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# Essays on Growth and Business Cycles

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# Abstract

This thesis is comprised of two papers contributing research output to the field of Macroeconomics, focusing on the nexus between growth and business cycles.

The first paper represents a theoretical contribution to the literature attempting to shed light on the mechanics behind economic recovery after negative shocks, as well as the role played by policy interventions in such context. The work proposes a model to generate V-shaped and L-shaped recoveries, in line with observed economic dynamics, and discusses the crucial importance of monetary policy interventions in determining the shape of the recovery.

The second paper comprises an empirical exercise and aims to contribute to the literature focusing on the rise of the intangible economy. The paper answers two research questions relevant to build a better understanding of the consequences of the structural transformation process towards an economy that relies increasingly on intangible assets for production. First, this work includes an analysis of the role played by different categories of intangible investment for firm performance. Second, it investigates weather the rise of intangible intensity was affected by the Great Recession, contributing novel empirical evidence on the medium to long run effects of recessions.

## Acknowledgements

This thesis was the result of a four year effort, resulting not only in research output, but also in substantial personal growth. I have many people to thank for helping me through this rewarding but challenging time.

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# Declaration

The first paper, described in Chapter 2, is co-authored with Omar Licandro (Nottingham), and was previously circulated as a working paper for the Centre for Finance, Credit and Macroeconomics (CFCM) of the University of Nottingham (CFCM WP 20/02).

It was under review at the time of submission of this thesis and it was presented at the following outlets:

1. European Economic Association Virtual Conference (August 2020)
2. Money Macro and Finance Society Virtual PhD Conference (August 2020)
3. $1^{st}$ Oxford NuCamp Virtual PhD workshop (April 2020)
4. Virtual Nottingham Macro Working Group (March 2020)
5. RIDGE workshop: Growth and Development in Macroeconomics/ International Trade (Montevideo, December 2019)
6. $7^{th}$ Workshop in Macro Banking and Finance, (Collegio Carlo Alberto, October 2019)
7. European Economics and Finance Annual Conference (Genova, June 2019)

The second paper, described in Chapter 3, is co-authored with Maren Froemel (Bank of England), who joined the project when she became my supervisor at the Bank of England, within the scope of a PhD internship over the summer of 2020.

The paper was presented at the following event:

1. Bank of England Summer Interns PhD Workshop (September 2020)

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# Chapter 1

# Introduction

This thesis is comprised of two papers who share a common theme: the nexus between growth and business cycles. In particular, the aim of my work is to contribute to the body of literature attempting to shed light on the medium to long run effects of recessions on economic capacity.

This topic has gained interest and traction in the aftermath of the Great Recession, as the recovery was L-shaped. The level of GDP fell sharply in the United States and in other advanced countries, and never returned to its original growth trajectory. This fact caught the profession by surprise, and fuelled a general re-thinking of the underlying mechanisms of growth across academics and policy-makers. *"Extreme economic events have often challenged existing views of how the economy works and exposed shortcomings in the collective knowledge of economists. (...) The financial crisis and its aftermath might well prove to be a similar sort of turning point."*[1] Two hypotheses have become objects of debate: secular decline vs endogenous response to the crisis. The former is advocated by Fernald et al. (2017), who argue that the slowdown in TFP growth prior to the Great Recession casts doubt on the hypothesis of a causal link between downturns and changes in potential output. Such findings are consistent with ideas expressed by Gordon (2015), who points to supply-side headwinds to explain the change in GDP trend.

[1] Janet Yellen, Chair of the Board of Governors of the Federal Reserve System 2014–2018, 14 October 2016.

On the other hand, studies that advocate the endogenous response hypothesis stress that evidence of the unfading effects of recessions was already available prior to the Great Recession. For example, some noteworthy empirical papers argued that financial crises tend to lead to shortfalls in aggregate supply across developed and developing countries (Cerra & Saxena, 2008) (Reinhart & Rogoff, 2014). Moreover, the idea that demand-driven recessions could have permanent supply effects, *i.e.* hysteresis, had already been an object of debate in the 1980s, as Blanchard and Summers (1986) argued this possibility. However, this strand of literature was mostly abandoned due to the advent of the so-called Great Moderation, a period characterized by reduced macroeconomic volatility. Negative shocks were small in size and the GDP trend remained stable. Many studies have been conducted on the drivers of this phenomenon, which is considered to be the result of good luck and/or good policy.[2] The hypothesis of output hysteresis has gained new traction in the aftermath of the Great Recession and is developing even more prominence in the current debate over the long term effects of the COVID-19 recession, leading to a re-evaluation of the role of policy interventions as well.

This thesis contributes theoretical and empirical evidence to this debate, advocating for the existence of an important link between output fluctuations and economic potential, growth and business cycles.

In the first paper, I propose a model to replicate episodes of L-shaped and V-shaped recovery in a single theoretical framework. The motivation directly comes from failure of GDP to return to its growth trajectory following the Great Recession in the U.S., in contrast with past downturns, where recessions were commonly followed by V-shaped recoveries. In the case of an L-shaped recovery, potential output moves to a permanently lower level, *i.e.* it switches track. The paper argues that the L-shaped recovery is not consistent with the standard Cobb-Douglas production function used in the literature, because this implies diminishing returns to capital, so that a negative shock affecting the capital stock would increase the return to capital, sustaining

[2]See for example Clarida, Galí, and Gertler (2000) and Stock and Watson (2002).

investment and bringing GDP back to its original growth trajectory. Conversely, an endogenous growth model is consistent with L-shaped recovery episodes because the return to capital is constant, so that a lower capital stock does not generate a higher return to capital and thus stimulus to invest after a shock.

The paper proposes a novel framework to combine endogenous growth and DSGEs with financial frictions, and shows that a learning-by-doing technology (AK in aggregate) à la Romer (1986) is consistent with both V-shaped and L-shaped recovery episodes, once the role of monetary policy is taken into account. The paper builds on a DSGE model with financial frictions by Christiano, Motto, and Rostagno (2014), and introduces a novel amplification mechanism through bankruptcy spillovers on the depreciation rate of capital, so that an increase in risk and bankruptcy leads to capital destruction. Moreover, the standard model is augmented by allowing for the *switching-track*, *i.e.* the revision of potential output estimates by the central bank.

Calibration of the U.S. economy shows that in normal times, *i.e.* the Great Moderation, a simple Taylor rule with a positive weight on the output gap could give enough stimulus to generate a recovery with small TFP shocks and demand shocks. On the other hand, a large and highly persistent demand shock such as the Great Recession has a permanent effect on the supply side through the capital destruction channel, caused by an increase in bankruptcy. In order to generate this last result, allowing for the *switching-track* in the Taylor rule is key. If the central bank updates its belief on the level of potential output based on past observed GDP, as the latter falls due to the crisis, the estimate of potential output will follow, so that the output gap will shrink over time, and the policy stimulus will get increasingly weaker. The potential output *switching-track* in the Taylor rule replicates the timing of the potential output revisions carried out by the FED.

The paper also provides a noteworthy contribution to the literature by formalizing a novel transmission mechanism of monetary policy: the destruction prevention channel. The policy intervention aiming to close the output gap acts as a cushion in the model, mitigating the negative impact of the shocks by keeping the depreciation rate closer to

its normal value.

The second paper also contributes to this literature, by providing empirical evidence of the medium to long run effects of the Great Recession on economic dynamics. In particular, the paper focuses on the impact of the shock on the structural transformation process towards intangible intensive production. Intangible investment is categorized as innovation, *i.e.* $R\&D$, as well as firm specific intangibles ($FSI$), comprising software, databases, marketing and training. The role played by each category of intangibles is considered separately and jointly, and the empirical analysis conducted for the United States shows that the Great Recession was associated with a slowdown in the intangible intensity trend, driven by a slowdown in innovation intensity. The paper also points to the fact that firms switched between intangibles, reducing the innovation effort in favour of $FSI$ in the aftermath of the recession.

The paper also contributes empirical evidence to the recent theoretical literature evaluating the role of intangible investments on firm behaviour and firm performance, see for example Roldan and Cavenaile (2020), De Ridder (2019), Caggese and Pérez-Orive (2020). In particular, the role played by the availability of $FSI$ and $R\&D$ investment opportunities for firm performance is still not well understood, and the paper contributes to this debate by providing evidence that both categories of intangible investment are associated with higher firm growth. The results hold for innovative as well as non innovative firms, suggesting that firms could grow by investing in $FSI$ only, and that the two categories could thus be substitutes. Overall, results suggest that intangible investment matters for the growth potential of the economy and that recessions can have a long term impact on the structural transformation process towards higher intangible intensive production.

To sum up, the thesis offers theoretical and empirical contributions to the debate on the interaction between growth and business cycles.

# Chapter 2

# Switching-track after the Great Recession

**Abstract:** We propose a theoretical framework to reconcile episodes of V-shaped and L-shaped recovery, encompassing the behaviour of the U.S. economy before and after the Great Recession. In a DSGE model with endogenous growth, negative demand shocks destroy productive capacity, pushing the economy towards a lower trend. A Taylor rule policy designed to reduce the output gap may counterbalance the shocks, preventing the destruction of economic capacity and inducing a V-shaped recovery. However, when shocks are deep and persistent enough, like during the Great Recession, they call for a downward revision of potential output measures, the so-called *switching-track*, weakening the recovering role of monetary policy and inducing a L-shaped recovery. When calibrated to the U.S. economy, the model generates V-shaped recoveries from small shocks, whilst large and persistent demand shocks lead to a *switching-track* and affect the supply side permanently.

## 2.1 Introduction

The Great Recession had a profound impact on the economic performance of OECD countries. Crucially, the crisis had a persistent level effect on GDP, which still remains

below its pre-crisis trend for the vast majority of advanced economies (Ball, 2014). Focusing on the United States, past recessions were typically followed by a temporary acceleration of growth, with GDP converging back to its original trend, in line with the pre-recession path of potential output. This is commonly referred to as a V-shaped recovery. During the last twelve years, however, we saw potential output *switching-track* in conjunction with the crisis, as the deep and persistent fall in economic activity led to a downward swerve of the GDP trend from its original path. Consequently, the output gap closed following the *switching-track* of potential output, rather than faster GDP growth, giving rise to a so-called L-shaped recovery (see Figure 2.1).

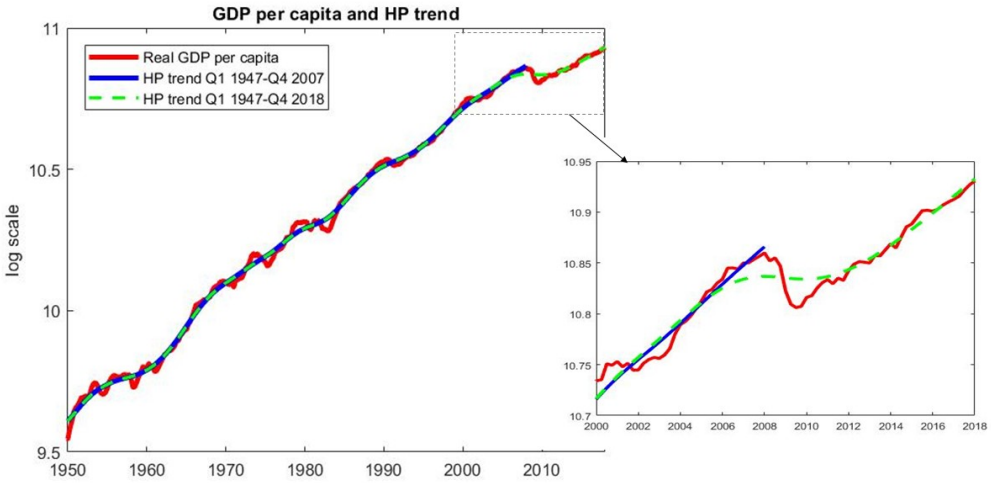



Figure 2.1: U.S. GDP per capita.

This fact challenged the general consensus on the distinct relationship between trend, growth and business cycles. If recessions are not followed by recoveries, downturns will affect the long run path of GDP, implying that potential output cannot be represented by a stable trend in the productive capacity of the economy.

We see the Great Recession as a large demand shock deeply reducing economic activity for an unusually long period, then translating into a permanent supply-side effect. As a consequence, GDP moved down to a lower trend, gradually inducing a change in measured potential output. The economy then converged to its new lower potential output path, ending the recession without a full recovery. In this context, potential

output is a measure of policy makers' beliefs about the level of GDP that can feasibly be sustained in the long run, a key indicator affecting monetary policy interventions in the recovery process. The model we suggest in this paper aims to reproduce the dynamics of GDP after the Great Recession, relying on the combination of four key assumptions. First, we embed learning-by-doing à la Romer (1986) into a DSGE model with financial frictions à la Christiano et al. (2014). Under this assumption, aggregate technology faces constant returns to capital. Consequently, a negative shock to the capital stock would not allow the economy to return to its previous growth trajectory, affecting the level of GDP permanently. Second, in line with Christiano et al. (2014), the Great Recession is modelled as a large negative shock to aggregate demand that induces a surge in bankruptcy. Third, the depreciation rate is assumed to be endogenous and positively related to the bankruptcy rate. A sudden increase in bankruptcy will then deplete the capital stock, inducing a permanent decline in output. Finally, the monetary authority is assumed to follow a standard Taylor rule, but also to revise potential output when recessions are deep and persistent. This way, we introduce the *switching-track* in the model, consistently with the unprecedented downward revision of potential output estimates produced by the Congressional Budget Office following the large and long lasting decline in GDP observed during the Great Recession. Figure 2.2 shows that the output gap closed following the potential output *switching-track* process instead of faster growth, and thus the strength of the policy intervention weakened over time.

