of becoming a zombie. The results suggest that, on average, for mid-cap firms in the UK, the probability of becoming a zombie increases by 0.14% for every 1% increase in the leverage ratio (*TDTA).* In contrast, a 1% increase in the profitability (*EBITS)* and the cash-generating ability *(CFOTA)* of the mid-cap firms tend to lower the probability of becoming a zombie by 1.74% and 0.29%, respectively. Furthermore, mid-cap firms that do not make dividend payments are 4.58% more likely to become zombies than those firms that pay dividends. Similarly, the probability of becoming a zombie for firms whose CEO (or equivalent) resigns is, on average, 3.33% higher than it is for more viable firms with no such drastic changes in their top management.

With respect to estimating the impact of the recent GFC and the firm-specific determinants of capital structure on firms' leverage ratios, we estimate two different models: a base model and a zombie model. The base model is estimated to provide an understanding of the firm-specific determinants and the impact of the recent Global Financial Crisis (GFC) on the leverage ratios of the FTSE 250 Index constituents over the period 2004-2012. Furthermore, the zombie model is estimated to test if the capital structure of zombies and non-zombies are determined differently, and to assess the empirical relevance of the general frim-specific determinants of capital structure over the post-crisis period covering 2008-2012.

The means and the pairwise correlations for the analysis variables are presented and discussed for different sample breakdowns, in order to provide a better understanding of the data over the pre-crisis and post-crisis periods and for zombie and non-zombie groups. Furthermore, in order to test the generality of the estimation model and employing the appropriate estimation techniques, the normality and the heteroskedasticity of the residuals have been tested and addressed accordingly.

In order to demonstrate the empirical procedure of choosing the final estimator and model specification, we start our analysis by estimating static versions of the base model and the zombie model specified in Section 3.4, using the standard Ordinary

Least Squares (OLS) estimators (i.e., pooled OLS; Random Effect; and Fixed Effect). Performing different pre- and post-estimation tests to determine the appropriate estimator, the final estimation results of the static base model suggest that, leverage increases with growth opportunities, firm size, degree of asset tangibility, and the amount of non-debt tax shields and decreases with profitability. Furthermore, the parameter coefficient estimates for the zombie model suggest that, while zombies tend to have higher leverage ratios than non-zombies, leverage ratio, over the post-crisis period, seems to increase with growth opportunities, firm size and earnings' volatility and decrease with profitability.

Different specification tests are performed to ensure the dynamic estimation model is correctly specified, and then the final model specification is identified using different information criteria measures.

Our empirical findings regarding the firm-specific determinants of capital structure are generally consistent with the previous findings in the literature. Overall, our results suggest that leverage decreases with profitability and increases with firm size, growth opportunities, non-debt tax shields, asset tangibility, and business risk. Furthermore, the positive and significant coefficient on the 1-year lagged leverage ratio confirms the dynamic nature of the capital structure decisions, suggesting a gradual adjustment towards the target leverage. Turning to the impact of the recent GFC, the results indicate a general increase in leverage ratios in the years before the crisis and a substantially steeper downward trend of leverage ratios for the period after the GFC. Furthermore, the substantially larger reported coefficients for the annual time dummies in the post-crisis than for those in the pre-crisis may be inferred as an indication of the stronger negative impact of financial crises on leverage ratios than the positive impact of economic booms on leverage ratios.

Reporting the estimation results for the zombie model, we find that, while all other firms-specific determinants of capital structure seem to play a significant role in determining firms' leverage ratios in the post-crisis period, growth opportunities and business risk do not exert any significant effect on the financing decisions of firms in the years following the GFC. Furthermore, we find that, despite zombies' significantly deteriorated ability to meet financial obligations relative to non-zombies, their leverage ratios do not seem to be determined any differently. We propose that,

the reported insignificant coefficient on the zombie variable may be due to the type of support and loan forbearances received by the zombies in our sample. Finally, the results are shown to be generally robust to the measure of capital structure.

5. Conclusion

This Thesis has multiple research objectives, these include: investigating the impact of the recent Global Financial Crisis (GFC) and the commonly used firm-specific determinants of the capital structure on firms' leverage ratios on firms' leverage ratios; constructing an indicator to identify zombie firms in our analysis sample; and developing an empirical model to identify the determinants of zombieness status and estimating their impact on the probability of becoming a zombie.

In order to develop a conceptual framework for the main empirical analysis of the Thesis and inform the choice of analysis variables, we provide a review of the capital structure literature in Chapter 2. Reviewing the theories of capital structure, we emphasise the Modigliani-Miller irrelevance theory, the trade-off theory, the agency theory and the pecking order theory of capital structure. While the Modigliani-Miller theorem proposes that choice of capital structure is irrelevant to the overall value of the firm, the other three theories offer alternative explanations in support of the relevance of the capital structure. For example, the trade-off theory suggests that optimal capital structure, which maximises firm values, is determined via the trade-off between tax benefits of debt and the associated bankruptcy costs. Looking from another perspective, the agency theory proposes that, the optimal capital structure of the firm is obtained at the debt-to-equity ratio that minimises total agency costs. Finally, the pecking order theory focuses on the hierarchy of the firm's financing sources, which depends on information asymmetries and adverse selection problems associated with issuing the new securities.

We also conduct a review of the empirical literature of capital structure and find that, the empirical studies of capital structure generally seem to agree that leverage increases with firm size and asset tangibility and decreases with growth opportunities, profitability, non-debt tax shields and business risk. Furthermore, while there have been inconsistencies concerning the *direction* of the impact of the recent GFC on firms' capital structure, all the reviewed empirical studies find supporting evidence for the *significance* of the impact.

Next, the choice of analysis variables was derived from a critical review of empirical studies of capital structure. Accordingly, estimating a dynamic model to capture the dynamic nature of capital structure decisions and control for the adjustment costs toward the optimal leverage, we use the book debt-to-capital leverage ratio as our measure of capital structure. Furthermore, proxy variables for growth opportunities (market-to-book ratio), firm size (natural log of total assets), degree of asset tangibility (tangible assets to total assets), profitability (return on assets), non-debt tax shields (depreciation and amortization expenses to total assets), and business risk (earnings' volatility) are used to control for the firm-specific determinants of capital structure. In addition, we use a set of annual time dummies (equal to 1 if in specific year, 0 all other years) to capture the impact of the GFC on firms' capital structure. Finally, after identifying zombies in our sample, a dummy variable (equal to 1 if zombie, 0 otherwise) is used to capture the variation in capital structure that is attributable to zombie-specific characteristics.

Having established the conceptual framework for the empirical analysis of the Thesis in Chapter 2, Chapter 3 provides details on the data and the choice of estimation method that are used to facilitate the main empirical analysis. Based on the definition of zombie firms, we construct an indicator to capture both the insolvent nature and the surviving status of zombies. Furthermore, having reviewed different estimation techniques to identify the determinants of zombieness status and estimate their impact on the probability of becoming zombie, logistic regression analysis is deemed as the most appropriate estimation method when the focus is on estimating the probability of the occurrence of an event (becoming a zombie in this case).

Conducting a critical evaluation of the properties of different estimation methods available to estimate linear dynamic panel models, we show that System Generalized Method of Moments (SYSGMM) estimator leads to consistent and efficient estimates of linear dynamic panel models. This is because, SYSGMM imposes an additional restriction on the initial conditions process, under which, all of the available moment conditions can be exploited by a linear GMM estimator in a system of first-difference and level equations. Accordingly, by using both the first differences of the level variables and the lagged levels of the first differenced variables as instruments, SYSGMM exploits all the available information in the sample. Thus, SYSGMM is

deemed as the most appropriate econometric technique for estimating a dynamic capital structure model.

Having decided on the data and the estimation method, we specify two specifications, a "base model" for the period 2004-2012 and a "zombie model" for the period 2008-2012. Accordingly, the base model investigates the general impact of the recent GFC and the firm-specific determinants of capital structure on firms' leverage ratios. Whereas, the zombie model examines whether capital structure of zombies and non-zombies are determined differently. Furthermore, the zombie model is also used to evaluate the empirical relevance of the commonly used firm-specific determinants of capital structure in a post-crisis environment. To address the possible endogeneity problem associated with dynamic models, we test for the endogeneity of the included regressors and identify their respective appropriate instruments. In particular, we perform three post-estimation tests to identify appropriate instruments: the underidentification test (to ensure instruments are relevant); the weak-identification test (to ensure instruments are not weak); and the test for overidentifying restrictions (to ensure instruments are valid). Furthermore, the results from the endogeneity tests, based on the difference-in-Hansen statistic, are deemed as valid, only if the corresponding set of instruments have passed all three instrument tests. Applying the above criteria to each of the included regressors in the base and zombie models, the proxy variable for business risk (in the base model) is found to be endogenous.

Chapter 4 provides the main findings and present a discussion of the estimation results. Our empirical analysis on zombies are presented in Section 4.2, where we identify zombies in our sample and investigate factors affecting the probability of becoming a zombie. Defining zombies as *surviving technically insolvent firms that are unable to generate enough revenues to even pay the interest expenses on their borrowings, let alone the repayment of the principal amount*, we use a two-condition selection criteria. First, an Adjusted Interest Coverage Ratio (AICR) is constructed to assess the technical insolvency condition (i.e., $AICR < 1$). Second, to ensure that detected technical insolvent firms meet the survival condition, we require zombies to have been a separate and active entity for at least 1 year after the period in which the AICR condition is met. Applying these criteria, we identify 42 firm-year zombie observations in our sample.

We then use logit regression analysis to identify the possible determinants of zombieness status and estimate their significance. Employing a range of econometric techniques, our results show that, highly indebted firms with low profitability and cash-generating ability are more likely to become zombies than highly profitable firms with greater cash-generating ability and lower financial leverage. In addition, we find evidence that, firms whose CEO (or equivalent) resigns during the fiscal year and do not make dividend payments are more likely to become zombies than the more viable and non-financially constrained firms without drastic changes in their top management and regular dividend payments.