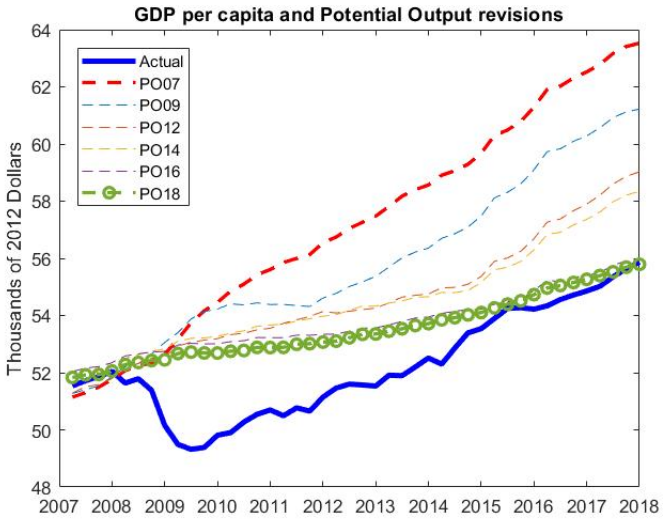



Figure 2.2: Potential Output *Switching-Track*.

Source: BEA and CBO data

Monetary policy plays a fundamental role in our model, by providing countercyclical stimulus to aggregate demand but also protecting the productive capacity of the economy by *preventing capital destruction*. The latter constitutes a novel transmission channel with potentially significant implications for the conduct of monetary policy and, more generally, the consensus concerning its role. The idea that large shocks can negatively affect the productive capacity of the economy permanently has gained traction in the aftermath of the Great Recession, and it is becoming even more prominent in the face of the COVID-19 crisis, especially for monetary policy-makers. During the press conference to announce measures in response the economic shock from Covid-19, Mark Carney (BoE) remarked: *"In this situation, it's disruption not destruction of supply. Part of our job is to make sure that that is indeed the case, and so that we're bridging, and that's very much part of the analysis."*[1] We aim to contribute to this debate and this paper is, to the best of our knowledge, the first to model the *destruction prevention channel* explicitly. Monetary policy operates as a cushion, protecting the economy from negative shocks.

We also show that in periods characterised by small shocks that are not overly per-

[1]Bank of England Press Conference, $11^{th}$ March 2020. For similar examples see the blog post by Christine Lagarde, President of the ECB, $9^{th}$ April 2020 and FED's Chair Jerome Powell's speech on $9^{th}$ April 2020 "COVID-19 and the Economy".

sistent, the Taylor rule is enough to generate a full recovery, making the economy converge to the past trend despite aggregate constant returns to capital. The Taylor rule is sufficient to drive a V-shaped recovery in normal times and results hold for TFP shocks and small demand shocks. Our model can reconcile the dynamics of the U.S. economy before and after the Great Recession. In a context of reduced macroeconomic volatility and consistent monetary policy interventions, such as the so-called Great Moderation, monetary policy generates V-shaped recoveries, whilst when shocks are large and persistent policy makers revise their beliefs on potential output and allow the economy to stabilise on a lower level, resulting in a L-shaped recovery. This represents another contribution of our work, as existing models provide insights on the possible mechanisms through which endogenous growth can lead to output shortfalls, but such theories tend to remain silent concerning the drivers of recovery in the past.

In particular, Benigno and Fornaro (2018) build a Schumpeterian framework, in the spirit of Aghion and Howitt (1992), with nominal rigidities and a Taylor rule targeting the employment rate. Their model shows two stationary solutions, a good one and a *stagnation trap*, with low growth and unemployment. We can interpret the Great Recession in this framework as a fall in demand that moves the economy from the good stationary equilibrium to the stagnation trap. Pessimistic believes and the zero-lower bound (ZLB) are crucial to generate their results. In particular, the existence of a stagnation trap is a consequence of the ZLB constraint on monetary policy, which would otherwise restore full employment. When believes eventually become optimistic again, the economy escapes the stagnation trap, moving back to the good stationary equilibrium. Since the Taylor rule aims to restore the initial level of employment, but not the initial level of output, the production capacity lost during the recession is not recovered and the economy converges to a lower trend, with the initial growth rate but a lower intercept. Similarly, in our paper we find that monetary policy is a key element in determining the level of economic activity after a demand shock bringing the economy to the ZLB. Differently from them though, our Taylor rule aims to close the output gap, so the convergence to a lower intercept after the Great Recession requires

a downward revision of potential output to close the output gap, *i.e.* the *switching-track*. More importantly, in the Benigno and Fornaro (2018) framework, the property that makes the economy converge to a lower trend would also apply to less severe shocks, due to the fact that the Taylor rules aims at restoring employment but not the productive capacity. In our framework, shocks in normal times are not deep and persistent enough to generate a revision of potential output, implying that the output gap remains large, and the stimulus provided by monetary policy is strong enough to prevent a permanent loss in productive capacity.

Garga and Singh (2020) take a similar approach, focusing on the response of the economy to negative demand shocks taking the economy to the ZLB. They propose a Schumpeterian framework with a Taylor rule targeting employment and find that demand shocks generate L-shaped recoveries. They also stress that monetary policy interventions may reduce the negative impact of demand shocks on potential output and improve welfare under alternative rules, but their result does not hold in the case of TFP shocks.

Other papers focus on explaining the lack of recovery following financial crises in particular, and thus bring together endogenous growth and financial shocks. Bianchi, Kung, and Morales (2019) also propose a Shumpeterian model, adding financial frictions to explore the properties of different kinds of financial shocks, and their long lasting effects on the economy. Cozzi et al. (2017) propose an estimated Shumpeterian DSGE model and stress how the inclusion of endogenous growth leads to the amplification of financial shocks.

Anzoategui et al. (2019) build on the pioneering work of Comin and Gertler (2006), proposing an endogenous growth model à la Romer (1990) with endogenous diffusion and financial frictions.[2] Their model generates an endogenous response of TFP to aggregate demand shocks through the R&D and diffusion channels. Their analysis also shows that this response is consistent with the observed cyclicality of the speed

[2]Comin and Gertler (2006) analysed the link between short and medium-term variations in economic activity, drawing attention to medium-term business cycles and pointing out that recessions can have lasting effects.

of diffusion of new technologies. Their estimation reveals that a shock equivalent to a risk shock can generate medium to long-term effects on the level of TFP, and thus output, due to a temporary slowdown in productivity enhancing investments and, most importantly, technology diffusion.

Ikeda and Kurozumi (2019) choose a similar framework and, just like us, they propose a model where financial shocks can generate permanent shortfalls in GDP, resulting in a parallel downward shift in the level of economic activity. However, their framework does not provide a mechanism to generate V-shaped recoveries in normal times. Monetary policy does not induce a recovery, as the class of Taylor rules they consider employs the growth rate of GDP rather than the output gap. Queralto (2020) also contributes to this literature, by focusing on banking crises in an open economy expanding product variety framework. The paper shows that financing frictions can affect the introduction of new varieties, and thus endogenous TFP.

This paper aims to complement the literature by providing a framework to reconcile episodes of economic recovery in periods characterised by small shocks, such as the Great Moderation, with episodes of no recovery, such as the Great Recession. To achieve this, we propose a novel way of incorporating endogenous growth into DSGE models with financial frictions, employing a learning-by-doing technology à la Romer (1986), where knowledge is crucial for economic growth, and its accumulation is directly linked to the capital stock. We choose this specification to show that a relatively small departure from a standard DSGE model can generate a rich departure from its predictions on the medium to long-run scars of large recessions. We picked the simplest growth model which allows us to explore the role of capital destruction in shaping the dynamics of potential output. We also introduce a new mechanism for capital depreciation and a Taylor rule that allows for the *switching-track*.

The rest of the paper is organised as follows: Section 2.2 discusses the role of capital destruction, Section 2.3 explains the model, Section 2.4 reports the calibration, Section 2.5 contains results for the Great Recession simulations, Section 2.6 describes normal times, Section 2.7 relaxes the AK assumption and Section 2.8 concludes.

## 2.2 Capital destruction: evidence and literature

In order to represent the dynamic of GDP during the the Great Recession we make the following modelling choices. First, we model the Great Recession as a demand shock that combines higher aggregate risk and lower consumer confidence, reducing investment and consumption demand. Like in Christiano et al. (2014), an increase in credit risk reduces credit and raises the probability of bankruptcy in equilibrium.

Secondly, the rise in bankruptcies that follows the demand shock causes capital destruction and thus a permanent supply effect. To generate this result, we augment the framework in Christiano et al. (2014) by positively linking the probability of bankruptcy to the depreciation rate of capital. During the Great Recession, a surge of bankruptcies thus leads to a depletion of the capital stock. The recession is then driven by a large shock to aggregate demand inducing supply effects. Our choice is motivated by empirical work by R. E. Hall (2015, 2016), who identifies the shortfalls in business capital and total factor productivity as the main drivers of the deviation of GDP from its previous trend. This paper represents the idea by associating the Great Recession with a substantial decline of the stock of capital and, through learning-by-doing, of total factor productivity.

Identifying capital destruction in the data is notoriously difficult. National Accounts estimates of the capital stock are constructed using the perpetual inventory method, and typically employ geometric depreciation rates, held constant over time.[3] As a consequence, measurement of the capital stock in National Accounts reflects movements of investment, but cannot reflect cyclical capital destruction. Nonetheless, the idea that recessions destroy capital is not new, and we aim to provide new insights to the existing literature. For example, in a vintage capital framework, Caballero and Hammour (1994) provided a rational to the evidence stated by Davis and Haltiwanger (1990) that job destruction is much more cyclically responsive than job creation. Which bring them to see recessions as cleansing periods, when the productive system eliminates outdated

[3]For the United States, see Fraumeni (1997).

techniques and products. In their view, the associated physical capital becomes obsolete and is then scrapped. More recently, Gourio (2012) built a business cycle model with disaster risk, characterizing disasters as episodes of large capital destruction. He noted that economic downturns are associated with large reallocation of capital, leading to the loss of firm specific specialised capital goods as well as intangible capital. Recent theoretical work by Lanteri (2018) and Kozlowski et al. (2020) also contributes to this literature, and the authors provide empirical grounding for the idea of capital destruction following the Great Recession.

Lanteri (2018) analyses the dynamics of the second-hand market for equipment in the United States.[4] He finds that quantities sold vary procyclically and that the price of second-hand equipment is procyclical and more volatile than the price of new equipment, showing a significant decline at the beginning of the Great Recession. This evidence indicates that the value of existing capital declined in real terms during the Great Recession (see Figure 2.3), suggesting a fall in productive capacity.[5] Additional evidence is provided by Kozlowski et al. (2020), who construct a measure of the quality of corporate non-financial assets. As can be observed in Figure 2.4, their measure of capital quality was unusually low in conjunction with the Great Recession, which can be interpreted in their framework as an increase in the depreciation rate of capital (see Appendix A4). Overall, these findings suggest that the productive capacity of capital goods fell during the Great Recession, and constitutes additional evidence indicating that downturns can be associated with increasing capital depreciation rates. Motivated by these measures, we introduce an endogenous countercyclical depreciation rate in the model, which results in a decline in the relative price of the second-hand market for capital and the destruction of its productive capacity following a negative shock.

[4] Lanteri (2018) collects data on quantities and prices from sales of second-hand capital, including commercial aircrafts, ships, and construction equipment, among others.

[5] In a recent paper, Gavazza and Lanteri (2018) analysed the market for vehicles, and found that the fall in the price of used cars was associated with a drop in upgrading during the Great Recession. As a consequence, the overall age, and thus quality and value of the vehicle stock declined.

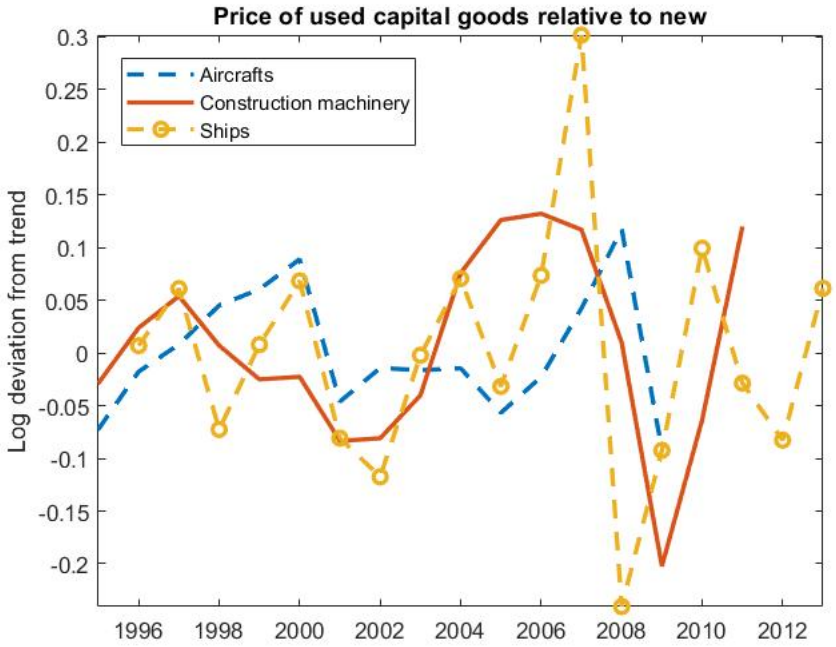



Figure 2.3: Price of used capital goods relative to new.

Log-deviation from trend of the price of used compared to new capital goods. Data made available by Lanteri (2018).

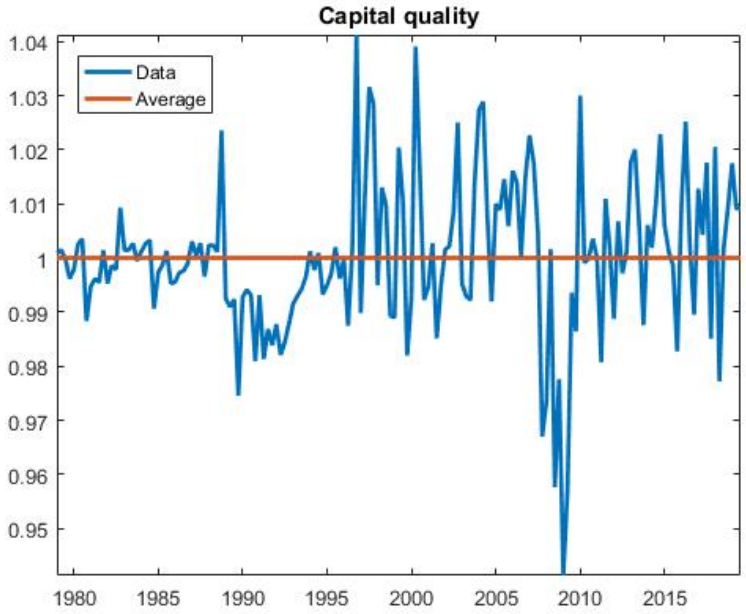



Figure 2.4: Capital quality.