Furthermore, we estimate Average Marginal Effects (AMEs) to quantify the impact of the identified determinants. Our results indicate that profitability has the greatest impact on the probability of becoming a zombie, followed by cash-generating ability and leverage ratio. Furthermore, while the dichotomous variables concerning the ability to pay dividends and the viability of business (as perceived by its top management) show significantly larger impacts, their AMEs are not directly comparable with those of the other 3 continuous variables. Finally, the overall performance of the model is tested using different measures of goodness-of-fit. Results collectively suggest that the estimation model is doing a significantly good job in explaining the probability of becoming a zombie and correctly classifying the observations into zombies and non-zombies.

Section 4.3 presents the estimation results for both the base model and the zombie model of capital structure and test the robustness of our main empirical findings. Overall, the results for the base model suggest that, leverage decreases with profitability and increases with firm size, growth opportunities, non-debt tax shields, asset tangibility, and business risk. Furthermore, a positive and significant coefficient on the 1-year lagged leverage ratio confirms the dynamic nature of the capital structure decisions, suggesting a gradual adjustment towards the target leverage. Moreover, the reported coefficients on the annual time dummies indicate a general increase in firms' leverage ratios in the years before the GFC while suggesting a significant negative impact on leverage ratios after the crisis.

Our findings regarding the firm-specific determinants of capital structure are better explained under the pecking order theory framework. That is, except for the positive

impact of size on leverage (predicted by the trade-off and the agency theory), the direction of the impact of all firm-specific determinants of capital structure are in line with the general predictions of the pecking order theory. Having said that, the positive and significant coefficient on the 1-year lagged leverage ratio provides support for the existence of an optimal leverage ratio for individual firms. This is in line with the predictions of the trade-off and the agency theory but in contrast to pecking order theory. Accordingly, consistent with Myers' (2003: p. 217) comment: "*there is no universal theory of the debt-equity choice, and no reason to expect one*", we also find that, different theories tend to capture different factors affecting the financing decisions of firms.

The overall estimation results from the zombie model suggest that, although the magnitude of the impact changes depending on the analysis period, the direction of the impact of firm-specific determinants of capital structure remains generally unaffected to the economic environment they are applied to. We further find that, while all other firms-specific determinants of capital structure seem to play a significant role in determining firms' leverage ratios in the post-crisis period, growth opportunities and business risk do not exert any significant effect on the financing decisions of firms in the years following the GFC. We, therefore propose, that the scarcity of investment opportunities, and hence the weaker need for external financing after the 2008/9 recession, may have caused growth opportunities and business risk losing their explanatory power in a post-crisis environment. In addition, the smaller coefficient on profitability (i.e., as a measure of firms' ability to finance their investments internally) for the zombie model as opposed to the base model is also in line with the scarcity of investment opportunities argument.

The results of the zombie model further indicate that, despite zombies' significantly deteriorated ability to meet financial obligations relative to non-zombies, their leverage ratios do not seem to be determined any differently. We propose two possible explanations for this finding. The first possibility is that, zombies in our sample simply have not been subject to any additional support from the government or their lenders and, these factors certainly have not contributed to their survival. Hence, no significant difference in leverage ratios. Alternatively, we propose that, the reported insignificant coefficient on the zombie variable may be due to the type of

support and loan forbearances received by the zombies. That is, while zombies have been subject to the external supports, these supports have been mostly in different forms than additional lending or refinancing packages. So that, additional borrowings, if any, have not been large enough to cause a significant difference in leverage ratios of the recipients. This argument is also consistent with evidence in the financial news regarding the renegotiations of the zombies with their creditors, which have mostly been in the form of granting waivers to breach of pre-agreed loan covenants, switching to an interest-only loan, offering payment holidays, and loan restructurings such as lowering the interest rate and extending the maturity. Finally, to examine the robustness of the estimation results, the market leverage ratio is used as an alternative measure of capital structure. Our results suggest that the relationship between leverage and firms-specific determinants of capital structure and the impact of the GFC on firms' leverage ratios is not likely to be driven by the measure of leverage. However, the magnitude and significance of the impact is likely to depend on the way the leverage ratio is constructed.

In conclusion, we find supporting evidence for the significant impact of both the firm-specific characteristics and the overall economic conditions on firms' financing decisions. In particular, controlling for firm-specific variables, the changes in overall economic conditions have been found to cause significant reductions in firms' leverage ratios over the post-crisis period. We further show that, while the nature of the relationships between commonly used firm-specific determinants of capital structure and observed leverage ratio remain unchanged, their empirical relevance is affected by the general economic environment during the analysis period. Accordingly, one must choose the relevant explanatory variables that are developed from a similar economic environment to that of the analysis period of interest. In addition, we have found empirical evidence of the existence of zombies in the UK. Furthermore, although we do not find a significant difference between the capital structure of zombies and non-zombies, the zombieistic characteristics are potentially more than only high leverage ratios. In fact, we find that the degree of leverage has the least effect on the probability of becoming a zombie in comparison with the viability of business (as perceived by its top management), profitability, cash-generating ability and the ability to pay dividends. Accordingly, one must at least take account of zombies in the micro-level analysis of the above firm characteristics in the

UK. Similarly, the existence of zombies in the UK calls into question whether we should investigate the existence and the extent of the prevalence of zombies in other countries that were affected by the GFC. Finally, it should be remembered that we find only 42 zombie observations from a total sample of 711 firm-year observations, so the zombie apocalypse™ is not here yet!

Policy Recommendations:

While at the end of the previous recessions an increase in corporate insolvency cleared the ground for a quicker return to growth, zombies have emerged and managed to survive after the 2007 GFC and the consequent economic recession, due to the near-zero interest rates, banks forbearances on non-performing loans and different government-sponsored support schemes. The results of R3's July 2012 report shows that, there are 160,000 'near-insolvency' zombies among the UK SMEs, that are only able to pay the interest on their debts but unable to reduce the debt itself. Furthermore, our investigation on the constituents of the FTSE 250 Index identifies 29 'surviving insolvent' zombies, that are unable to generate enough revenues to even pay the interest expenses on their borrowings, let alone the repayment of the principal amount.

Recalling the economic stagnation of Japan in the 1990s and the evidence of zombies' contribution to the impediment of labour productivity of the UK, if history tells us anything is that zombies can have a detrimental effect on economic growth, and hence must be watched for. That is, if zombies are prevented from default, the economy will stack up with progressively weaker business models and growth will go into reverse. This is because keeping zombies alive could hold back banks from new lending and the resources tied up in zombies would not available for more vibrant and dynamic businesses, both of which are needed to boost the economy.

Thus, to the extent that the existence of zombies lead to inefficient reallocation of resources, they are expected to contribute to the lower than expected productivity and sluggish recovery of economic output. Essentially, the UK has become like a forest floor that is being clogged with weeds, choking off nutrients and light to saplings with a chance of becoming trees, and thus needs is a fire to clear out the undergrowth. Therefore, if UK wants to generate long-term growth, speed up the economic recovery

and improve productivity level, it needs to allow 'creative destruction', as new companies cannot grow when they are blocked by failing incumbents!

Accordingly, we would recommend the relevant authorities and policy makers to interfere and facilitate creative destruction by requiring banks to impose greater level of scrutiny when assessing loan applications and implement a more rigorous monitoring system to ensure zombie landings are written off in a timely manner and not postponed to avoid crystallising losses. Furthermore, capital requirement regulations can be adjusted to motivate banks to write off non-performing loans without the consequent significant capital injections. These actions, which are aimed to minimise the possibility of loan forbearances on non-performing loans of zombie borrowers, could be accompanied by tighter monetary policy such as an increase in interest rates for more promising results. This is because at the existing near-zero interest rates many unviable business can afford to service their debt and satisfy the banks' requirement for interest income, and hence are more likely to receive forbearance.

The need for immediate and prompt actions to put a stop to zombies dragging the economy and to prevent the emergence of zombies in future is intensified by the decision of the UK to exit the EU following the referendum in June 2016. In response to the UK's decision for Brexit, the BoE for the first time since March 2009 reduced interest rates from 0.5% to 0.25% (the lowest in 322 years, the entire lifetime of the BoE). At the new rate, banks can borrow from the central bank at almost no cost, encouraging them to make more loans. In addition to this, the BoE created a £100bn 'term funding scheme' which is designed to encourage banks to lend more money by helping them deal with the profit squeeze from low rates. Such loose monetary stimulus are in fact providing zombies with a greater chance of survival, as more business will be able to afford the interest payments on their existing borrowings.

Simply forcing zombies to 'adapt or die' by raising interest rates or refusing forbearance on non-performing loans may be perceived as a brutal way to tackle the zombie problem. The less brutal alternative and a softer way to help zombies out of business would be to combat the cost of insolvency. For many firms, insolvency is too expensive, particularly for larger firms, meaning they have no choice but to carry

on operating[209]. Accordingly, if the cost of insolvency continues to fall, many of the zombie firms in the UK may have an affordable way out of business.

All that being said, it is worth noting that motivating banks for creative destruction may not always work. That is, at least in some instances, the arbitrary interventions of policy makers that try to impose regulations that strictly prevent any zombie lending, might be actually more harmful than the harm imposed by the inefficient reallocation of resources. For instance, in cases where banks have loan portfolios with similar types of collaterals (which is typically the case for borrowers from the same industry), banks may be forced to postpone liquidation of one firm in order not to jeopardize the repayment of debt from other firms. This is because when one firm defaults and its collateral is sold on the market, the value of collateral held by the other firms also drops. In particular, if the price function is steep enough, there may be one firm big enough to cause a substantial drop in the market price of collateral. Then, the owners of some smaller firms might even prefer to surrender their collateral rather than repay the loan. This suggests that, policy makers must seek to find the right balance between different negative 'unintended consequences' of their actions.

Accordingly, there is not a single 'fit-all' policy to resolve the problem of zombies. That is, setting policy, particularly interest rates, too loose and you will keep alive companies that should go bust or be restructured to use resources more efficiently. But, set policy too tight and you will kill companies that are temporarily in trouble, exacerbating a downturn and destroying valuable economic resources. Accordingly, we propose that a possible solution to prevent zombie lending and the cascade of new defaults would be for the policy maker to implement a 2-pronged strategy involving: first, imposing lending restriction on banks as well as reducing bankruptcy costs in order to avoid zombie lending and help unviable businesses to default; second, engaging in direct collateral purchases in order to stop further declines in the value of the collaterals.