Constructed following methodology suggested by Kozlowski et al. (2020), all details in the Appendix.

## 2.3 The Model

We build a New Keynesian model of endogenous growth by introducing a learning-by-doing technology à la Romer (1986) in a Dynamic Stochastic General Equilibrium model with financial frictions. We build on the financial accelerator framework introduced by Bernanke, Gertler, and Gilchrist (1999) and draw from Christiano et al. (2014) for risk shocks. Households gain utility from consumption, dis-utility from labour, and are subject to confidence shocks, *i.e.* reductions in their marginal utility of consumption. The production sector is comprised of a labour union, final good producers, intermediate good producers, capital producers and entrepreneurs. The latter face financial frictions, since they need to fund part of their capital expenditure with external resources, exposing themselves to the possibility of bankruptcy. We model a risk shock as an increase in the probability of bankruptcy for entrepreneurs. The financial sector acts as an intermediary between the production side and households, by providing loans to entrepreneurs and selling bonds to savers. The monetary authority sets the nominal interest rate according to a Taylor rule, factoring in the deviation of inflation from its target and the output gap. We also assume that potential output is measured as an average of past GDP values, so that large negative shocks lead to downward revisions. The following sections describe the behaviour of all agents in the model.

### 2.3.1 Labour Packer

Households, indexed by $\ell \in (0,1)$, supply differentiated labour input to a labour packing firm, *i.e.* a union, which then supplies an homogeneous labour input $h_t^p$ to the production sector. The bundling technology is

$$h_t^p = \left( \int_0^1 h_t(\ell)^{\frac{\varepsilon-1}{\varepsilon}} \mathrm{d}\ell \right)^{\frac{\varepsilon}{\varepsilon-1}}. \tag{2.1}$$

The parameter $\varepsilon > 1$ represents the elasticity of substitution across types of labour, which are assumed to be gross substitutes, and $h_t(\ell)$ represents hours worked by household $\ell$. Labour demand by the labour packer is

$$h_t(\ell) = \left(\frac{W_t(\ell)}{W_t}\right)^{-\varepsilon} h_t^p, \tag{2.2}$$

where $W_t(\ell)$ is the wage of labour variety $\ell$. Substituting (2.2) into (2.1), we obtain the aggregate wage index

$$W_t^{1-\varepsilon} = \int_0^1 W_t(\ell)^{1-\varepsilon} \mathrm{d}\ell. \tag{2.3}$$

Thus total employment (measured in hours worked) is given by

$$h_t \equiv \int_0^1 h_t(\ell)\mathrm{d}\ell = h_t^p \int_0^1 \left(\frac{W_t(\ell)}{W_t}\right)^{-\varepsilon} h_t^p \mathrm{d}\ell. \tag{2.4}$$

Defining $\int_0^1 \left(\frac{W_t(\ell)}{W_t}\right)^{-\varepsilon} \mathrm{d}\ell$ as a measure of wage dispersion across varieties implies that if the latter is larger than 1, then aggregate labour used in production is smaller than total employment. However, in this paper we will only consider symmetric equilibria, implying that the total labour supply $h_t^p = h_t$.

### 2.3.2 Households

There is a continuum of households of measure one. The $\ell$-type household consumes, supplies labour, buys bonds and owns firms subject to wage frictions à la Rotemberg (1982);[6] when changing its wage, it incurs in a cost assumed to be proportional to aggregate output. Since households are assumed to be identical, differing only on the type of labour they offer, labour market equilibrium is symmetric. We will then omit index $\ell$ to simplify notation.

A representative household, offering a particular type of labour, maximises utility

[6]We choose this specification for price and wage frictions because they are better suited in the context of large shocks compared to the standard Calvo style. The letter imply a constant probability of resetting prices, which does not account for size effects. For a detailed discussion see Karadi and Reiff (2019).

subject to its budget constraints and labour demand (2.2),

$$\max_{c_t, w_t, B_{t+1}} \quad u_t = E_t \left[ \sum_{j=0}^{\infty} \beta^j \epsilon_t^c \left( \log \left( c_{t+j} - \chi c_{t-1+j} \right) - \psi \frac{h_{t+j}^{1+\nu}}{1+\nu} \right) \right] \tag{2.5}$$

$$\text{s.t.} \quad B_{t+1} + P_t c_t = R_{t-1} B_t + P_t w_t h_t - \frac{\chi^\omega}{2} \left( \frac{w_t}{w_{t-1}} - 1 \right)^2 P_t Y_t + D_t - \tau_t, \tag{2.6}$$

where $c_t$ is consumption and $h_t$ is labour, $\beta \in (0,1)$ is the time discount factor, $\chi > 0$ regulates the degree of habit formation, $\nu > 0$ is the inverse of labour supply elasticity, $\psi > 0$ is a parameter regulating labour hours in steady state and $\chi^w > 0$ regulates price frictions. $B_{t+1}$ represent risk-less one period nominal bonds, purchased at time $t$, earning the risk-less nominal interest rate $R_t$.[7] Variable $w_t$ represents the real wage rate, $P_t$ is the price of the final good, $D_t$ are profits redistributed to households by firms and $\tau_t$ are taxes. $\epsilon_t^c$ is a confidence shock, affecting the marginal utility of consumption, which follows an AR(1) process: $\log(\epsilon_t^c) = \rho_c \log(\epsilon_{t-1}^c) + \epsilon_{c,t}$, where $\rho_c \in (0,1)$ and $\epsilon_{c,t} \sim N(0, \sigma_c^2)$ . This is a simple way of generating the fall in consumption demand as well as the nominal interest rate observed during the Great Recession. Guerrieri and Lorenzoni (2017) provide insights into the underlying mechanism through the lens of a model with heterogeneous households. They show that when the economy's borrowing capacity is impaired, debtors reduce their demand for loans and creditors increase precautionary savings, resulting in lower demand and a fall in the nominal interest rate.

The FOCs for $c_t$ and $B_{t+1}$ in real terms are:

$$\lambda_t = (c_t - \chi c_{t-1})^{-1} \epsilon_t^c - \beta \chi E_t (c_{t+1} - \chi c_t)^{-1} \epsilon_{t+1}^c \tag{2.7}$$

$$\lambda_t = \beta E_t R_t \frac{\lambda_{t+1}}{\pi_{t+1}}, \tag{2.8}$$

where $\lambda_t$ is the Lagrange multiplier associated to the budget constraint and $\pi_t = \frac{P_t}{P_{t-1}}$.

[7] All nominal variables in this paper are defined in an arbitrary numeraire.

The FOC for $w_t$ gives the wage Phillips curve:

$$w_t = \frac{\varepsilon}{\varepsilon - 1}\frac{\psi h_t^{\nu}\epsilon_t^c}{\lambda_t} + E_t\left[\beta\frac{\lambda_{t+1}}{\lambda_t}\Omega_{t+1}Y_{t+1}\frac{1}{h_t}\right] - \Omega_t\pi_t\frac{Y_t}{h_t} \tag{2.9}$$

$$\Omega_t = \frac{\chi^w}{\varepsilon - 1}(\pi_t^w - 1)\pi_t^w \tag{2.10}$$

$$\frac{w_t}{w_{t-1}} = \frac{\pi_t^w}{\pi_t}, \tag{2.11}$$

where $\varepsilon$ is the degree of substitution across labour types. The RHS of (2.9) shows that wages depend on the wage mark-up, the marginal rate of substitution and expectations. The expectation term implies that the labour supply is forward looking, and therefore will be less sensitive to contemporaneous shocks. Equation (2.11) is an identity to pin down the equilibrium.

### 2.3.3 Final Good Sector

The final good $Y_t$ is produced under perfect competition and can be turned into consumption or investment, as well as used to cover the costs associated with financial, price and wage frictions. Production uses intermediate goods as inputs according to the following CES technology

$$Y_t = \left(\int_0^1 y_t(i)^{\frac{\theta-1}{\theta}}\mathrm{d}i\right)^{\frac{\theta}{\theta-1}} \tag{2.12}$$

with the elasticity of substitution $\theta > 1$. The associated demand function for intermediate goods is

$$y_t(i) = \left(\frac{p_t(i)}{P_t}\right)^{-\theta} Y_t \tag{2.13}$$

with aggregate price index

$$P_t = \left(\int_0^1 p_t(i)^{1-\theta}\mathrm{d}i\right)^{\frac{1}{1-\theta}}. \tag{2.14}$$

### 2.3.4 Intermediate Good Sector

Each intermediate firm $i$, $i \in (0,1)$ operates under monopolistic competition. It employs capital services and labour by the mean of the following technology

$$y_t(i) = a_t K_t^{\eta} k_t(i)^{\alpha} h_t(i)^{1-\alpha}, \qquad \alpha \in (0,1) \tag{2.15}$$

where $K_t$ represents a measure of knowledge, freely available to all firms and acquired through learning-by-doing. We assume that $K_t = k_t$, where $k_t = \int_0^1 k_t(i)\mathrm{d}i$. This implies that $K$ is a pure externality that comes from the aggregate level of capital employed in the economy, and $0 \leq \eta \leq 1-\alpha$ represents the strength of the spillovers. $a_t$ is an aggregate productivity shock, following

$$\log(a_t) = \rho_a \log(a_{t-1}) + \epsilon_{a,t},$$

$\rho_a \in (0,1)$ and $\epsilon_{a,t} \sim \mathrm{N}(0, \sigma^2)$. This is a moderate shock, typical of business cycle dynamics.

Solving the firm's problem, we find labour and capital services demand

$$w_t = (1-\alpha) s_t \frac{y_t(i)}{h_t(i)} \tag{2.16}$$

$$r_t^k = \alpha s_t \frac{y_t(i)}{k_t(i)}, \tag{2.17}$$

where $s_t$ is the real marginal cost function

$$s_t = \frac{1}{\alpha^{\alpha}(1-\alpha)^{1-\alpha}} \frac{1}{a_t K_t^{\eta}} w_t^{1-\alpha} (r_t^k)^{\alpha}. \tag{2.18}$$

Intermediate good producers are monopolistically competitive and they face an adjustment cost when changing prices. Following Rotemberg (1982), the adjustment cost increases with the magnitude of the change in prices and the size of the economy. It is

given by

$$\frac{\phi_p}{2}\left(\frac{P_t(i)}{P_{t-1}(i)}-1\right)^2 Y_t, \tag{2.19}$$

where $\phi_p \geq 0$ is a measure of price rigidities.

Using the demand function for intermediate goods and assuming symmetry, the first order condition of the optimization problem yields the New Keynesian Phillips curve:

$$(1-\theta)+\theta s_t-\pi_t\phi_p(\pi_t-1)+\beta E_t\left[\frac{\lambda_{t+1}}{\lambda_t}\pi_{t+1}\phi_p(\pi_{t+1}-1)\frac{Y_{t+1}}{Y_t}\right]=0. \tag{2.20}$$

### 2.3.5 Capital Producers

There is a unit mass of identical perfectly competitive capital producers. Each period $t$, the representative capital producer buys from entrepreneurs the current capital $k_t$ and uses it to produce new capital $k_{t+1}$ by combining it with investment $i_t$, and then sells $k_{t+1}$ units to entrepreneurs at nominal price $q_t$. Since on average current capital depreciates at rate $\delta_t$, $\delta_t \in (0,1)$, the average nominal price of second-hand capital is $q_t(1-\delta_t)$. Where note that $1-\delta_t$ relates to the relative price of second-hand to new capital in Lanteri (2018). The behaviour of the endogenous depreciation rate $\delta_t$ is modelled in the following subsection. The evolution law of raw capital reads

$$k_{t+1}=i_t\left(1-S\left(\frac{i_t}{i_{t-1}}\right)\right)+(1-\delta_t)k_t. \tag{2.21}$$

As in Christiano et al. (2014), investment is subject to the adjustment cost function $S\left(\frac{i_t}{i_{t-1}}\right)$. This assumption helps reducing the volatility of investment and tames inflation as the reaction of investment to shocks is smoother. As we will show at the end of Section 2.5, the Great Recession generates a temporary increase in $\delta_t$, destroying productive capacity permanently.

Capital producers maximise their flow of profits, where $\hat{q}_t = q_t/P_t$ is the real price of

capital, subject to the evolution law of capital above. The FOC reads:

$$1 = \hat{q}_t \left( -S' \left( \frac{i_t}{i_{t-1}} \right) \left( \frac{i_t}{i_{t-1}} \right) + 1 - S \left( \frac{i_t}{i_{t-1}} \right) \right) + \beta E_t \frac{\lambda_{t+1}}{\lambda_t} \hat{q}_{t+1} S' \left( \frac{i_{t+1}}{i_t} \right) \left( \frac{i_{t+1}}{i_t} \right)^2, \tag{2.22}$$

### 2.3.6 Entrepreneurs and Financial Intermediation

This section closely follows Christiano et al. (2014), with a few differences designed to generate an endogenous depreciation rate depending on the fraction of firms going bankrupt. There is a unit mass of perfectly competitive entrepreneurs. At the end of any period $t$, each entrepreneur has a net worth $N$, $N > 0$.[8] Even if the net worth of a particular entrepreneur is changing over time, we omit index $t$ to simplify notation. At equilibrium, net worth is distributed $f_t(N)$ across entrepreneurs, with total net worth

$$\bar{N}_{t+1} = \int_0^\infty N f_t(N) \, \mathrm{d}N. \tag{2.23}$$

At the end of period $t$, entrepreneurs use their net worth $N$ and loans $B^N_{t+1}$, $B^N_{t+1} \geq 0$, to acquire capital $k^N_{t+1}$ from capital producers.[9] They pay price $q_t$ for any capital unit they buy such that

$$q_t k^N_{t+1} = N + B^N_{t+1}. \tag{2.24}$$

At equilibrium, all capital is allocated to entrepreneurs, s.t.,

$$k_{t+1} = \int_0^\infty k^N_{t+1} f_t(N) dN. \tag{2.25}$$

As shown below, like in Christiano et al. (2014), the equilibrium debt-to-net-worth ratio does not depend on $N$, implying that loans and capital are proportional to it. At $t+1$, entrepreneurs use capital $k^N_{t+1}$ to produce capital services $\omega k^N_{t+1}$ that they sell to

[8] As for financial frictions, the model mainly draws from Bernanke et al. (1999), so we assume that the entrepreneur employs its own net worth $N$ as well as loans from financial intermediaries, *i.e.* mutual funds, to finance his venture.