[209] According to R3, the majority of Insolvency Practitioners (IPs) work in small or medium-sized firms and are likely to charge between £100 and £300 per hour, while IPs in larger firms could charge up to £800 per hour.

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7. Appendix

Table 7.1 Analysis Variable Construction

Variable	*Bloomberg Definition*	*Bloomberg Item No.*
Cash & Cash Equivalents	Includes cash and liquid securities that can be converted into cash quickly at a reasonable price. Calculated as: Cash & Near Cash Items + Marketable Securities & ST Investment + LT Marketable Securities	RR253
Current Assets	The total of all Current Assets as reported. Calculated as: Cash & Cash Equivalents + Marketable Securities & Other Short-term Investments + Accounts & Notes Receivable + Inventories + Other Current Assets.	BS015
Current Liabilities	Calculated as: Accounts Payable + ST Borrowings + Other ST Liabilities.	BS050
Depreciation & Amortization Expenses	Includes all expense charged against earnings to write off the cost of a plant or machine over its useful life, giving consideration to wear and tear, obsolescence, and salvage value plus the amortization on Intangible Assets.	CF011
Discontinued Operations	Monetary impact of business operations sold, disposed of or abandoned.	IM197
Dividends Paid	Includes dividends actually paid out as cash disbursements including both common stock of the parent company and preferred stock of all companies consolidated.	CF026
EBITDA	An indicator of a company's financial performance which is essentially net income with interest, taxes, depreciation, and amortization added back to it, and can be used to analyse and compare profitability between companies and industries because it eliminates the effects of financing and accounting decisions. Calculated as: Operating Income + Depreciation & Amortization Expenses	RR009
Interest Income	Includes interest income that is considered non-operating. Excludes interest income that is considered operating (i.e.: a financial subsidiary's interest income).	IS011
Inventory	The components of inventory vary depending on the industry. Includes raw materials, work in progress, finished goods, completed but not billed on long-term contracts, and other adjustments to Inventory.	BS013
Long-term Debt	All interest-bearing financial obligations that are not due within a year, and includes convertible, redeemable, retractable debentures, bonds, loans, mortgage debts, sinking funds, and long-term bank overdrafts.	BS051
Net Fixed Assets	Those assets of a permanent nature required for the normal conduct of a business, and which will not normally be converted into cash during the ensuring fiscal period. Calculated as: Gross fixed Assets - Accumulated Depreciation.	BS032
Net Profit/Loss	The profit after all expenses have been deducted. Includes the effects of all one-time, non-recurring, and extraordinary gains, losses, or charges.	IS050
Net Worth	The amount that all common shareholders have invested in a company. Calculated as: Share Capital & Additional Paid in Capital + Retained Earnings and Other Equity.	RR010
Number of CEO and Equivalent Changes During FY	Number of Chief Executive Officer (CEO) and equivalent changes during fiscal year.	CG051

Operating Cash Flow	Total amount of cash a firm generates from its operation. Calculated as: Net Income + Depreciation & Amortization + Other Noncash Adjustments + Changes in Non - Cash Working Capital.	CF015
Operating Expenses	Includes selling & administrative expenses and other operating expenses after cost of goods sold	IS032
Operating Profit/Loss	Calculated as: Net Sales + Other Operating Income - Cost of Goods Sold - Other Operating Expenses. The reported operating income (loss) is adjusted to correct for non-operating gains and expenses that are included	IS033
Quick Assets	Cash & Near Cash Items + Short-term Investments + Account Receivables	BS010+BS 011+BS012
Retained Earnings	Accumulated earnings, earned surplus, or unappropriated profit that has been retained by the company, and includes legal reserves and the current year's net profit.	BS190
Sales (Net Sales)	Total of operating revenues adjusted for returns, discounts, allowances, excise taxes, insurance charges, sales taxes, and value added taxes (VAT).	IS010
Total Assets	The total of all short and long-term assets as reported on the Balance Sheet. Calculated as: Current Assets + Non-Current Assets	BS035
Total Capital	Total investment that shareholders and debtholders have made in a company. Calculated as: Short Term Borrowings + Long Term Borrowings + Preferred Equity + Minority Interest + Total Common Equity	RR006
Total Debt	Firm’s total interest-bearing financial obligations. Calculated as: Short-term Debt + Long-term Debt	RR251
Total Equity	Firm's total assets minus its total liabilities. Calculated as: Common Equity + Minority Interest + Preferred + Equity	RR007
Total Interest Expense	Total interest incurred during the period which includes interest charged to income statement and interest capitalized. Calculated as: Interest Expense + Capitalized Interest	RR011
Total Liabilities	Firm’s total interest-bearing and non-interest bearing financial obligations. Calculated as: Current Liabilities + Non-current Liabilities	RR005
Total Market Value	Calculated as: Market Capitalization + Preferred Equity + Short-Term & Long-Term Debt + Other Long-Term Liabilities + Minority Interest - Cash & Cash Equivalents.	RR254
Working Capital	Calculated as: Current Assets - Current Liabilities	RR150

Table 7.2 The Identified Firm-Year Zombie Observations

Name	*GICS Industry*	*Year*
Carphone Warehouse Group PLC\Old	Specialty Retail	2008
Balfour Beatty PLC	Construction & Engineering	2012
Barratt Developments PLC	Household Durables	2008
Barratt Developments PLC	Household Durables	2009
Bodycote PLC	Machinery	2008
Bodycote PLC	Machinery	2009
Burberry Group PLC	Textiles, Apparel & Luxury Goods	2008
Bellway PLC	Household Durables	2009
Carpetright PLC	Specialty Retail	2012
CSR PLC	Semiconductors & Semiconductor Equipment	2010
Daily Mail & General Trust PLC	Media	2009
Darty Plc	Specialty Retail	2008
Darty Plc	Specialty Retail	2011
Dixons Retail PLC	Specialty Retail	2008
Dixons Retail PLC	Specialty Retail	2010
Dixons Retail PLC	Specialty Retail	2011
Dixons Retail PLC	Specialty Retail	2012
GKN PLC	Auto Components	2009
HomeServe PLC	Commercial Services & Supplies	2008
Laird PLC	Electronic Equipment, Instruments & Components	2010
Laird PLC	Electronic Equipment, Instruments & Components	2011
Mitchells & Butlers PLC	Hotels, Restaurants & Leisure	2009
Mitchells & Butlers PLC	Hotels, Restaurants & Leisure	2010
Marston's PLC	Hotels, Restaurants & Leisure	2012
Misys Ltd	Software	2011
National Express Group PLC	Road & Rail	2009
Ocado Group PLC	Internet & Catalog Retail	2010
Ocado Group PLC	Internet & Catalog Retail	2011
Ocado Group PLC	Internet & Catalog Retail	2012
Petropavlovsk PLC	Metals & Mining	2012
Punch Taverns PLC	Hotels, Restaurants & Leisure	2009
Punch Taverns PLC	Hotels, Restaurants & Leisure	2010
QinetiQ Group PLC	Aerospace & Defense	2009
QinetiQ Group PLC	Aerospace & Defense	2012
Redrow PLC	Household Durables	2008
Rentokil Initial PLC	Commercial Services & Supplies	2011
SIG PLC	Trading Companies & Distributors	2009
SIG PLC	Trading Companies & Distributors	2010
Salamander Energy PLC	Oil, Gas & Consumable Fuels	2010
Tate & Lyle PLC	Food Products	2009
Taylor Wimpey PLC	Household Durables	2009
Vesuvius PLC	Machinery	2009

Table 7.3 Pearson Correlation Matrix – Univariate Logit Variables

	TDTA	*EBITS*	*ROA*	*ROE*	*NSTA*	*CFOTA*	*SIZE*	*CEOCHNG*	*DVDND*	*RTIL*	*GDP*
TDTA	1.000										
EBITS	0.051	1.000									
ROA	-0.152	0.081	1.000								
ROE	0.091	0.005	0.053	1.000							
NSTA	-0.079	-0.644	0.508	-0.012	1.000						
CFOTA	-0.100	0.088	0.714	0.025	0.584	1.000					
SIZE	0.362	-0.014	-0.462	-0.007	-0.269	-0.481	1.000				
CEOCHNG	0.058	0.007	0.003	-0.028	0.000	-0.002	-0.001	1.000			
DVDND	0.013	-0.103	-0.180	-0.043	0.050	-0.089	0.102	-0.020	1.000		
RTIL	-0.090	0.005	0.028	-0.026	-0.043	0.022	-0.069	0.012	0.070	1.000	
GDP	-0.101	-0.010	0.071	-0.070	0.034	-0.006	0.024	0.007	-0.049	0.040	1.000

Where, the analysis period is 2008-2012; $TDTA = \frac{Total\ Debt}{Total\ Assets}$ denotes leverage ratio; $EBITS = \frac{Earnings\ Before\ Inerest\ \&\ Taxes}{Sales}$, $ROA = \frac{Net\ Profit\ (Loss)}{Sales}$, and $ROE = \frac{Net\ Profit\ (Loss)}{Net\ Worth}$ denote measures of profitability; $NSTA = \frac{Net\ Sales}{Total\ Assets}$ denotes activity ratio; $CFOTA = \frac{Operating\ Cash\ Flow}{Total\ Assets}$ denotes cash-generating ability; $SIZE = \ln(Total\ Assets)$ denotes firm size; *DVDND* is a dummy variable that takes value of 1 if firm does not make dividend payment during the year and 0 otherwise; *RTIL* is a dummy variable that takes value of as 1 if firm belongs to the Retail sector and 0 otherwise; *CEOCHNG* is a dummy variable that takes value of 1 if CEO (or equivalent) resigned during the year and 0 otherwise; *GDP* denotes the annual growth in the Real Gross Domestic Product (GDP).