[9] As usual, for an arbitrary asset $X$, $X_{t+1}$ refers to the amount of this asset transferred from $t$ to $t+1$.

intermediate firms at price $r^k_{t+1}P_{t+1}$, where $\omega$ is an entrepreneur specific productivity shock and $P_{t+1}$ is the aggregate price index. Entrepreneurs draw the idiosyncratic productivity $\omega$ at period $t$ after buying capital $k^N_{t+1}$. Idiosyncratic productivity $\omega$ is assumed to be i.i.d. across time and firms, drawn at $t$ from the c.d.f. $\mathrm{F}_t(\omega)$, log-normally distributed, with unit mean and standard deviation $\sigma_t$.

An entrepreneur with net worth $N$ obtains a loan $B^N_{t+1}$ from mutual funds at the interest factor $Z_{t+1}$. The interest factor is contingent on the state of the economy in $t+1$ and, as shown below, it is independent of $N$ at equilibrium. For this reason, index $N$ is omitted. On top of aggregate risks, the debt contract has to take into account the presence of idiosyncratic risk, since entrepreneurs facing low realizations of the shock $\omega$ may be unable to repay the loan, and go bankrupt. Conversely, entrepreneurs with sufficiently high returns on their capital will repay their loans and make positive cash flow. For a given state contingent interest factor $Z_{t+1}$, let us define $\bar{\omega}_{t+1}$ as the state contingent productivity $\omega$ that zeroes the entrepreneur's cash flow at $t+1$, *i.e.*,

$$\Pi^N_{t+1}(\bar{\omega}_{t+1}) = \bar{\omega}_{t+1}R^k_{t+1}\, q_t k^N_{t+1} - B^N_{t+1}Z_{t+1} = 0, \tag{2.26}$$

where $\Pi^N_{t+1}(\omega)$ represents the entrepreneur's cash flow.[10] If $\omega > \bar{\omega}_{t+1}$, then $\Pi^N_{t+1}(\omega) > 0$, whilst if $\omega < \bar{\omega}_{t+1}$, the entrepreneur goes bankrupt. The fraction of firm that go bankrupt at period $t$ is then $\mathrm{F}_{t-1}(\bar{\omega}_t)$.

At $t+1$, after production takes place, an $\omega$-type successful entrepreneur sells its undepreciated capital $(1-\hat{\delta}_{t+1})\omega$ back to capital producers at price $q_{t+1}$. The depreciation rate of capital is $\hat{\delta}_{t+1} = \delta\left(\frac{\mathrm{F}_{t-1}(\bar{\omega}_t)}{\mathrm{F}(\bar{\omega})}\right)^{a_{\bar{\omega}}}$, $a_{\bar{\omega}} \geq 0$, where $\delta \in (0,1)$ is a parameter representing the depreciation rate at steady state. This specification includes negative network spillovers from entrepreneurs that went bankrupt in the previous period. It is a simplified way of representing the negative network effects on capital value associated with the disruptions in the production process generated by economic downturns and bankruptcy. A larger bankruptcy rate will make the capital of surviving firms less pro-

[10] Like $Z_{t+1}$, $\bar{\omega}_{t+1}$ is independent of $N$ at equilibrium. For this reason, index $N$ is omitted.

ductive in the future due to the destroyed links. When the probability of bankruptcy is at its steady state value $\mathrm{F}(\bar{\omega})$, the impact of spillovers is normalised to 1. The ex-post return at $t+1$ to a unit of capital bought at $t$ for an $\omega$-type successful entrepreneur is $\omega R^k_{t+1}$, with

$$R^k_{t+1} = \frac{r^k_{t+1} P_{t+1} + (1 - \hat{\delta}_{t+1}) q_{t+1}}{q_t}. \tag{2.27}$$

In case of bankruptcy, the mutual fund pays a monitoring cost $\mu$, $\mu \in (0,1)$, to appropriate the payments generated by the capital services provided to intermediate firms as well as the capital stock, which is then liquidated, subject to physical depreciation and obsolescence. Moreover, when an entrepreneur goes bankrupt, the steady state depreciation rate of capital is $\kappa$, $\kappa \in (\delta, 1)$ which is meant to capture both physical depreciation and obsolescence, obsolescence being measured by the difference $\kappa - \delta$. Negative network spillovers affect bankrupt entrepreneurs too, so that $\hat{\kappa}_{t+1} = \kappa \left( \frac{\mathrm{F}_{t-1}(\bar{\omega}_t)}{\mathrm{F}(\bar{\omega})} \right)^{a_{\bar{\omega}}} \quad a_{\bar{\omega}} \geq 0$. The ex-post return to capital for bankrupt $\omega$-type entrepreneur is $\omega R^f_{t+1}$, with

$$R^f_{t+1} = \frac{r^k_{t+1} P_{t+1} + (1 - \hat{\kappa}_{t+1}) q_{t+1}}{q_t} \tag{2.28}$$

which in this case is appropriated by mutual funds.

At time $t$ mutual funds issue bonds to households at the risk-less factor $R_t$ to raise the resources needed to finance entrepreneurs. They also receive a transfer from the Monetary Authority. The transfer is financed by a tax on household's profits from entrepreneurial activity, and is thus proportional to the return to capital of successful entrepreneurs. The parameter $\xi$ regulates the size of the transfer. This is a measure implemented to relax the cash constraint, aiming to promote credit provision in bad times, and will assure steady state values in line with U.S. data. For simplicity, let us assume that mutual funds specialise in entrepreneurs with net worth $N$ and operate under perfect competition. Since the interest factor $Z_{t+1}$ is state contingent, at each

state of nature a zero profit condition holds, *i.e.*:

$$(1-\mu)q_t k_{t+1}^N \int_0^{\bar{\omega}_{t+1}} \omega R_{t+1}^f \mathrm{dF}_t(\omega) + \big(1-\mathrm{F}_t(\bar{\omega}_{t+1})\big) B_{t+1}^N Z_{t+1} + \xi \int_0^{\bar{\omega}_{t+1}} \omega \mathrm{dF}_t(\omega) R_{t+1}^k q_t k_{t+1}^N = B_{t+1}^N R_t. \tag{2.29}$$

Divide both sides by $R_{t+1}^k q_t k_{t+1}^N$, use (2.26) and define leverage $L_t = \frac{N+B_{t+1}^N}{N}$ to get

$$(1-\mu)\frac{R_{t+1}^f}{R_{t+1}^k} \int_0^{\bar{\omega}_{t+1}} \omega \mathrm{dF}_t(\omega) + \bar{\omega}_{t+1}(1-\mathrm{F}_t(\bar{\omega}_{t+1})) + \xi \int_0^{\bar{\omega}_{t+1}} \omega \mathrm{dF}_t(\omega) = \frac{R_t}{R_{t+1}^k} \frac{L_t - 1}{L_t}.$$

The zero profit condition above can then be used to find an expression for leverage

$$L_t = \left(1 - \frac{R_{t+1}^k}{R_t}\Big(\bar{\omega}_{t+1}(1-\mathrm{F}_t(\bar{\omega}_{t+1})) + (1-\mu)H_t(\bar{\omega}_{t+1}) + \xi G_t(\bar{\omega}_{t+1})\Big)\right)^{-1}, \tag{2.30}$$

where

$$H_t(\bar{\omega}_{t+1}) = \frac{R_{t+1}^f}{R_{t+1}^k} \int_0^{\bar{\omega}_{t+1}} \omega \mathrm{dF}_t(\omega)$$

$$G_t(\bar{\omega}_{t+1}) = \int_0^{\bar{\omega}_{t+1}} \omega \mathrm{dF}_t(\omega).$$

$G(\bar{\omega})$, $G(\bar{\omega}) < 1$, represents unsuccessful entrepreneurs' contribution to the average $\omega$, and $H(\bar{\omega})$, $H(\bar{\omega}) < G(\bar{\omega})$, is corrected by the ratio of unsuccessful to successful returns.

Notice that the loan contract $(Z_{t+1}, B_{t+1}^N)$ can be also written as a contract on $(\bar{\omega}_{t+1}, L_t)$. Any pair $(\bar{\omega}_{t+1}, L_t)$ that satisfies (2.30) is a $(t+1)$-state contingent contract offered to entrepreneurs. As it will become clear below, at equilibrium, the conditions of the loan contract $(\bar{\omega}_{t+1}, L_t)$ are the same for all entrepreneurs irrespective of their net worth $N$. On one side, for a given net worth $N$, choosing loan $B^N$ is equivalent to choosing leverage $L$. On the other side, setting the nominal interest rate $Z$ determines the cut-off productivity $\bar{\omega}$.

At time $t+1$, for any realization of the aggregate shocks, the debt contract $(\bar{\omega}_{t+1}, L_t)$ for an entrepreneur with net worth $N$ is expected to generate the cash flow

$$\int_{\bar{\omega}_{t+1}}^{\infty} \Pi_{t+1}^N(\omega)\, \mathrm{dF}(\omega) = \Big(1 - \Gamma_t(\bar{\omega}_{t+1})\Big)\, R_{t+1}^k L_t N, \tag{2.31}$$

where $\Big(1 - \Gamma_t(\bar{\omega}_{t+1}\Big)$ is the expected share of total revenues retained for successful entrepreneurs, with

$$\Gamma_t(\bar{\omega}_{t+1}) = G_t(\bar{\omega}_{t+1}) + \bar{\omega}_{t+1}\Big(1 - \mathrm{F}_t(\bar{\omega}_{t+1})\Big) \tag{2.32}$$

being the expected share going to the mutual fund.

For any state of nature in $t+1$, the entrepreneur chooses the contract that maximises expected profit, which is equivalent to[11]

$$\max_{\bar{\omega}_{t+1}} \frac{1-G_t(\bar{\omega}_{t+1})-\bar{\omega}_{t+1}\big(1-\mathrm{F}_t(\bar{\omega}_{t+1})\big)}{1-\frac{R^k_{t+1}}{R_t}\Big(\bar{\omega}_{t+1}(1-\mathrm{F}_t(\bar{\omega}_{t+1}))+(1-\mu)H_t(\bar{\omega}_{t+1})+\xi G_t(\bar{\omega}_{t+1})\Big)} = \max_{\bar{\omega}_{t+1}} L_t(\bar{\omega}_{t+1})\big(1-\Gamma_t(\bar{\omega}_{t+1})\big). \tag{2.33}$$

Thus the FOC pinning down the equilibrium $\bar{\omega}_{t+1}$ reads:

$$\frac{1-\mathrm{F}_t(\bar{\omega}_{t+1})}{1-\Gamma_t(\bar{\omega}_{t+1})} = \frac{\frac{R^k_{t+1}}{R_t}[1-\mathrm{F}_t(\bar{\omega}_{t+1})-\mathrm{G}'_t(\bar{\omega}_{t+1})\big(1-\frac{R^F_{t+1}}{R^k_{t+1}}(1-\mu)-\xi\big)]}{1-\frac{R^k_{t+1}}{R_t}\Big(\bar{\omega}_{t+1}(1-\mathrm{F}_t(\bar{\omega}_{t+1}))+(1-\mu)H_t(\bar{\omega}_{t+1})+\xi G_t(\bar{\omega}_{t+1})\Big)}. \tag{2.34}$$

This shows that the loss of accepting a higher threshold for entrepreneurs equals the benefit of higher leverage. The LHS is the elasticity of the share the entrepreneur keeps w.r.t. $\bar{\omega}_{t+1}$, whilst the RHS is the elasticity of leverage w.r.t. $\bar{\omega}_{t+1}$.[12] Also, notice that this specification implies that the elasticity of leverage is affected by credit subsidies.

It is easy to see that the equilibrium $\bar{\omega}_{t+1}$ does not depend on $N$. From (2.30), leverage does not depend on it either. Consequently, from (2.26), mutual funds set the same $(t+1)$-state contingent interest factor $Z_{t+1}$ irrespective of net worth.

Let us assume the standard deviation of $\mathrm{F}_t(\omega)$ follows

$$\log\left(\frac{\sigma_t}{\bar{\sigma}}\right) = \rho_\sigma \log\left(\frac{\sigma_{t-1}}{\bar{\sigma}}\right) + \epsilon_{\sigma,t},$$

with $\bar{\sigma} > 0$, $\rho_\sigma \in (0,1)$ and the risk shock $\epsilon_{\sigma,t}$ being i.i.d. Notice that a higher value of $\sigma_t$ implies a higher probability of drawing a low value of $\omega$. As the variance of the shock increases, the tails of the distribution get thicker, increasing the probability of tail events and modifying the threshold for $\bar{\omega}$, *i.e.*. increasing the probability of bankruptcy.

Let us finally assume that at the end of period $t+1$ (after entrepreneurs pay back to mutual funds their period $t$ debt) a fraction $(1-\gamma)$ of successful entrepreneur's cash flow

[11] Use (2.30) to substitute for $L_t$ in (2.31), then divide by $R^k_{t+1}N$ to get (2.33).

[12] The FOC also shows that our framework reduces to the standard model in Christiano et al. (2014) in the case $R^k = R^F$ and $\xi = 0$.

$\Pi^N_{t+1}(\omega)$ gets transferred to households, $\gamma \in (0,1)$. Moreover, each entrepreneur receives a transfer $w^e\, P_{t+1} k^N_{t+1}$ from households, $w^e \in (0,1)$, as a form of insurance, to compensate for risk taking, and assuring that bankrupt entrepreneurs will keep a strictly positive net worth allowing them to buy some capital for the following period.

Since liquidating the capital of failed entrepreneurs generates physical capital depletion, the depreciation of capital is endogenous and depends on the fraction of entrepreneurs going bankrupt. The aggregate depreciation rate at time $t$ reads

$$1 - \delta_t = (1 - \hat{\kappa}_t)\, \mathrm{F}_{t-1}(\bar{\omega}_t) + (1 - \hat{\delta}_t)\big(1 - \mathrm{F}_{t-1}(\bar{\omega}_t)\big).$$

The intuition is that when bankruptcy happens some capital (tangible or intangible) is destroyed in the process, reducing the overall value of capital. The externality aims to capture negative disruptive spillovers generated by bankruptcy. These could be the result of some specialised machines not being reallocated as effectively as in normal times or knowledge embedded in intangible capital being lost. Moreover, we think of depreciation spillovers as (small) bankruptcy shocks with aggregate effects through the production network, resulting in an increase in the depreciation rate of capital for the whole economy. This interpretation draws inspiration from Acemoglu, Akcigit, and Kerr (2016), who document significant network-based propagation channels stemming from small shocks.

### 2.3.7 Aggregate Economy

The quantity of capital produced by capital producers must be equal to the capital purchased by entrepreneurs:

$$k_{t+1} = \int_0^\infty k^N_{t+1} f_t(N) dN.$$

From (2.24), (2.30) and the definition of leverage, $L_t = \frac{N + B^N_{t+1}}{N}$, the equation above becomes

$$q_t k_{t+1} = \frac{1}{1 - \frac{R^k_{t+1}}{R_t}\Big(\bar{\omega}_{t+1}(1 - \mathrm{F}_t(\bar{\omega}_{t+1})) + (1-\mu)\mathrm{H}_t(\bar{\omega}_{t+1}) + \xi G_t(\bar{\omega}_{t+1})\Big)} \bar{N}_{t+1}. \tag{2.35}$$

Consequently, the level of capital in the economy depends on aggregate net worth, as defined in (2.23), and financial conditions.

All intermediate firms face the same wage and capital cost, therefore, by symmetry:

$$\frac{k_t(i)}{h_t(i)} = \frac{k_t}{h_t}, \tag{2.36}$$

for all $i \in (0,1)$. Also, market clearing for capital and labour implies $\int_0^1 k_t(i)\mathrm{d}i = k_t$ and $\int_0^1 h_t(i)\mathrm{d}i = h_t$. Notice that if firms could change their prices in every period, they will choose the same price and produce the same quantity. In which case, $P_t(i) = P_t$ and $Y_t(i) = Y_t$, hence aggregate production would become

$$Y_t = a_t k_t^{\alpha+\eta} h_t^{1-\alpha}. \tag{2.37}$$

Therefore, if $\eta = 1 - \alpha$ aggregate technology has an AK structure.

Aggregate profits of all entrepreneurs at the end of time $t$ are $[1 - \Gamma_{t-1}(\bar{\omega}_t)]R_t^k q_{t-1} k_t$, so that aggregate net worth at $t+1$ is:

$$\bar{N}_{t+1} = \gamma[1 - \Gamma_{t-1}(\bar{\omega}_t)]R_t^k q_{t-1} k_t + P_t w^e k_t \tag{2.38}$$

Using the aggregate production function and $K_t = k_t$:

$$r_t^k = \alpha s_t a_t k_t^{\alpha+\eta-1} h_t^{1-\alpha} \tag{2.39}$$

$$w_t = (1-\alpha) s_t a_t k_t^{\alpha+\eta} h_t^{-\alpha} \tag{2.40}$$

$$s_t = \frac{1}{\alpha^\alpha (1-\alpha)^{1-\alpha}} \frac{1}{a_t k_t^\eta} w_t^{1-\alpha} (r_t^k)^\alpha \tag{2.41}$$

All bonds held by households must be equal to the amount of loans in aggregate, and transfers to mutual funds must equal taxes:

$$q_t k_{t+1} - \bar{N}_{t+1} = B_{t+1}$$

$$\xi \int_0^{\bar{\omega}_{t+1}} \omega \mathrm{d}\mathrm{F}_t(\omega) R_{t+1}^k q_t k_{t+1}^N = \tau_t$$

Output is allocated to consumption and investment, but also to intermediary production

aimed to cover price and wage adjustment costs as well as monitoring costs, *i.e.*:

$$Y_t = \underbrace{c_t + i_t}_{\text{GDP}} + \mu \int_0^{\bar{\omega}_t} \omega d\mathrm{F}(\omega) R_t^F \frac{\hat{q}_{t-1}}{\pi_t} k_t + \frac{\phi_p}{2} (\pi_t - 1)^2 Y_t + \frac{\chi^w}{2} (\pi_t^w - 1)^2 Y_t. \tag{2.42}$$

GDP is then defined as the sum of consumption and investment, measuring aggregate demand.

### 2.3.8 Monetary Authority

The monetary authority uses the Taylor rule to set the nominal interest rate, subject to the zero lower bound constraint:

$$R_t^m = \bar{R}^m + \rho_\pi(\pi_t - \bar{\pi}^m) + \rho_y \log\left(\frac{\hat{\text{GDP}}_t}{y_t^p}\right) \tag{2.43}$$

$$R_t = \max(1, R_t^m), \tag{2.44}$$

where $\bar{R}^m$ and $\bar{\pi}$ are target values, $\rho_\pi > 0$ and $\rho_y > 0$ are policy parameters, and $y_t^p$

$$y_t^p = y_{t-1}^p + \rho \left( \frac{1}{n} \sum_{j=1}^{n} \hat{\text{GDP}}_{t-4-j} - y_{t-1}^p \right) \quad 0 > \rho > 1 \tag{2.45}$$

is a measure of potential output. It is computed as a moving average of past GDP values, de-trended by the stationary growth rate of the economy $g_z$, so that $\hat{\text{GDP}}_t = \frac{\text{GDP}_t}{(1+g_z)^t}$.

We define this measure to take into account the revisions carried out by central banks in the context of the Great Recession. We implicitly assume that the monetary authority does not have full information about the functioning of the economy, and it infers the underlying path from observed values of GDP. In particular, our measure takes into account the lag in potential output revisions, as we disregard the most recent 4 periods. This implies that the estimate of potential output is not very sensitive to negative shocks if they are small in size and duration. We set $n$ equal to 10, to allow the central bank to consider a long enough period of time in the estimation of the underlying trend, but also react relatively quickly to shocks.

As we will show in the following sections, the Taylor rule provides stimulus to the economy, inducing it to close the output gap after a negative shock. Despite the fact that the aggregate

technology is AK, and because of the monetary policy intervention, GDP appears to fluctuate around a stable linear trend in normal times, appearing consistent with diminishing returns to capital. However, if the shock is large and prolonged, potential output will be revised downwards and the stimulus to the economy will lose strength over time. As a result, the economy will reveal its AK structure and the recovery will fail to materialise.

## 2.4 Baseline Calibration

We calibrate the model on quarterly data for the United States, considering the period 1980-2008 as our reference. We choose data covering this time span to characterise the steady state of the model before the Great Recession for two main reasons. Firstly, we are interested in a period of time when the conduct of monetary policy was consistent and in line with the Taylor rule, so the Volcker era is an optimal candidate. Secondly, we do not take a stand on whether an endogenous growth model has always been a good representation of GDP, as it is possible that that the U.S. economy evolved from a Neoclassical structure to an AK structure over time due to technological change. For example, the increasing importance of intangible capital, human capital and knowledge spillovers for production, as documented by Haskel and Westlake (2018), could have led to such a transformation in the production technology. In this sense, it may be that the economy today works differently compared to the 1960s and 1970s, so we do not aim to reproduce those dynamics with our model.

In order for the model to have an aggregate AK technology, we set $\eta = 1 - \alpha$. The return to capital is thus positive and constant, generating endogenous growth. The resulting economy is on a balanced growth path, growing at the rate $g_z$. We transform equilibrium conditions by de-trending all non-stationary variables using the the stationary growth rate, so that $\tilde{c}_t = \frac{c_t}{(1+g_z)^t}$, $\tilde{y}_t = \frac{Y_t}{(1+g_z)^t}$, and so on. Then we solve the stationarised system of non-linear equations, calibrating the model to match key data moments. Table A.1 in Appendix A.2 shows the comparison between the steady state of the model and U.S. data. To characterise the stationary equilibrium, we target a labour share of 60.8%, in line with the average value of the share of labour compensation in GDP. This is achieved by setting $\alpha = 0.24$ and assuming a price mark-up of 25%. The latter implies a value of 5 for the elasticity of substitution across intermediate good, $\theta$. We also calibrate the model to have zero inflation in steady state and a

quarterly growth rate of 0.6%. The latter depends on the return to capital and the financial frictions. We thus set labour hours in steady state to 0.2, in line with the average of annual hours worked by persons engaged, choose $\gamma = 0.966$ (close to Bernanke et al. (1999)), with $\delta$ set to 0.028 and $\kappa$ to 0.04. These are somewhat higher than standard values, but we make this choice because our definition of capital is wider compared to National Accounts, including all categories of intangible capital. Although these stocks are not fully included in GDP measures, they do affect the outcome of production, and they depreciate faster than traditional measures of capital, so we account for their depreciation in our calibration. Monitoring costs are set to $\mu = 0.21$, in line with Christiano et al. (2014) and within the rage suggested by Carlstrom and Fuerst (1997). We set $\xi = (1-\mu)\left(1 - \frac{R^F_{ss}}{R^k_{ss}}\right)$ to obtain a steady state bankruptcy rate of approximately 1%, similarly to Christiano et al. (2014).

For Rotemberg adjustment costs, we follow the approaches proposed by Ascari and Rossi (2012) and Born and Pfeifer (2020), calculating them as follows:

$$\phi^p = \frac{(\theta - 1)\theta^p}{(1 - \theta^p)(1 - \beta\theta^p)} \tag{2.46}$$

$$\chi^w = \frac{(\epsilon - 1)^{\frac{\theta-1}{\theta}}(1 - \alpha)\theta^w}{(1 - \theta^w)(1 - \beta\theta^w)} \tag{2.47}$$

where $\theta^w = \theta^p = 0.75$ represent the probabilities of not being able to reset prices and wages.

Finally, we set $a_{\bar{\omega}}$ to 0.15, which implies that a 1% deviation of the probability of bankruptcy from its normal value leads to an increase in the depreciation rate of approximately 0.1%. This is considerably smaller compared to the values in Lanteri (2018)'s data and capital quality shocks in Kozlowski et al. (2020), but our choice is conservative as the model is not expected to represent all dimensions of the data. Our view is that there is sufficient evidence to support the capital destruction channel as quantitatively relevant, but a precise estimate to base the calibration on is not available. We therefore choose the parameter $a_{\bar{\omega}}$ to bring our model simulations close to the fall in GDP observed in the data. The persistence of the Great Recession shocks, $\rho_c = 0.9$ and $\rho_\sigma = 0.97$ is taken from Christiano et al. (2014).

| Parameter | Value | Description |
|---|---|---|
| *Standard parameters in DSGEs* | | |
| $\beta$ | 0.99 | Discount factor |
| $\theta$ | 5 | Substitution in final good |
| $\nu$ | 1 | Inverse of Frisch elasticity |
| $\epsilon$ | 21 | Substitution in labour input |
| $\psi$ | 16.8 | Scaling parameter for labour hours |
| S” | 5 | Investment adjustment costs |
| $\mu$ | 0.21 | Monitoring costs |
| $\gamma$ | 0.966 | Fraction of profits going to entrepreneur |
| $w^e$ | 0.0005 | Transfer from household |
| $\chi^w$ | 141.7 | Rotemberg wage adjustment parameter |
| $\phi_p$ | 46.6 | Rotemberg price adjustment parameter |
| *Technology* | | |
| $\alpha$ | 0.24 | Power on firm capital in production |
| $\eta$ | 0.76 | Power on knowledge spillovers in production |
| $\delta$ | 0.028 | Successful entrepreneurs' depreciation rate |
| $\kappa$ | 0.04 | Bankrupt entrepreneurs' depreciation rate |
| $a_{\bar{\omega}}$ | 0.15 | Strength of depreciation spillovers |
| *Monetary Policy* | | |
| $\rho_\pi$ | 1.5 | Policy response to inflation |
| $\rho_y$ | 0.125 | Policy response to output gap |
| $\rho$ | 0.7 | Speed of potential output revision |
| $n$ | 10 | Number of past periods in moving average |
| *Shocks* | | |
| $\rho_\sigma$ | 0.97 | Persistence of the risk shock |
| $\rho_c$ | 0.9 | Persistence of the confidence shock |
| $\rho_a$ | 0.79 | Persistence of the TFP shock |

Table 2.1: Quarterly calibration parameters.

## 2.5 The Great Recession

**Demand Shock.** We model the Great Recession as the reaction of the economy to a large and persistent demand shock that combines a risk shock and a confidence shock, hitting at the same time.[13] The magnitude of the risk shock is set to increase the bankruptcy probability from a baseline value of 1% to 4%, in line with the estimation conducted by Christiano et al. (2014). This is achieved by setting the magnitude of the risk shock to 15.7%.