Table 7.4 Test of Multicollinearity – Univariate Logit Variables

Variable	*VIF*	*1/VIF*
SIZE	6.68	0.15
CFOTA	5.82	0.17
TDTA1	3.57	0.28
EBITS	3.45	0.29
NSTA	3.11	0.32
ROA	2.73	0.37
DVDND	1.30	0.77
RTIL	1.17	0.85
CEOCHNG	1.17	0.85
ROE	1.09	0.92
GDP	1.06	0.94
Mean VIF	2.83	

Where, the analysis period is 2008-2012; $TDTA = \frac{Total\ Debt}{Total\ Assets}$ denotes leverage ratio; $EBITS = \frac{Earnings\ Before\ Inerest\ \&\ Taxes}{Sales}$, $ROA = \frac{Net\ Profit\ (Loss)}{Sales}$, and $ROE = \frac{Net\ Profit\ (Loss)}{Net\ Worth}$ denote measures of profitability; $NSTA = \frac{Net\ Sales}{Total\ Assets}$ denotes activity ratio; $CFOTA = \frac{Operating\ Cash\ Flow}{Total\ Assets}$ denotes cash-generating ability; $SIZE = \ln(Total\ Assets)$ denotes firm size; *DVDND* is a dummy variable that takes value of 1 if firm does not make dividend payment during the year and 0 otherwise; *RTIL* is a dummy variable that takes value of as 1 if firm belongs to the Retail sector and 0 otherwise; *CEOCHNG* is a dummy variable that takes value of 1 if CEO (or equivalent) resigned during the year and 0 otherwise; *GDP* denotes the annual growth in the Real Gross Domestic Product (GDP).

Table 7.5 Pooled Regression Results – Robust

Zombie	*Coef.*	*Robust Std. Err.*	*z*	*P* > | z |
TDTA	0.097	0.036	2.680	0.007
EBITS	-1.244	0.284	-4.370	0.000
CFOTA	-0.212	0.108	-1.960	0.050
DVDND	3.275	1.094	2.990	0.003
CEOCHNG	2.293	0.856	2.680	0.007
_cons	-0.487	0.867	-0.560	0.575
Obs.				425
Log Likelihood				-20.357
Wald Chi2(5)				38.13
Prob > Chi2				0.000
Pseudo-R^2				0.828

Where, the analysis period is 2008–2012; $Zombie = \ln(\frac{\Pr(y_{it}=1)}{\Pr(y_{it}=0)})$ denotes the log of odds ratio of becoming a zombie (i.e., $AICR = \frac{Operating\ Income + Interest\ Income}{Total\ Interest\ Expense} < 1$); $TDTA = \frac{Total\ Debt}{Total\ Assets}$ denotes leverage ratio; $EBITS = \frac{Earnings\ Before\ Inerest\ \&\ Taxes}{Sales}$ denotes profitability; $CFOTA = \frac{Operating\ Cash\ Flow}{Total\ Assets}$ denotes cash-generating ability; *DVDND* is a dummy variable that takes value of 1 if firm does not make dividend payment during the year and 0 otherwise; *CEOCHNG* is a dummy variable that takes value of 1 if CEO (or equivalent) resigned during the year and 0 otherwise; *Robust Std. Err*. denotes the Huber-White heteroskedasticity-robust standard errors.

Figure 7.1 Test for Normality (KD, SNP, and QQ Plots) – RE – Base Model

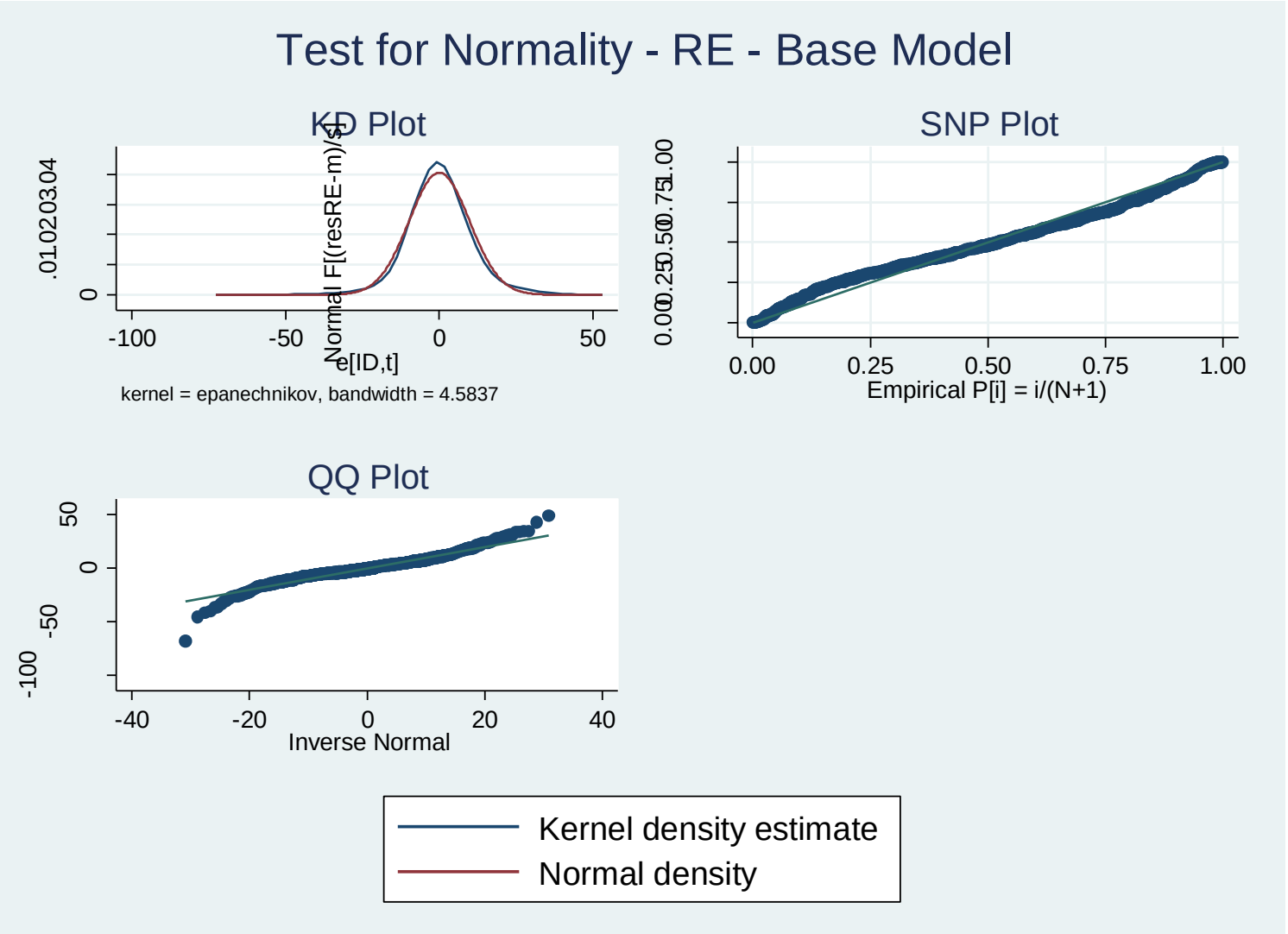


Figure 7.2 Test for Normality (KD, SNP, and QQ Plots) – FE - Base Model

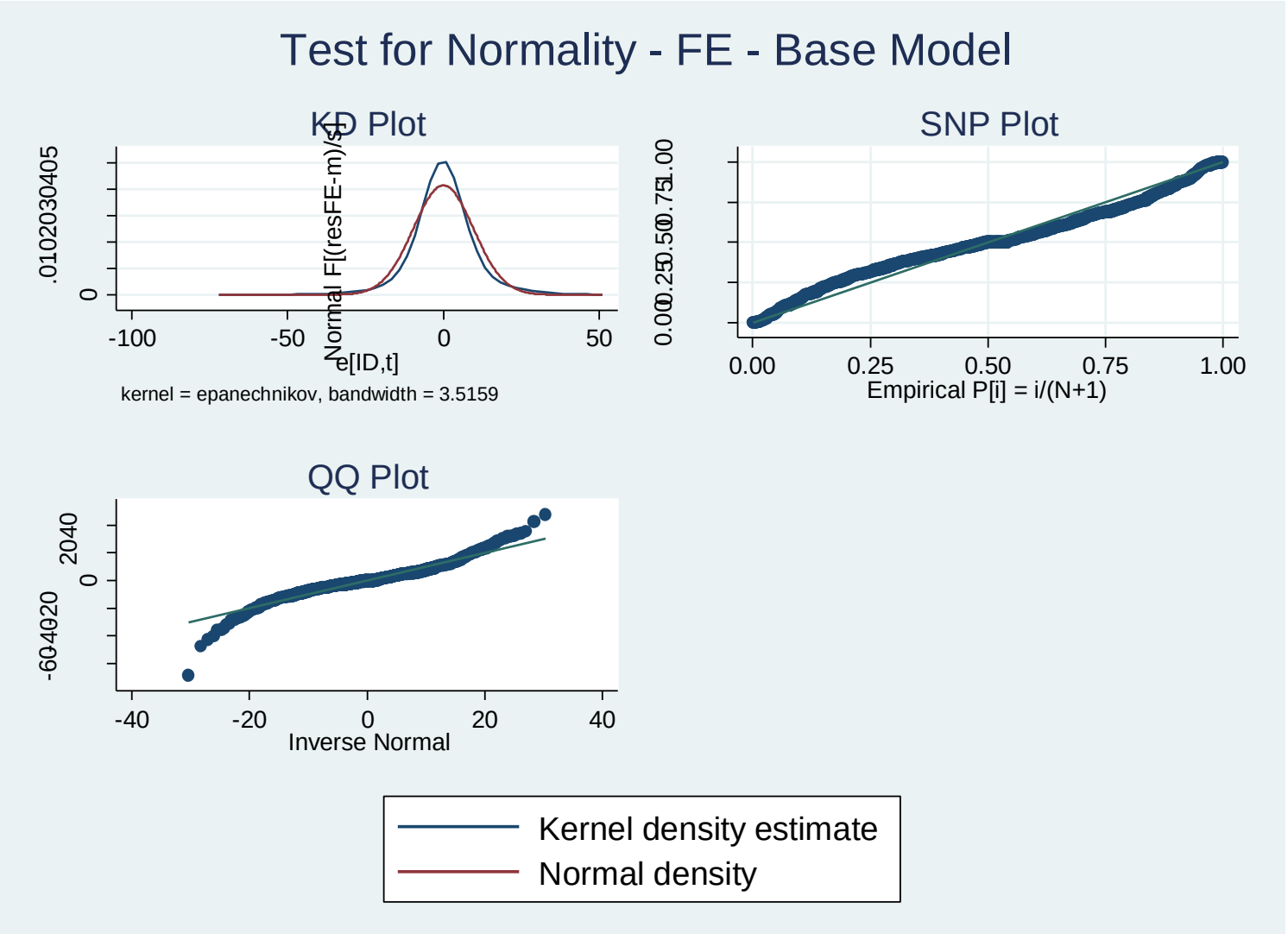


Figure 7.3 Test for Normality (KD, SNP, and QQ Plots) – RE - Zombie Model

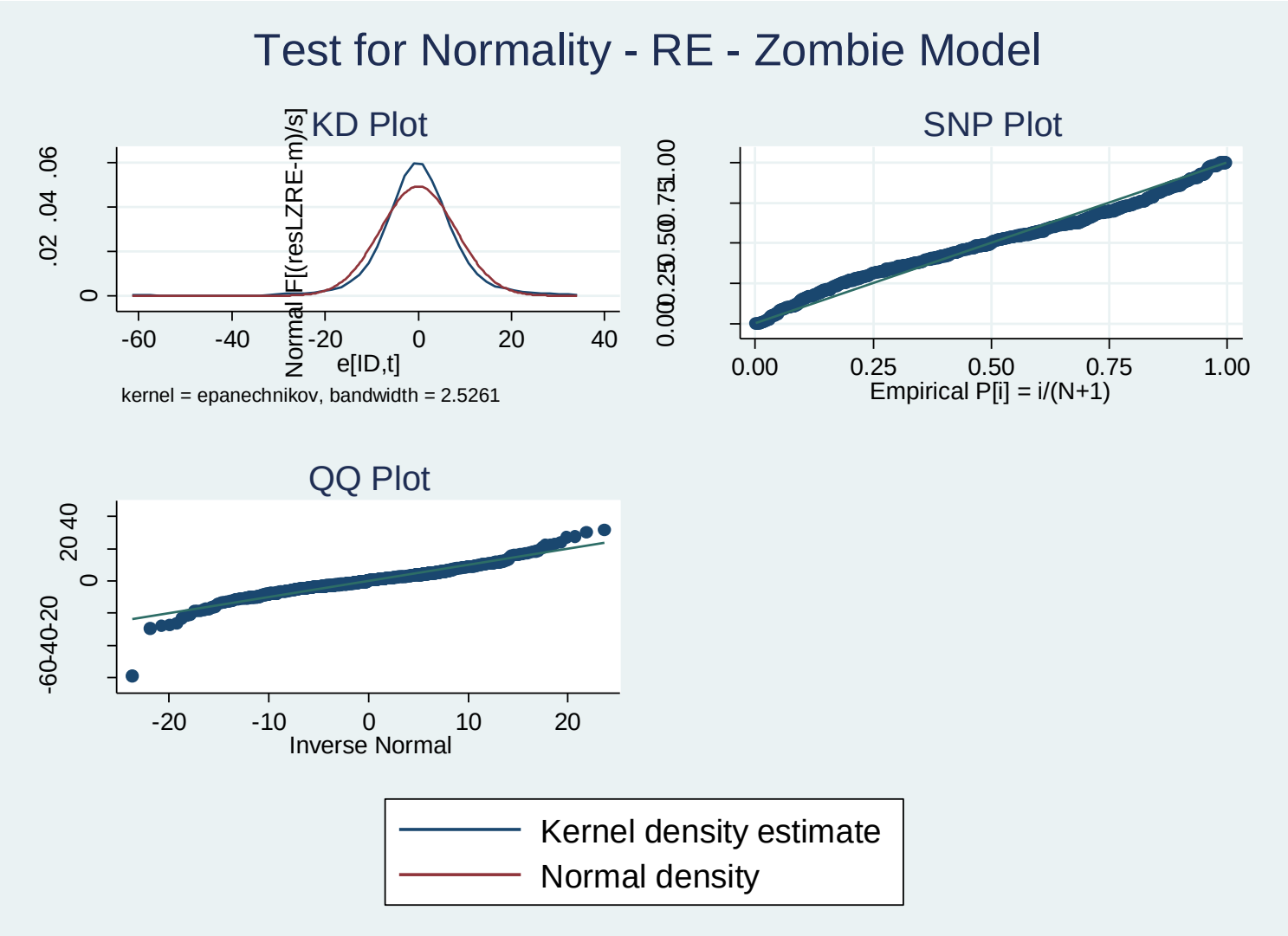


Figure 7.4 Test for Normality (KD, SNP, and QQ Plots) – FE - Zombie Model

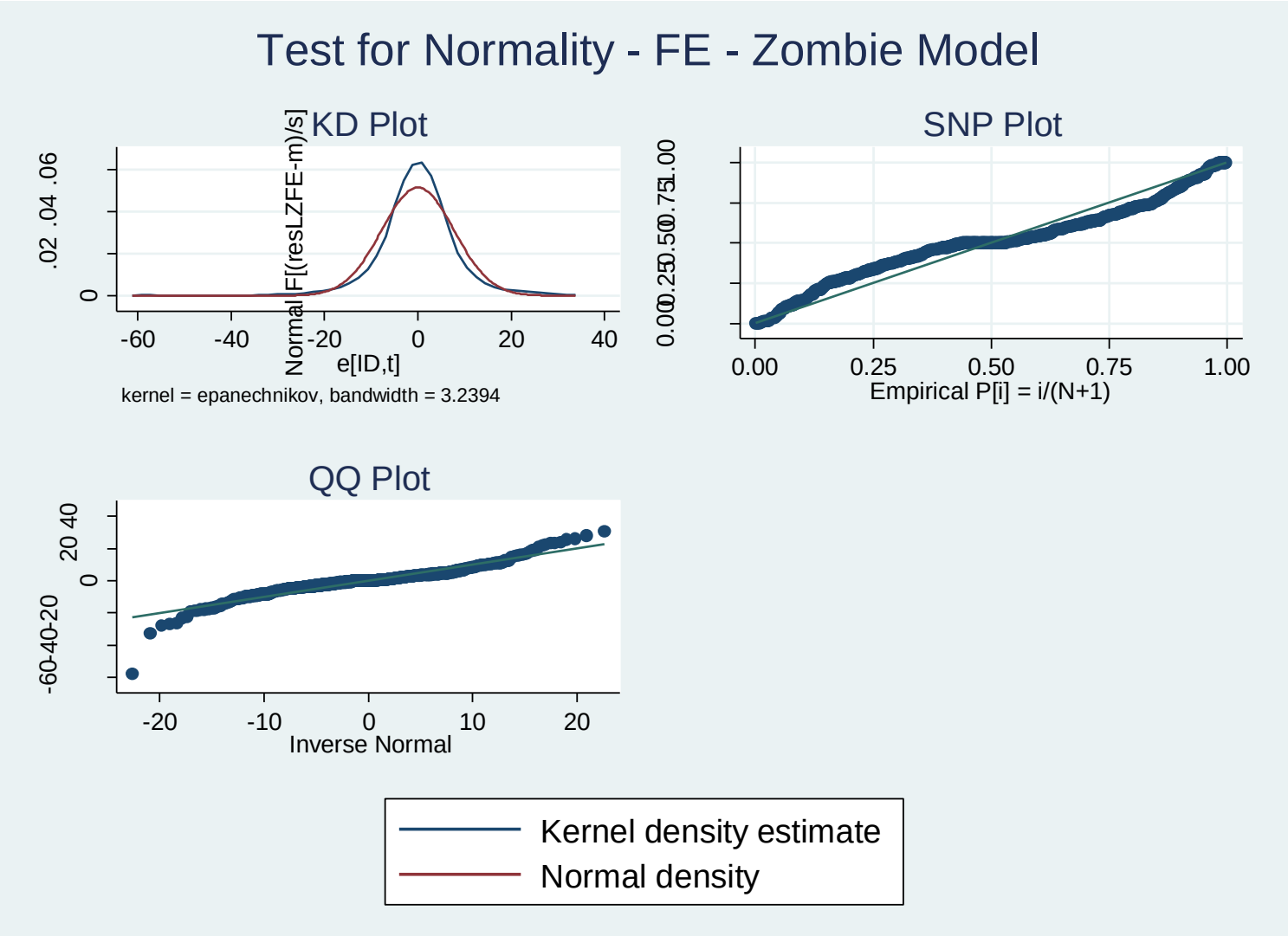


Table 7.6 Test for Heteroskedasticity – RE Estimator

Model	*Modified Wald test for groupwise heteroskedasticity*	
	Chi2	*Prob > Chi2*
Base Model	2.10e+05	0.000
Zombie Model	5.00e+06	0.000

Table 7.7 Test for Heteroskedasticity – FE Estimator

Model		*F-statistic*	*Prob > F*
Base Model	W0	4.072	0.000
	W50	1.938	0.000
	W10	4.072	0.000
Zombie Model	W0	3.713	0.000
	W50	1.467	0.000
	W10	3.713	0.000

Table 7.8 Static – OLS (Non-Robust) – Base Model

Leverage	*Coef.*	*Std. Err.*	*t*	*P > | t |*
GRT	0.043	0.006	7.660	0.000
SIZ	10.611	0.751	14.130	0.000
TNG	0.190	0.028	6.880	0.000
PRF	-0.596	0.097	-6.160	0.000
NDTS	1.204	0.221	5.450	0.000
RSK	0.001	0.027	0.030	0.979
YR04	-4.109	2.504	-1.640	0.101
YR05	-1.140	2.449	-0.470	0.642
YR06	-3.086	2.423	-1.270	0.203
YR08	-0.707	2.442	-0.290	0.772
YR09	-7.951	2.443	-3.250	0.001
YR10	-11.264	2.461	-4.580	0.000
YR11	-11.571	2.440	-4.740	0.000
YR12	-12.238	2.445	-5.000	0.000
_cons	-190.254	16.042	-11.860	0.000
Obs.				1197
F (14, 1182)				33.22
Prob > F				0.000
R^2				0.282
Adjusted-R^2				0.274
RMSE				19.999

Where, the analysis period is 2004–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; $YR04$–$YR12$ are the annual time dummies with 2007 used as the base year; *Std. Err*. denotes the standard errors associated with the coefficients; and t and $p > |t|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 7.9 Static – OLS (Non-Robust) – Zombie Model