As for the confidence shock, it aims to make the economy hit and remain in the ZLB region

[13]In order to appropriately account for the size of the shock and the ZLB constraint, we solve the model non-linearly, employing a Newton-type method (Adjemian et al., 2011) (Juillard et al., 1996).

for a few quarters, consistently with the behaviour of the U.S. economy. Notice that our model does not capture unconventional monetary policies implemented by the FED, nor forward guidance, hence we calibrate the size and persistence to generate a zero lower bound episode in line with what a standard Taylor rule would have implied. In order to quantify this, we build a measure of the alternative policy, using U.S. data.[14] We calculate the nominal interest rate (in annual terms) emerging from the Taylor rule as follows:

$$\mathrm{TR} = \max\left\{0, \overline{\mathrm{TR}} + 1.5\left(\pi_t - \bar{\pi}\right) + 0.5\,\log\left(\frac{\mathrm{GDP}_t}{\overline{\mathrm{GDP}_t}}\right)\right\},$$

setting the target nominal interest rate $\overline{\mathrm{TR}}$ to the 2004-2007 average of the Federal Funds Rate ($\overline{\mathrm{TR}} = 3.64\%$) and the inflation target $\bar{\pi}$ to its official value of 2%. Quarterly GDP is measured in real terms and potential output $\overline{\mathrm{GDP}_t}$ is constructed from CBO data (in 2012 dollars), employing the estimates published at the beginning of each year, and thus capturing the unfolding of all revisions. Inflation is measured as the GDP deflator.[15] The resulting Taylor rule predicts a much shorter ZLB episode compared to the Federal Funds Rate, as displayed in Figure 2.5. The predicted interest rate stays at the ZLB for a few quarters. To generate results in line with this, we calibrate the size of the confidence shock to 13.345%

**Data Comparison.** In order to compare the simulations with key data dynamics in the U.S., we follow the approach of Christiano, Eichenbaum, and Trabandt (2015) to estimate target gap ranges from the data. We measure the deviation of variables from the path they would have followed, had the recession not happened, by calculating the percentage difference from a linear trend, fitted on past data. In order to select time intervals, we aim to follow the CBO's methodology for projections of potential output as closely as possible. *"Typically, a trend is considered to extend from at least one previous business cycle through the most recent quarter of data (because the peak of the current cycle is not known at the time of a forecast)."*[16] They consider full peak-to-peak business cycles, so we build our estimates by including data from the business cycles peaks preceding the Great Recession, up to the period before the downturn. We construct min-max targets by considering the intervals $[x : 2008Q2]$,

[14] A similar exercise was also conducted by the Board of Governors of the Federal Reserve System, among others, with comparable results. See link here.

[15] Additional Details on data series used can be found in the Appendix.

[16] 'Revisions of CBO's potential output since 2007', February 2014 report.

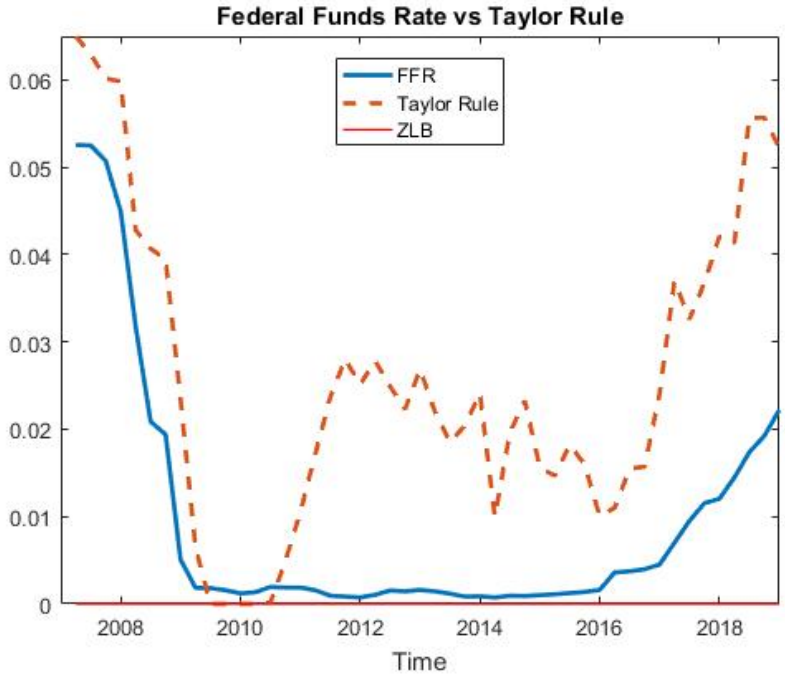



Figure 2.5: Federal Funds Rate vs Taylor Rule.

with $x = (1990Q3, 2001Q1)$. We consider aggregate series retrieved from the FRED database for GDP, consumption, investment, credit and the Federal Funds Rate. Finally, in order to compare the *switching-track* of potential output in our model and in the data, we employ the measure of potential output we built to calculate the Taylor rule in Figure 2.5. More details on data sources can be found in the Appendix.

**Great Recession.** Figure 2.6 shows impulse responses for some key variables in our model to the Great Recession shock. The fall in confidence affects consumption demand and the sharp rise in risk depresses investment demand and raises the depreciation rate. As bankruptcy rates increase, capital depreciates faster resulting in capital destruction. Even when the shock subsides and financial variables converge back to the previous steady state values, the negative effects on GDP, consumption and investment do not dissipate and the economy displays an L-shaped recovery. Our model fits the data quite well, especially for GDP and consumption, which both fall by almost 10% at the new steady state, converging monotonically in the same way as the data. As for investment, the simulation does not capture the full depth of the total shortfall, which was partially driven by the the real estate market. Nonetheless, results are in line with private non-residential investment data. The model fits the data for credit well at the beginning of the sample, set aside the collapse of

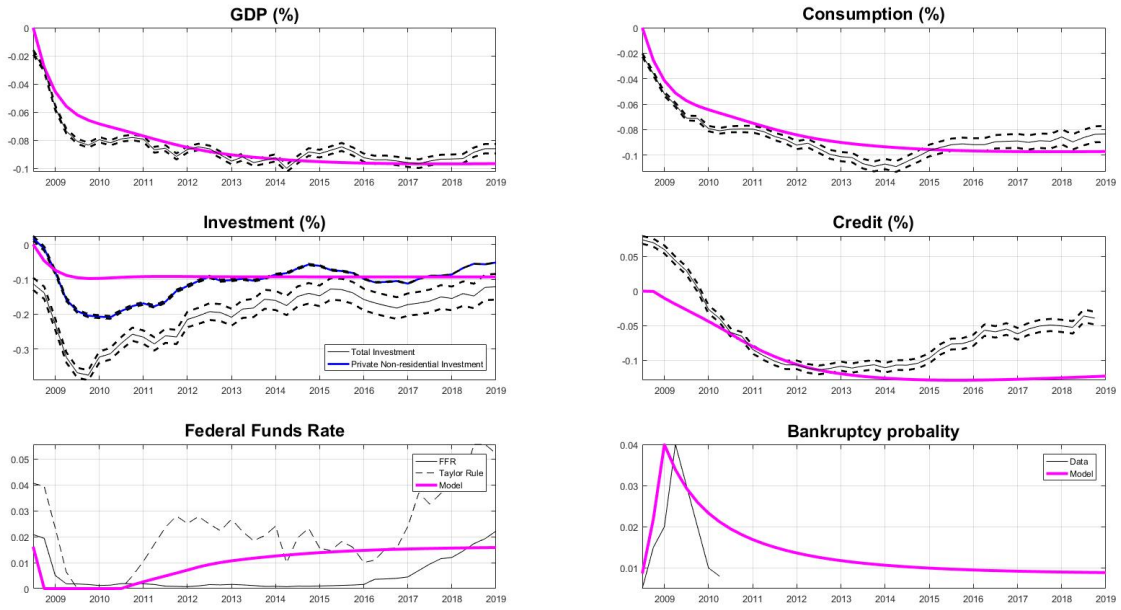



Figure 2.6: Model impulse responses to Great Recession shocks vs U.S. data.

the credit boom that we do not model, and performs worse for later periods. This is likely because we are not modelling unconventional monetary policies providing credit easing. The behaviour of the nominal interest rate is in line with the Taylor rule estimated in Figure 2.5, and thus does not replicate the Federal Funds Rate after 2010, which remains for a long while at the ZLB, likely due to unconventional monetary policies.

**Switching-track.** Figure 2.7 clearly shows that the model economy replicates quite well the *switching-track* of potential output in the data.[17] The estimated output gap shrinks with time, thus reducing its impact on the Taylor rule. Our simulations are in line with the U.S experience, and our specification can also approximate the timing of output gap dynamics observed in the data.

In order to better understand the mechanics of the two shocks, Figure A.5 in the Appendix includes the impulse response of other variables to the Great Recession shocks. As it is common in financial crises, credit declines and net worth contracts, mirroring a stock market

[17]The figure shows a slight increase in potential output in 2013, which is the result of the comprehensive revision of the national income and product accounts (NIPAs), to include new investment categories. This led to an increase in GDP value. We adjusted the potential output measures published, following the methodology indicated by the CBO in their 2014 report, but a small margin of error remains.

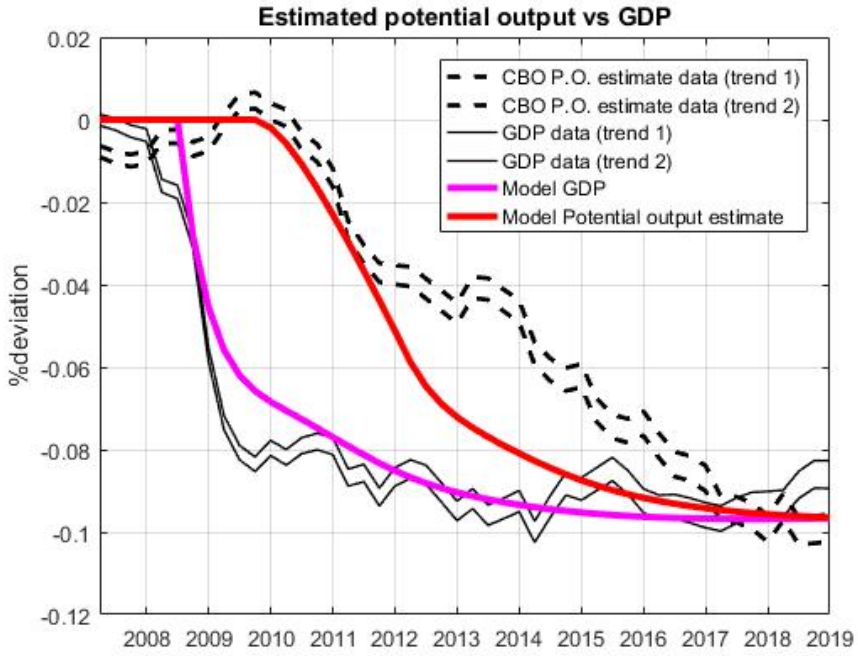



Figure 2.7: GDP and potential output: data and model.

crash. Monetary policy is in place to mitigate the shock, but the ZLB constraint limits its effectiveness and, most importantly, the severity and the length of the recession put downward pressure on potential output estimates, giving rise to a *switching-track*. Without a strong policy intervention, the economy moves to a lower growth path, revealing its AK nature. In Figure A.8 in the Appendix, we compare the results of our baseline calibration with the case in which the central bank's measure of potential output is much less sensitive to past observed data. In this case, the policy remains much stronger, and the negative level effects on GDP trend are considerably reduced, showing the policy's potential effect on recovery in the model. A slower revision of potential output (inducing a weaker *switching-track*) sustains consumption and investment demand, generating stronger inflation, and allowing the real interest rate to rise faster, promoting savings and a stronger recovery compared to the baseline simulation. The policy then induces households to consume and save more, and entrepreneurs to invest more, with the economy moving to a higher trend.

**Zero-Lower-Bound.** Figure A.6 in the Appendix highlights the role of the ZLB constraint in our results, showing that the level effect on GDP would have been less severe had the constraint not been binding. We also show that the risk shock is the main driver of these

results (Figure A.7), but the economy does not reach the ZLB in this scenario, as the severe supply effect of the shock drives inflation up.

**Welfare Losses.** In order to evaluate the impact of the policy, we calculate consumption equivalent welfare losses, by comparing the path of utility following the Great Recession shocks to the path of utility at the initial steady state (where the economy would have stayed had the Great Recession not happened). We conduct the analysis for 500 periods. Moreover, we calculate welfare for different intensities of potential output revision (*switching-track*). The Baseline column in Table 2.2 gives the welfare losses produced by the Great Recession demand shock when output gap is revised following the baseline revision rule. The other two columns do the same for alternative revision rules. Comparing columns, we conclude that faster revision rules generate larger losses, which implies that a weaker policy intervention in the model wouldn't have been optimal. This is likely because the growth rate of a learning-by-doing economy is suboptimal, and thus some additional effort leading to a faster growth rate is Pareto improving.

| Intensity of revision | Faster than baseline | Baseline | Slower than baseline |
|---|---|---|---|
| $\rho$ | 0.9 | 0.7 | 0.04 |
| Welfare losses | -7.3% | -6.8% | -6.4% |

Table 2.2: Welfare losses for different intensity of potential output revision.

In an AK world, when capital is destroyed output moves to a lower path. The optimal reaction to such a shock is to remain in the new lower balanced growth path. A monetary policy forcing households to save more than optimal in order to make capital return to its previous trend has to be suboptimal. Why is then the case that a Taylor rule forcing output to go back to its previous trend generates welfare gains? The fundamental reason has to be related to the learning-by-doing nature of the model. Since in this framework private returns to capital are smaller than social returns, the equilibrium growth rate is sub-optimally low. As a result, monetary policy improves welfare by increasing the growth rate.