Leverage	*Coef.*	*Std. Err.*	*t*	*P > | t |*
GRT	0.159	0.014	11.010	0.000
SIZ	11.430	1.083	10.550	0.000
TNG	0.171	0.035	4.930	0.000
PRF	-0.484	0.171	-2.820	0.005
NDTS	1.191	0.343	3.470	0.001
RSK	0.063	0.047	1.330	0.184
ZMB	-2.158	3.428	-0.630	0.529
YR08	4.435	2.624	1.690	0.091
YR09	-5.448	2.591	-2.100	0.036
YR10	-9.527	2.586	-3.680	0.000
YR11	-8.345	2.588	-3.220	0.001
YR12	-11.459	2.552	-4.490	0.000
_cons	-227.867	24.250	-9.400	0.000
Obs.				577
F (14, 1182)				24.42
Prob > F				0.000
R^2				0.342
Adjusted-R^2				0.328
RMSE				17.788

Where, the analysis period is 2008–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; ZMB denotes a dummy variable takes a value of 1 if firm is identified as zombie and 0 otherwise; $YR08$–$YR12$ are the annual time dummies with 2007 used as the base year; *Std. Err*. denotes the standard errors associated with the coefficients; and t and $p > |t|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 7.10 Means of Total Interest Expenses vs. Depreciation & Amortization Expenses

Year	*Variable*	*Obs.*	*Mean (£m)*
2004	TIE	122	19.3
	DAE	123	47.4
2005	TIE	132	24.1
	DAE	132	41.5
2006	TIE	137	25.4
	DAE	137	40.3
2007	TIE	136	28.9
	DAE	136	40.0
2008	TIE	135	31.2
	DAE	135	45.8
2009	TIE	135	25.2
	DAE	135	52.1
2010	TIE	129	22.6
	DAE	130	53.6
2011	TIE	132	18.7
	DAE	135	55.4
2012	TIE	132	17.3
	DAE	134	52.4

Section B. Estimation Results for Alternative Model Specifications

Table 7.11 L.LVG with Lag Limits (1 1) – Base Model

Leverage	*Coef.*	*Corrected Std. Err.*	*z*	*P > | z |*
L.LVG	0.530	0.082	6.440	0.000
GRT	0.027	0.007	3.810	0.000
SIZ	5.454	1.165	4.680	0.000
TNG	0.108	0.034	3.170	0.002
PRF	-0.397	0.079	-5.050	0.000
NDTS	0.531	0.241	2.210	0.027
RSK	0.089	0.017	5.330	0.000
YR04	-3.420	1.473	-2.320	0.020
YR05	0.631	1.571	0.400	0.688
YR06	-3.096	1.398	-2.210	0.027
YR08	0.053	1.395	0.040	0.970
YR09	-6.658	1.396	-4.770	0.000
YR10	-8.273	1.228	-6.740	0.000
YR11	-5.976	1.235	-4.840	0.000
YR12	-6.439	1.415	-4.550	0.000
_cons	-98.240	22.371	-4.390	0.000
Wald Chi2(15)				1024.58
Prob > Chi2				0.000
No. of instruments				47
AR(1)				0.000
AR(2)				0.949
Hansen				0.488
AIC				6220.707
BIC				6302.107
RSS				210608.1

Where, the analysis period is 2004–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt+Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets-Book\ Value\ Equity+Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; $YR04–YR12$ are the annual time dummies with 2007 used as the base year; *Corrected Std. Err.* denotes the Windmeijer standard errors which are the heteroskedasticity-robust standard errors that are also corrected for finite sample bias; and z and $p > |z|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 7.12 L.LVG with Lag Limits (1 2) – Base Model

Leverage	*Coef.*	*Corrected Std. Err.*	*z*	*P > | z |*
L.LVG	0.515	0.082	6.320	0.000
GRT	0.027	0.006	4.630	0.000
SIZ	5.611	1.193	4.700	0.000
TNG	0.104	0.037	2.780	0.005
PRF	-0.414	0.079	-5.240	0.000
NDTS	0.550	0.247	2.230	0.026
RSK	0.089	0.016	5.510	0.000
YR04	-3.104	1.475	-2.100	0.035
YR05	0.666	1.445	0.460	0.645
YR06	-2.771	1.250	-2.220	0.027
YR08	-0.152	1.361	-0.110	0.911
YR09	-6.568	1.318	-4.980	0.000
YR10	-8.687	1.264	-6.870	0.000
YR11	-6.076	1.321	-4.600	0.000
YR12	-6.397	1.473	-4.340	0.000
_cons	-100.564	22.767	-4.420	0.000
Wald Chi2(15)				1055.87
Prob > Chi2				0.000
No. of instruments				54
AR(1)				0.000
AR(2)				0.968
Hansen				0.326
AIC				6241.923
BIC				6323.325
RSS				214374.5

Where, the analysis period is 2004–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; $YR04$–$YR12$ are the annual time dummies with 2007 used as the base year; *Corrected Std. Err.* denotes the Windmeijer standard errors which are the heteroskedasticity-robust standard errors that are also corrected for finite sample bias; and z and $p > |z|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 7.13 L.LVG with Lag Limits (1 3) – Base Model

Leverage	*Coef.*	*Corrected Std. Err.*	*z*	*P > | z |*
L.LVG	0.484	0.085	5.690	0.000
GRT	0.027	0.005	5.060	0.000
SIZ	6.092	1.207	5.050	0.000
TNG	0.110	0.041	2.680	0.007
PRF	-0.415	0.079	-5.240	0.000
NDTS	0.617	0.253	2.440	0.015
RSK	0.092	0.017	5.600	0.000
YR04	-3.254	1.474	-2.210	0.027
YR05	-0.039	1.493	-0.030	0.979
YR06	-3.054	1.187	-2.570	0.010
YR08	-0.391	1.328	-0.290	0.769
YR09	-7.295	1.328	-5.490	0.000
YR10	-9.009	1.240	-7.270	0.000
YR11	-6.750	1.374	-4.910	0.000
YR12	-7.184	1.544	-4.650	0.000
_cons	-109.729	23.018	-4.770	0.000
Wald Chi2(15)				995.53
Prob > Chi2				0.000
No. of instruments				60
AR(1)				0.000
AR(2)				0.994
Hansen				0.253
AIC				6287.694
BIC				6369.095
RSS				222730.4

Where, the analysis period is 2004–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; $YR04$–$YR12$ are the annual time dummies with 2007 used as the base year; *Corrected Std. Err.* denotes the Windmeijer standard errors which are the heteroskedasticity-robust standard errors that are also corrected for finite sample bias; and z and $p > |z|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 7.14 L.LVG with Lag Limits (1 4) – Base Model

Leverage	*Coef.*	*Corrected Std. Err.*	*z*	*P > | z |*
L.LVG	0.497	0.085	5.820	0.000
GRT	0.028	0.006	4.540	0.000
SIZ	5.883	1.208	4.870	0.000
TNG	0.103	0.040	2.550	0.011
PRF	-0.397	0.079	-5.030	0.000
NDTS	0.618	0.243	2.540	0.011
RSK	0.091	0.017	5.300	0.000
YR04	-3.371	1.467	-2.300	0.022
YR05	0.073	1.466	0.050	0.960
YR06	-2.884	1.193	-2.420	0.016
YR08	-0.411	1.388	-0.300	0.767
YR09	-7.254	1.348	-5.380	0.000
YR10	-9.017	1.253	-7.190	0.000
YR11	-6.615	1.418	-4.660	0.000
YR12	-6.919	1.586	-4.360	0.000
_cons	-106.268	23.260	-4.570	0.000
Wald Chi2(15)				981.42
Prob > Chi2				0.000
No. of instruments				65
AR(1)				0.000
AR(2)				0.980
Hansen				0.260
AIC				6267.422
BIC				6348.823
RSS				218990.1

Where, the analysis period is 2004–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt+Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets-Book\ Value\ Equity+Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; $YR04–YR12$ are the annual time dummies with 2007 used as the base year; *Corrected Std. Err.* denotes the Windmeijer standard errors which are the heteroskedasticity-robust standard errors that are also corrected for finite sample bias; and z and $p > |z|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 7.15 L.LVG with Lag Limits (1 5) – Base Model

Leverage	*Coef.*	*Corrected Std. Err.*	*z*	*P > | z |*
L.LVG	0.477	0.085	5.580	0.000
GRT	0.028	0.006	4.800	0.000
SIZ	6.279	1.212	5.180	0.000
TNG	0.109	0.042	2.610	0.009
PRF	-0.403	0.078	-5.150	0.000
NDTS	0.636	0.251	2.540	0.011
RSK	0.095	0.018	5.300	0.000
YR04	-3.317	1.488	-2.230	0.026
YR05	0.044	1.478	0.030	0.976
YR06	-2.816	1.190	-2.370	0.018
YR08	-0.492	1.400	-0.350	0.725
YR09	-7.416	1.375	-5.390	0.000
YR10	-9.230	1.261	-7.320	0.000
YR11	-6.830	1.425	-4.790	0.000
YR12	-7.515	1.536	-4.890	0.000
_cons	-113.745	23.313	-4.880	0.000
Wald Chi2(15)				985.19
Prob > Chi2				0.000
No. of instruments				69
AR(1)				0.000
AR(2)				0.990
Hansen				0.308
AIC				6301.403
BIC				6382.804
RSS				225295.9

Where, the analysis period is 2004–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt+Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets-Book\ Value\ Equity+Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; $YR04–YR12$ are the annual time dummies with 2007 used as the base year; *Corrected Std. Err.* denotes the Windmeijer standard errors which are the heteroskedasticity-robust standard errors that are also corrected for finite sample bias; and z and $p > |z|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 7.16 L.LVG with Lag Limits (1 6) – Base Model