**Capital Destruction Channels.** The model has two capital destruction channels: the direct effect on the capital stock of entrepreneurs going bankrupt or *liquidation costs*, and the negative externality that bankruptcy has in the capital value of all entrepreneurs or

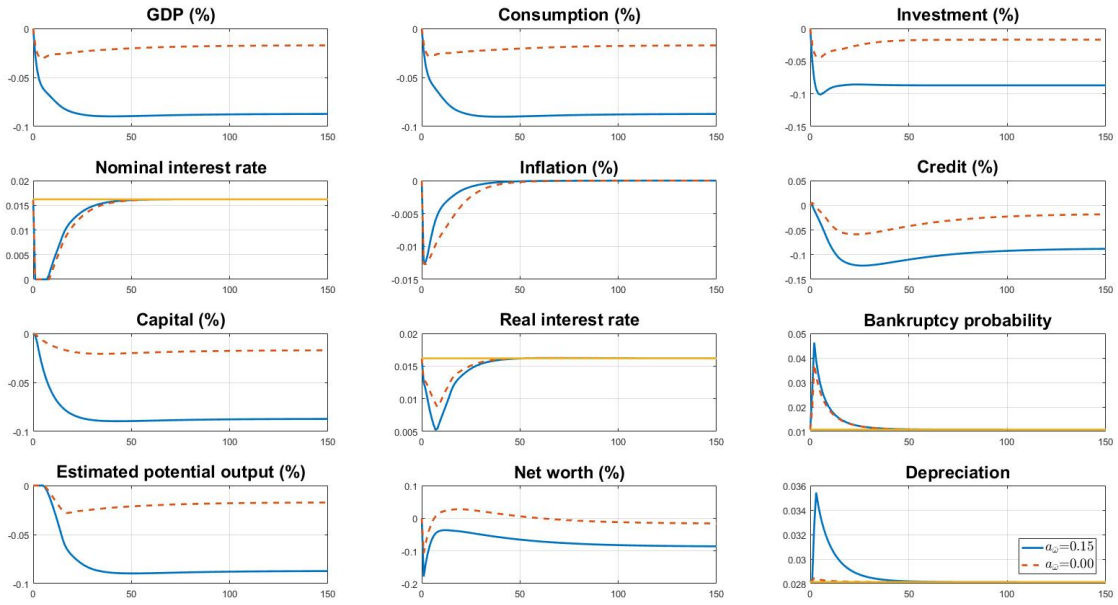



Figure 2.8: Baseline simulation vs case without disruption spillovers.

*disruption spillovers*. The first captures the role of entrepreneurs exiting the economy through bankruptcy, as we assume a liquidation cost in terms of capital such that $\kappa > \delta$. These firms are hit by the risk shock the hardest, and their exit affects the aggregate economy, but not enough to generate a downturn as large as the Great Recession. Figure 2.8 shows that the same demand shock generates a permanent level effect on GDP even with no disruption spillovers, but the magnitude of the impact is considerably smaller. The second channel is the result of disruption spillovers. This modelling choice is motivated by Lanteri (2018) data, which shows that the price of used capital goods relative to new ones fell in the whole secondary market, and not just for bankrupt firms. Moreover, this aims to capture the idea that in downturns most firms are worse off, not just the ones that exit. This second channel is key to replicate the magnitude of the Great Recession in the model, as it is clear from Figure 2.8.[18]

[18]In a previous version of the model we only considered the spillover channel and this was sufficient to generate the dynamics presented in this manuscript.

## 2.6 The Great Moderation: Normal Times

In this section, we aim to analyse the model's reaction to moderate shocks, consistently with pre-Great Recession downturns.[19] All along this section, we hold the value of potential output constant, so that the output gap measures the deviation of GDP from the balanced growth path trend.[20] We do not update the potential output measure because the revision procedure adopted after the Great Recession started was the first of its kind in the U.S. experience, as documented by Coibion, Gorodnichenko, and Ulate (2017). In normal times, *"Recessions typically have little effect on historical estimates of potential output because the methodology aims to exclude cyclical effects"* (Shackleton, 2014).

### 2.6.1 TFP Shocks

In order to show that our model can also be consistent with fast recovery episodes, we consider a textbook 1% TFP shock. In Figure 2.9, we plot simulation results for our baseline calibration as well as for a Taylor rule with no weight on the output gap. This figure shows that small shocks have permanent effects on GDP when $\rho_y = 0$, whilst the economy recovers when $\rho_y = 0.125$. The persistence of the shock is in line with the literature, and was selected to illustrate a case where the economy quickly recovers to the previous steady state.[21] A positive weight on the output gap implies that the monetary authority will respond with stimulus to aggregate demand when the output gap is negative, by offering a lower interest rate for each level of inflation. A negative TFP shock reduces the supply of output, which puts pressure on prices to increase, raising inflation. The presence of the output gap in the Taylor rule, compared to a scenario where the weight of the output gap is zero, puts additional pressure on prices by leading to higher consumption and investment.

[19] Since in normal time the ZLB is never binding, we solve the model with perturbation methods.

[20] An alternative practice, perhaps even more common in DSGEs, is to model potential output as the level of output that would prevail without nominal rigidities. We do not adopt this measure because all frictions affect the impact of the policy intervention in our framework. Without them, monetary policy would not be able to influence the real interest rate, hence they are important to determine the new equilibrium after a shock. In Figure A.10 in the Appendix, we show that removing price and wage rigidities results in monetary policy losing power. Moreover, measures of potential output as deviations of output from trend tend to be the instrument of choice for central banks. For example, see Edge et al. (2008) for a discussion of the FED's FRB/US model or Vetlov et al. (2011), for the ECB's NAWM.

[21] The Taylor rule systematically generates a full recovery after a TFP shock, but Figure A.9 in the Appendix shows that the recovery is fast as long as the persistence of the shock is not too high.

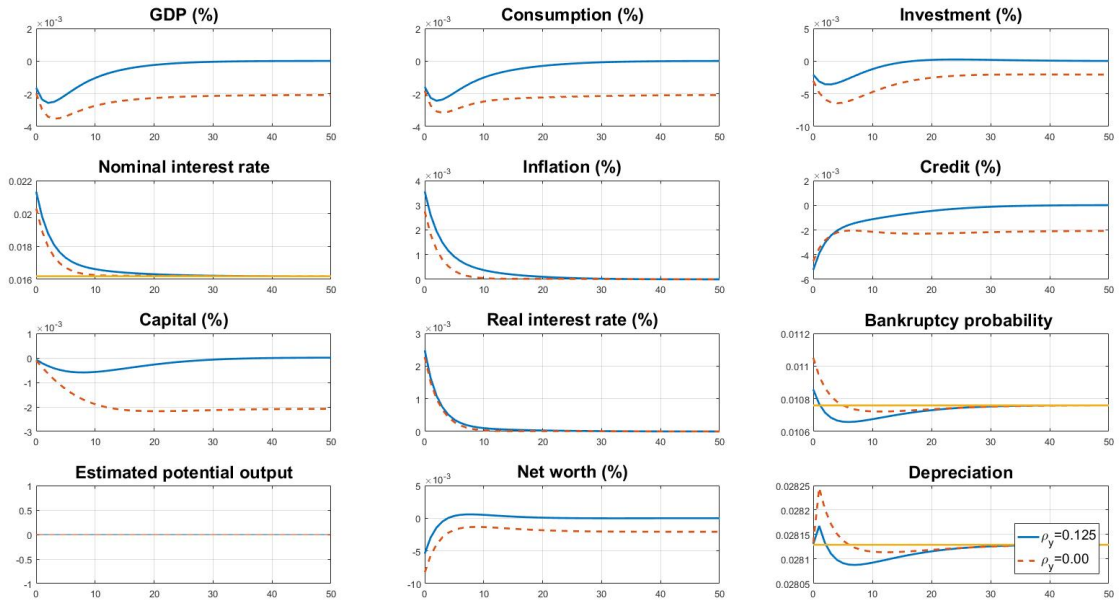



Figure 2.9: Effects of a 1% negative TFP shock.

The impact of the counter-cyclical policy intervention on investment is even more important to drive the recovery. The stimulus affects demand by lowering the wedge between the return to capital for successful entrepreneurs and the risk-less rate, thus effectively reducing the influence of financial frictions on the economy (see Figure A.11 in the Appendix). The condition for leverage (2.30), clearly shows that a fall in the wedge implies that financial intermediaries will offer contracts with lower leverage for each feasible value of $\bar{\omega}$. In equilibrium, the entrepreneur will then find it optimal to pick a contract with lower leverage and lower $\bar{\omega}$, keeping a larger share of her returns. Bankruptcy is thus reduced, leading to less capital destruction. The spread between the interest rate on loans and the risk-less rate is also reduced as a consequence of the policy intervention, so we conclude that a positive weight on the output gap tames risk in the economy overall, sustains aggregate demand and prevents capital destruction, keeping output and savings higher until the output gap closes and the economy displays a V-shaped recovery.

In order to compute welfare, we run the simulation with second-order perturbation methods, and we find that the policy intervention unequivocally improves welfare (Table 2.3).

| Weight on the output gap | $\rho_y = 0$ | $\rho_y = 0.125$ |
|---|---|---|
| 150 periods | -0.2% | -0.1% |

Table 2.3: Welfare losses of TFP shock compared to steady state for different weights on the output gap in the Taylor rule.

### 2.6.2 Demand Shocks

In this section, we aim to represent demand shocks in normal times, which we characterise as periods subject to shocks that are not as severe and persistent as during the Great Recession. We target an increase in the bankruptcy probability of approximately 0.5 percentage points, to mirror Christiano's estimation for the recessions preceding the financial crisis. Thus, we opt for a 5% increase in risk combined with a 4.5% confidence shock and we reduce the persistence of shocks to 0.7. This is close to pre-Great Recession estimates on confidence shocks documented by Angeletos, Collard, and Dellas (2018) and with the analysis of Christiano et al. (2015), who illustrate the increased persistence of financial shocks during the Great Recession compared to previous downturns. Figure 2.10 shows that monetary policy drives a V-shaped type of recovery in this case as well, although the economy will not converge back to the previous steady state within the 50 quarters period. Since we assume that potential output is never revised, the economy will eventually converge to the previous trend. In any case, the remaining output gap is small enough not to be perceived as a change of trend resulting from the demand shock. In our baseline calibration, we choose strong depreciation spillovers, but it is possible for the impact of spillovers to be non-linear in the size of shocks. As we reduce the parameter $a_{\bar{\omega}}$ in Figure 2.11, we see that the model can generate a full recovery even with demand shocks.

In order to understand the mechanics behind the recovery role of monetary policy, it is useful to think about the policy in place as a force counteracting the negative shocks. As the demand shock hits and GDP falls, a larger output gap gives the policy strength, but as the recovery starts to materialise and inflation recovers, the monetary authority faces a trade-off between above target inflation and a negative output gap. The higher weight on inflation in the Taylor rule results in a slowdown in the recovery, although GDP will eventually go back to the initial steady state. As we reduce the strength of the capital destruction spillovers, the dynamics do not change, but a smaller shock allows a full recovery within the time-frame in which policy makers do not face the trade-off.

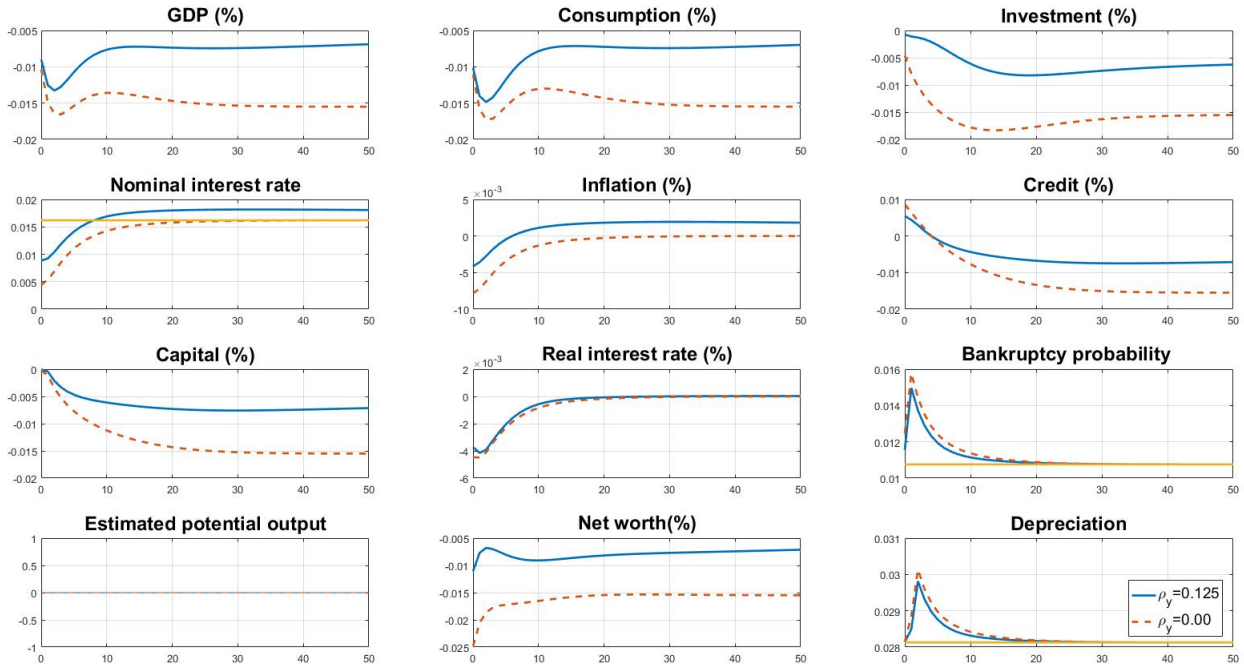



Figure 2.10: Effects of a small demand shock.