Leverage	*Coef.*	*Corrected Std. Err.*	*z*	*P > | z |*
L.LVG	0.471	0.085	5.560	0.000
GRT	0.028	0.006	4.600	0.000
SIZ	6.379	1.229	5.190	0.000
TNG	0.114	0.042	2.700	0.007
PRF	-0.402	0.077	-5.220	0.000
NDTS	0.642	0.243	2.640	0.008
RSK	0.096	0.018	5.370	0.000
YR04	-3.401	1.475	-2.310	0.021
YR05	-0.054	1.474	-0.040	0.971
YR06	-2.921	1.190	-2.450	0.014
YR08	-0.638	1.399	-0.460	0.648
YR09	-7.579	1.354	-5.600	0.000
YR10	-9.395	1.259	-7.460	0.000
YR11	-7.160	1.403	-5.100	0.000
YR12	-7.728	1.567	-4.930	0.000
_cons	-115.784	23.657	-4.890	0.000
Wald Chi2(15)				982.08
Prob > Chi2				0.000
No. of instruments				72
AR(1)				0.000
AR(2)				0.996
Hansen				0.320
AIC				6311.539
BIC				6392.940
RSS				227211.7

Where, the analysis period is 2004–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt+Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets-Book\ Value\ Equity+Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; $YR04–YR12$ are the annual time dummies with 2007 used as the base year; *Corrected Std. Err.* denotes the Windmeijer standard errors which are the heteroskedasticity-robust standard errors that are also corrected for finite sample bias; and z and $p > |z|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 7.17 L.LVG with Lag Limits (1 7) – Base Model

Leverage	*Coef.*	*Corrected Std. Err.*	*z*	*P > | z |*
L.LVG	0.472	0.084	5.630	0.000
GRT	0.028	0.006	4.620	0.000
SIZ	6.247	1.198	5.210	0.000
TNG	0.117	0.043	2.730	0.006
PRF	-0.406	0.077	-5.270	0.000
NDTS	0.651	0.243	2.670	0.007
RSK	0.096	0.017	5.470	0.000
YR04	-3.218	1.494	-2.150	0.031
YR05	-0.205	1.479	-0.140	0.890
YR06	-2.992	1.197	-2.500	0.012
YR08	-0.578	1.418	-0.410	0.684
YR09	-7.553	1.357	-5.560	0.000
YR10	-9.124	1.251	-7.290	0.000
YR11	-7.125	1.408	-5.060	0.000
YR12	-7.625	1.575	-4.840	0.000
_cons	-113.279	23.091	-4.910	0.000
Wald Chi2(15)				968.58
Prob > Chi2				0.000
No. of instruments				74
AR(1)				0.000
AR(2)				0.998
Hansen				0.327
AIC				6309.081
BIC				6390.482
RSS				226745.8

Where, the analysis period is 2004–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; $YR04$–$YR12$ are the annual time dummies with 2007 used as the base year; *Corrected Std. Err.* denotes the Windmeijer standard errors which are the heteroskedasticity-robust standard errors that are also corrected for finite sample bias; and z and $p > |z|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 7.18 L.LVG with Lag Limits (1 8) – Base Model

Leverage	*Coef.*	*Corrected Std. Err.*	*z*	*P > | z |*
L.LVG	0.473	0.084	5.630	0.000
GRT	0.028	0.006	4.640	0.000
SIZ	6.214	1.208	5.140	0.000
TNG	0.116	0.043	2.720	0.007
PRF	-0.407	0.077	-5.270	0.000
NDTS	0.654	0.243	2.700	0.007
RSK	0.095	0.017	5.480	0.000
YR04	-3.200	1.483	-2.160	0.031
YR05	-0.229	1.472	-0.160	0.876
YR06	-3.039	1.186	-2.560	0.010
YR08	-0.548	1.400	-0.390	0.696
YR09	-7.527	1.342	-5.610	0.000
YR10	-9.103	1.248	-7.300	0.000
YR11	-7.120	1.402	-5.080	0.000
YR12	-7.633	1.571	-4.860	0.000
_cons	-112.678	23.284	-4.840	0.000
Wald Chi2(15)				968.69
Prob > Chi2				0.000
No. of instruments				75
AR(1)				0.000
AR(2)				0.996
Hansen				0.358
AIC				6307.450
BIC				6388.851
RSS				226437.0

Where, the analysis period is 2004–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt+Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets-Book\ Value\ Equity+Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; $YR04–YR12$ are the annual time dummies with 2007 used as the base year; *Corrected Std. Err.* denotes the Windmeijer standard errors which are the heteroskedasticity-robust standard errors that are also corrected for finite sample bias; and z and $p > |z|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 7.19 L.LVG with Lag Limits (1 1) – Zombie Model

Leverage	*Coef.*	*Corrected Std. Err.*	*z*	*P > | z |*
L.LVG	0.488	0.207	2.350	0.019
GRT	0.023	0.030	0.790	0.432
SIZ	4.348	2.622	1.660	0.097
TNG	0.124	0.056	2.190	0.029
PRF	-0.260	0.161	-1.610	0.107
NDTS	0.521	0.421	1.240	0.216
RSK	0.310	0.359	0.860	0.388
ZMB	-1.359	2.469	-0.550	0.582
YR08	-3.574	2.246	-1.590	0.112
YR09	-9.767	1.903	-5.130	0.000
YR10	-10.495	1.989	-5.280	0.000
YR11	-7.717	1.913	-4.030	0.000
YR12	-7.396	2.668	-2.770	0.006
_cons	-73.345	53.669	-1.370	0.172
Wald Chi2(13)				249.10
Prob > Chi2				0.000
No. of instruments				22
AR(1)				0.010
AR(2)				0.603
Hansen				0.422
AIC				2989.575
BIC				3050.463
RSS				101388.8

Where, the analysis period is 2008–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; ZMB denotes a dummy variable takes a value of 1 if firm is identified as zombie and 0 otherwise; $YR08$–$YR12$ are the annual time dummies with 2007 used as the base year; *Corrected Std. Err. denotes* the Windmeijer standard errors which are the heteroskedasticity-robust standard errors that are also corrected for finite sample bias; and z and $p > |z|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 7.20 L.LVG with Lag Limits (1 2) – Zombie Model

Leverage	*Coef.*	*Corrected Std. Err.*	*z*	*P > | z |*
L.LVG	0.453	0.224	2.020	0.043
GRT	0.021	0.030	0.700	0.482
SIZ	4.581	2.900	1.580	0.114
TNG	0.139	0.062	2.250	0.025
PRF	-0.253	0.171	-1.480	0.139
NDTS	0.689	0.422	1.630	0.102
RSK	0.190	0.332	0.570	0.567
ZMB	-2.276	2.241	-1.020	0.310
YR08	-3.813	2.150	-1.770	0.076
YR09	-10.023	1.821	-5.500	0.000
YR10	-9.682	1.807	-5.360	0.000
YR11	-8.679	2.206	-3.930	0.000
YR12	-8.145	3.007	-2.710	0.007
_cons	-77.356	59.162	-1.310	0.191
Wald Chi2(13)				274.90
Prob > Chi2				0.000
No. of instruments				26
AR(1)				0.039
AR(2)				0.181
Hansen				0.184
AIC				2985.612
BIC				3046.500
RSS				100688.8

Where, the analysis period is 2008–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; ZMB denotes a dummy variable takes a value of 1 if firm is identified as zombie and 0 otherwise; $YR08$–$YR12$ are the annual time dummies with 2007 used as the base year; *Corrected Std. Err. denotes* the Windmeijer standard errors which are the heteroskedasticity-robust standard errors that are also corrected for finite sample bias; and z and $p > |z|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 7.21 L.LVG with Lag Limits (1 3) – Zombie Model

Leverage	*Coef.*	*Corrected Std. Err.*	*z*	*P > | z |*
L.LVG	0.435	0.210	2.070	0.038
GRT	0.021	0.029	0.710	0.475
SIZ	4.727	2.716	1.740	0.082
TNG	0.147	0.061	2.400	0.017
PRF	-0.239	0.161	-1.480	0.139
NDTS	0.698	0.418	1.670	0.095
RSK	0.290	0.253	1.150	0.252
ZMB	-2.376	2.103	-1.130	0.258
YR08	-3.806	2.153	-1.770	0.077
YR09	-9.833	1.807	-5.440	0.000
YR10	-9.820	1.805	-5.440	0.000
YR11	-8.871	2.163	-4.100	0.000
YR12	-8.253	2.863	-2.880	0.004
_cons	-80.238	56.010	-1.430	0.152
Wald Chi2(13)				294.58
Prob > Chi2				0.000
No. of instruments				29
AR(1)				0.029
AR(2)				0.430
Hansen				0.342
AIC				3027.719
BIC				3088.607
RSS				108380.4

Where, the analysis period is 2008–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; ZMB denotes a dummy variable takes a value of 1 if firm is identified as zombie and 0 otherwise; $YR08$–$YR12$ are the annual time dummies with 2007 used as the base year; *Corrected Std. Err. denotes* the Windmeijer standard errors which are the heteroskedasticity-robust standard errors that are also corrected for finite sample bias; and z and $p > |z|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 7.22 L.LVG with Lag Limits (1 4) – Zombie Model

Leverage	*Coef.*	*Corrected Std. Err.*	*z*	*P > | z |*
L.LVG	0.488	0.188	2.600	0.009
GRT	0.024	0.028	0.850	0.398
SIZ	4.199	2.502	1.680	0.093
TNG	0.134	0.059	2.250	0.024
PRF	-0.276	0.146	-1.890	0.058
NDTS	0.691	0.396	1.740	0.081
RSK	0.195	0.207	0.940	0.345
ZMB	-1.988	1.937	-1.030	0.305
YR08	-3.447	2.030	-1.700	0.090
YR09	-9.785	1.773	-5.520	0.000
YR10	-9.680	1.800	-5.380	0.000
YR11	-8.393	2.189	-3.830	0.000
YR12	-7.709	2.889	-2.670	0.008
_cons	-71.033	52.223	-1.360	0.174
Wald Chi2(13)				310.20
Prob > Chi2				0.000
No. of instruments				31
AR(1)				0.015
AR(2)				0.102
Hansen				0.292
AIC				2954.366
BIC				3015.254
RSS				95336.0

Where, the analysis period is 2008–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; ZMB denotes a dummy variable takes a value of 1 if firm is identified as zombie and 0 otherwise; $YR08$–$YR12$ are the annual time dummies with 2007 used as the base year; *Corrected Std. Err. denotes* the Windmeijer standard errors which are the heteroskedasticity-robust standard errors that are also corrected for finite sample bias; and z and $p > |z|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Section C. Pooled OLS and FE estimations of the Dynamic Models

Table 7.23 The Upper-Limit Value for L.LVG – Base Model

Leverage	*Coef.*	*Robust Std. Err.*	*t*	*P > | t |*
L.LVG	**0.757**	0.022	33.840	0.000
GRT	0.018	0.004	4.900	0.000
SIZ	2.246	0.516	4.350	0.000
TNG	0.064	0.018	3.500	0.000
PRF	-0.337	0.068	-4.960	0.000
NDTS	0.405	0.134	3.030	0.002
RSK	-0.016	0.020	-0.770	0.440
YR04	-4.106	1.549	-2.650	0.008
YR05	-0.425	1.918	-0.220	0.825
YR06	-4.302	1.670	-2.580	0.010
YR08	-0.650	1.662	-0.390	0.696
YR09	-8.347	1.507	-5.540	0.000
YR10	-8.610	1.509	-5.700	0.000
YR11	-5.751	1.472	-3.910	0.000
YR12	-4.910	1.421	-3.460	0.001
_cons	-36.365	10.576	-3.440	0.001
Obs.				1197
F (15, 1181)				202.46
Prob > F				0.000
Adjusted-R^2				0.726
RMSE				12.277

Where, the analysis period is 2004–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt+Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets-Book\ Value\ Equity+Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; $YR04–YR12$ are the annual time dummies with 2007 used as the base year; *Robust Std. Err*. denotes the Huber-White heteroskedasticity standard errors; and t and $p > |t|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 7.24 The Lower-Limit Value for L.LVG – Base Model

Leverage	*Coef.*	*Robust Std. Err.*	*t*	*P > | t |*
L.LVG	**0.312**	0.041	7.570	0.000
GRT	0.040	0.008	4.910	0.000
SIZ	12.612	2.185	5.770	0.000
TNG	0.029	0.108	0.270	0.786
PRF	-0.378	0.082	-4.590	0.000
NDTS	0.661	0.442	1.490	0.136
RSK	-0.002	0.006	-0.400	0.693
YR04	-0.236	1.879	-0.130	0.900
YR05	2.001	1.654	1.210	0.228
YR06	-1.978	1.436	-1.380	0.169
YR08	0.243	1.727	0.140	0.888
YR09	-6.652	1.695	-3.930	0.000
YR10	-9.144	1.646	-5.560	0.000
YR11	-8.312	1.787	-4.650	0.000
YR12	-9.568	1.927	-4.970	0.000
_cons	-239.661	44.466	-5.390	0.000
Obs.				1197
No. of groups:				263
Obs. per group:			*min*	1
			avg	4.6
			max	9
F (15 , 262)				16.64
Prob > F				0.000
Adjusted-R^2				0.807
sigma_u				14.846
sigma_e				10.316
rho				0.674

Where, the analysis period is 2004–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; $YR04$–$YR12$ are the annual time dummies with 2007 used as the base year; *Robust Std. Err*. denotes the Huber-White heteroskedasticity standard errors; and t and $p > |t|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 7.25 The Upper-Limit Value for L.LVG – Zombie Model

Leverage	*Coef.*	*Robust Std. Err.*	*t*	*P > | t |*
L.LVG	0.797	0.035	22.610	0.000
GRT	0.012	0.020	0.590	0.557
SIZ	0.847	1.204	0.700	0.482
TNG	0.051	0.029	1.740	0.082
PRF	-0.364	0.100	-3.660	0.000
NDTS	0.511	0.233	2.190	0.029
RSK	0.025	0.037	0.680	0.500
ZMB	-3.251	1.883	-1.730	0.085
YR08	-2.011	2.069	-0.970	0.331
YR09	-10.159	1.829	-5.550	0.000
YR10	-9.226	1.655	-5.570	0.000
YR11	-5.096	1.835	-2.780	0.006
YR12	-4.369	1.688	-2.590	0.010
_cons	-6.804	27.617	-0.250	0.805
Obs.				572
F (13, 558)				111.54
Prob > F				0.000
Adjusted-R^2				0.736
RMSE				11.282

Where, the analysis period is 2008–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt + Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets - Book\ Value\ Equity + Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; ZMB denotes a dummy variable takes a value of 1 if firm is identified as zombie and 0 otherwise; $YR08$–$YR12$ are the annual time dummies with 2007 used as the base year; *Robust Std. Err*. denotes the Huber-White heteroskedasticity standard errors; and t and $p > |t|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 7.26 The Lower-Limit Value for L.LVG – Zombie Model

Leverage	*Coef.*	*Robust Std. Err.*	*t*	*P > | t |*
L.LVG	0.276	0.099	2.780	0.006
GRT	0.049	0.022	2.160	0.032
SIZ	14.172	5.154	2.750	0.007
TNG	-0.055	0.169	-0.330	0.744
PRF	-0.304	0.162	-1.880	0.062
NDTS	0.037	0.681	0.050	0.957
RSK	0.046	0.027	1.710	0.089
ZMB	1.919	1.960	0.980	0.329
YR08	1.281	2.436	0.530	0.600
YR09	-6.763	2.389	-2.830	0.005
YR10	-9.727	2.023	-4.810	0.000
YR11	-9.184	2.280	-4.030	0.000
YR12	-9.969	2.465	-4.040	0.000
_cons	-266.527	108.039	-2.470	0.015
Obs.				572
No. of groups:				187
Obs. per group:			*min*	1
			avg	3.1
			max	6
F (13 , 186)				12.36
Prob > F				0.000
Adjusted-R^2				0.824
sigma_u				17.425
sigma_e				9.209
rho				0.782

Where, the analysis period is 2008–2012; $Leverage = \frac{Total\ Debt}{Total\ Debt+Total\ Equity}$ denotes book leverage ratio; $L.LVG$ denotes the 1-year lagged book leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets-Book\ Value\ Equity+Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; ZMB denotes a dummy variable takes a value of 1 if firm is identified as zombie and 0 otherwise; $YR08$–$YR12$ are the annual time dummies with 2007 used as the base year; *Robust Std. Err*. denotes the Huber-White heteroskedasticity standard errors; and t and $p > |t|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Section D: Pooled OLS and FE Estimations of the Robustness Models

Table 7.27 The Upper- and the Lower-Limit Values for L.MVLVG – Base Model

	Pooled OLS Estimator		*Fixed Effects Estimator*	
MVLeverage	*Coef.*	*P > | t |*	*Coef.*	*P > | t |*
L.MVLVG	**0.689**	0.000	**0.313**	0.000
GRT	0.007	0.010	0.004	0.285
SIZ	1.917	0.000	7.386	0.000
TNG	0.025	0.010	-0.049	0.268
PRF	-0.136	0.000	-0.168	0.000
NDTS	0.235	0.005	0.158	0.460
RSK	0.000	0.968	-0.002	0.760
YR04	-3.474	0.000	-0.020	0.987
YR05	-3.999	0.000	-1.633	0.088
YR06	-4.195	0.000	-2.474	0.002
YR08	2.488	0.014	2.755	0.002
YR09	-6.963	0.000	-4.204	0.000
YR10	-4.739	0.000	-4.798	0.000
YR11	-3.568	0.000	-4.419	0.000
YR12	-4.960	0.000	-6.254	0.000
_cons	-32.983	0.000	-137.793	0.000
Obs.		891		1197
F (15, 875)		131.35		
Prob > F		0.000		
F (15 , 202)				16.74
Prob > F				0.000

Where, the analysis period is 2004–2012; $MVLeverage = \frac{Total\ Debt}{Total\ Debt+Total\ Market\ Value}$ denotes market leverage ratio; $L.MVLVG$ denotes the 1-year lagged market leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets-Book\ Value\ Equity+Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; $YR04–YR12$ are the annual time dummies with 2007 used as the base year; and t and $p > |t|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.

Table 7.28 The Upper- and the Lower-Limit Values for L.MVLVG – Zombie Model

	Pooled OLS Estimator		*Fixed Effects Estimator*	
MVLeverage	*Coef.*	*P > | t |*	*Coef.*	*P > | t |*
L.MVLVG	**0.714**	0.000	**0.147**	0.033
GRT	0.005	0.141	-0.017	0.093
SIZ	1.869	0.000	11.939	0.000
TNG	0.037	0.013	-0.110	0.159
PRF	-0.091	0.051	-0.168	0.009
NDTS	0.177	0.111	0.455	0.126
RSK	-0.002	0.824	0.004	0.620
ZMB	-0.997	0.269	1.940	0.082
YR08	3.254	0.003	3.367	0.010
YR09	-8.046	0.000	-4.168	0.005
YR10	-5.011	0.000	-5.633	0.000
YR11	-2.942	0.002	-5.666	0.000
YR12	-5.313	0.000	-7.572	0.000
_cons	-31.862	0.001	-222.946	0.000
Obs.		611		611
F (13, 597)		107.11		
Prob > F		0.000		
F (13 , 188)				21.55
Prob > F				0.000

Where, the analysis period is 2008–2012; $MVLeverage = \frac{Total\ Debt}{Total\ Debt+Total\ Market\ Value}$ denotes market leverage ratio; $L.MVLVG$ denotes the 1-year lagged market leverage ratio; $GRT = \frac{Book\ Value\ Total\ Assets-Book\ Value\ Equity+Market\ Value\ Equity}{Book\ Value\ Total\ Assets}$ denotes growth opportunities; $SIZ = \ln(Total\ Assets)$ denotes firm size; $TNG = \frac{Net\ Fixed\ Assets}{Total\ Assets}$ denotes asset tangibility; $PRF = \frac{EBITDA}{Total\ Assets}$ denotes profitability; $NDTS = \frac{Depreciation\ and\ Amortization\ Expense}{Total\ Assets}$ denotes non-debt tax shields; $RSK = \frac{annual\ \%\ change\ in\ EBIT}{average\ \%\ change\ in\ EBIT}$ denotes business risk; ZMB denotes a dummy variable takes a value of 1 if firm is identified as zombie and 0 otherwise; $YR08$–$YR12$ are the annual time dummies with 2007 used as the base year; and t and $p > |t|$ denote the test-statistics and the 2-tailed p-values used for testing the significance of the coefficients, respectively.