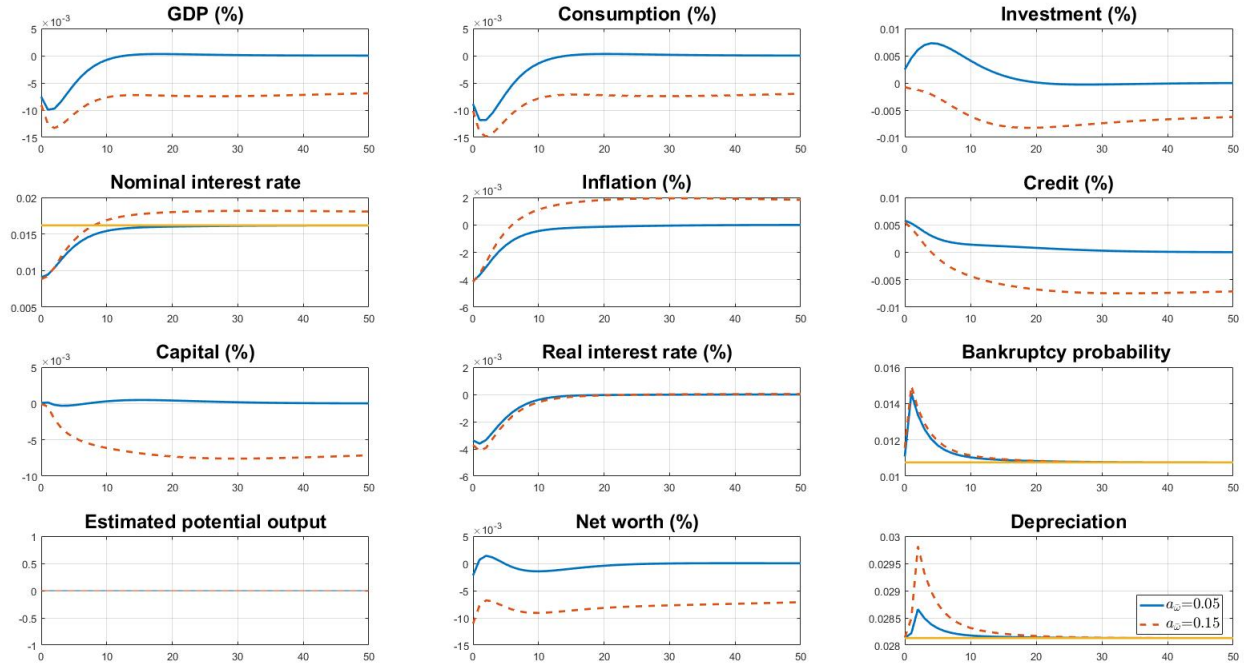



Figure 2.11: Effects of a small demand shock, with different intensity of depreciation spillovers.

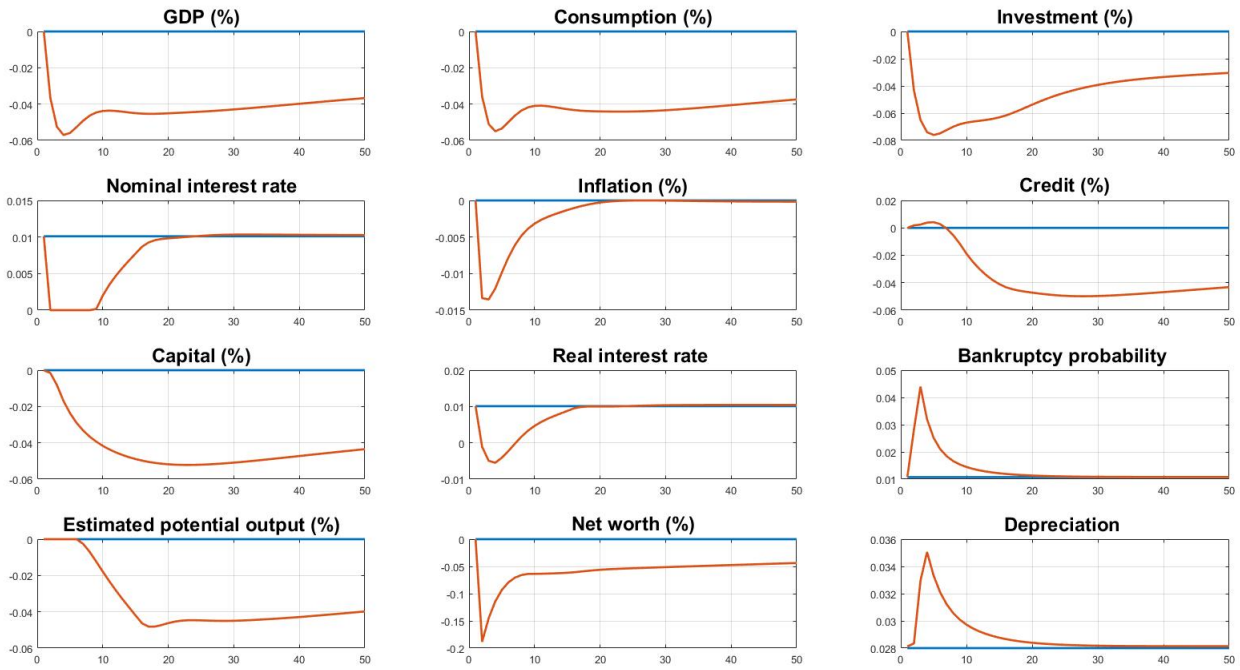



Figure 2.12: Great Recession shocks for $\eta = 0.6$.

## 2.7 What if We Relax the AK Assumption?

In the previous sections we assumed $\eta = 1 - \alpha$, which implies an aggregate AK technology. Is such a strong assumption necessary to generate our results? To test this, we simulate the model for lower values of $\eta$.[22] We pick $\eta = 0.06$ to get a quasi standard Cobb-Douglas technology. Figure A.12 in the Appendix shows that when we subject this version of the model to comparable shocks to simulate the Great Recession, and we keep potential output constant to reproduce a more standard DSGE, the model generates a quick and full recovery.[23] This shows that the AK technology, and not the nature of the shocks, is the source of the parallel downward shift of GDP in this model.

We then try an intermediate case, setting $\eta = 0.6$ to get closer to an AK model, and allowing potential output revisions as in our baseline. Figure 2.12 shows that the shocks result in a persistent recession of reduced depth. Although this version of the model could be

[22] Note that in this case the model does not grow endogenously any more, implying that the growth rate of the economy converges to zero.

[23] The model would also generate a similar recovery if we reduced the weight of the output gap in the Taylor rule, as the recovery is a consequence of diminishing returns to capital.

a good representation of GDP dynamics in the presence of additional shocks, we prefer our baseline specification, as it captures key aspects of the Great Recession in a parsimonious way. Simulations for normal times also show that the intensity of knowledge spillovers affects the severity of shocks as well as the speed of recovery, even with monetary policy in place (see Figure A.13 and A.14 in the Appendix).

## 2.8 Conclusion

Our paper contributes to the literature by showing that an endogenous growth model can reproduce the dynamics of U.S. GDP well, once the role of monetary policy is taken into account. In our framework, the differentiating factors between the Great Recession and the Great Moderation were the size and persistence of the shocks, the subsequent capital destruction, the binding of the zero lower bound and the introduction of the *switching-track*.

This paper opens several avenues for future research. Firstly, it would be interesting to explore whether the economy has in fact evolved from a Neoclassical technology to an AK model because of the rise of intangible capital. *"Because intangible investments, on average, behave differently from tangible investments, we might reasonably expect an economy dominated by intangibles to behave differently too."*[24] Secondly, we are keen to further investigate the destruction prevention channel of monetary policy and its implications for optimal monetary interventions. Lastly, this paper does not fully address the role of unconventional monetary policies implemented following the financial crisis. It would be interesting to explore this aspect, by evaluating further the impact of central bank credit policies on the recovery process in our model, following the example of Gertler and Karadi (2011).

[24] (Haskel & Westlake, 2018) page 10.

# Chapter 3

# The Economy after the Fall: Less Innovative, Less Intangible

**Abstract:** The rise of intangible investment across advanced countries is a well documented fact. This paper contributes empirical evidence to the recent theoretical literature evaluating the role of intangible investment on firm behaviour, over the long run and after negative shocks.

We pose two research questions:

*1. Does intangible intensity matter for firm growth?*

*2. Was the rise of intangible intensity accelerated or slowed down by the Great Recession?*

We document a positive link between investment in *R&D* as well as firm specific intangibles and firm growth, for both innovative and non innovative firms in the United States. Furthermore, we find that the Great Recession led to a deceleration of the rise of intangible intensity, driven by a slowdown in innovation intensity. This paper thus contributes to the literature by providing evidence reinforcing the theoretical notion that intangibles matter for long run growth, and by offering new insights on the medium to long run scarring effects of recessions.

## 3.1 Introduction

The rise of intangible investment across advanced countries is a well documented fact, owing to the work of Haskel and Westlake (2018), Peters and Taylor (2017) and Crouzet and Eberly

(2019), among others. Recent theoretical literature has proposed ideas to better understand the mechanisms through which intangibles affect firm performance and firm behaviour over the long run and after (large) negative shocks.[1] This paper provides an empirical evaluation of some of these hypotheses. In particular, we conduct an empirical exploration of the interaction between different types of intangible assets, the role they play for firm growth and how they are affected by recessions. We classify intangible investment according to three broad categories, following the seminal contribution of Corrado, Hulten, and Sichel (2005). These are computerized information, such as software and databases, economic competences, such as marketing and training, and intellectual property, *i.e.* $R\&D$ and patents. Throughout the paper we will refer to the latter as innovation investment and we will bundle the first two categories into a wider definition: firm specific intangibles ($FSI$).[2]

We analyse firm level data from COMPUSTAT between 1980 and 2018 across sectors for the United States, considering innovative as well as non-innovative firms, *i.e.* firms that never reported positive $R\&D$, with the aim to answer two research questions. Firstly, do intangible intensive firms grow faster? Our identification strategy draws inspiration from the the work of Haltiwanger, Jarmin, and Miranda (2013), who estimate the relationship between firm size an firm growth, as well as Akcigit and Kerr (2018) and Akcigit (2009), who analyse the connection between firm size and innovation. The empirical work in Roldan and Cavenaile (2020) is the closest to our approach, as they investigate the link between firm size and innovation intensity as well as adversing intensity in COMPUSTAT. We contribute by defining intangible intensity more broadly, and by investigating the nexus with firm growth. Findings suggest that all categories of intangible investment are associated with higher firm growth, measured as sales growth and employment growth, and that this positive correlation is consistent over time.

These results are in line with earlier empirical contributions documenting the link between intangible investment and firm growth. Notable examples include B. H. Hall (1987), who identifies a positive relationship between $R\&D$ investment, employment growth and survival, as well as Stiroh (2002), who finds a positive link between IT investment and productivity

[1] See for example Akcigit and Kerr (2018), De Ridder (2019), Roldan and Cavenaile (2020), Garcia-Macia (2017) or Caggese and Pérez-Orive (2020).

[2] An alternative name for this category widely used in the literature is organizational capital (Peters & Taylor, 2017). We prefer to use $FSI$ to avoid confusion, as organizational capital is considered a sub category of economic competences in Corrado, Haskel, Jona-Lasinio, and Iommi (2016).

growth.[3] More recently, Bloom, Sadun, and Van Reenen (2012) show that the combination of IT investment with effective managerial practices drove the success of U.S. firms compared to their European counterparts.

Our analysis also connects to the endogenous growth literature linking innovation and long term growth, stemming from the seminal contributions of Romer (1990) and Aghion and Howitt (1992). Overall, evidence suggest that intangible investment is positively associated with firm growth and thus with the growth potential of the economy.

These considerations motivate our second research question: do recessions slow down or accelerate the rise of intangible intensity? How do firms respond to negative shocks when they have the option to invest in innovation as well as firm specific intangibles? This aspect is interesting because changes in technology, *i.e.* the aggregate production function, can play an important role in shaping the recovery after a negative shock (Vinci & Licandro, 2020). Moreover, studies explicitly modelling growth through innovation and business cycle dynamics, such as Benigno and Fornaro (2018), and Anzoategui et al. (2019), show that an $R\&D$ intensive economy is more likely to display slow and incomplete recoveries. They show that a fall in $R\&D$ investment leads to a persistent decline in aggregate productivity and potential output.

The answer to our question is not obvious. Negative shocks could trigger creative-destruction led reallocations of productive resources, and thus improve the efficiency the economy after the recession, in line with a Schumpeterian view (Caballero & Hammour, 1994, 1996). Firms closer to the technological frontier, who tend to be more innovative, should then prevail and laggard firms should downsize or be pushed out. This idea is reinforced by more recent studies, who found complementarity between innovation and $FSI$ investment to promote firm performance in bad times. Gulati, Nohria, and Wohlgezogen (2010) analyse the performance of U.S. public firms during the recessions of 1980, 1990, and 2000 and find that firms who continued investing in $R\&D$ as well as $FSI$ were able to flourish after negative shocks. Gupta (2019) adds that innovative firms were able to diversify through marketing and this made them more resilient during the Great Recession in Spain. Consequentially, the whole economy should become more innovation intensive, and perhaps more intangible intensive compared to the counter-factual, *i.e.* had the recession not happened. In this scenario, large negative

[3] For an in-depth discussion of the literature see García-Manjón and Romero-Merino (2012).

shocks would accelerate the structural transformation process towards intangible intensive production.

On the other hand, Aghion et al. (2012) argue that credit constraints cause *R&D* investment to plummet during recessions and find that the subsequent recoveries are not strong enough to sustain the creative destruction hypothesis. Consequentially, it is reasonable to expect a financial crisis not to be cleansing. Foster, Grim, and Haltiwanger (2016) focus on the dynamics of job creation and job destruction and confirm the hypothesis that the Great Recession was not cleansing for the United States, as productivity enhancing reallocation was impaired, in contrast with past downturns.

Moreover, the Great Recession was associated with a large and long-lasting decline in the level of GDP, capital investment and *R&D* investment because the recovery was L-shaped.[4] As a consequence, the effect on the ratio, *i.e.* intangible intensity, is not well understood. In a representative agent framework, one could expect the ratio to decline in the aftermath of the recession, as the firm cuts down on investment as sales decline. However, in an heterogeneous firms framework, the aggregate result would depend on how the optimal choices of firms with different characteristics and subject to different shocks interact.

We address this question empirically, drawing from the estimation strategy of Hershbein and Kahn (2018), which allows to disentangle the effect of the negative shock on the path of intangible intensity over time by exploiting cross-sectional variation in the exposure to the Great Recession negative demand shock. We measure the shock as the fall in GDP at the 3 digit NAICS industry level for the whole economy, as well as the decline in exports for the manufacturing sector. The results of our estimation suggests that the Great Recession was associated with a slowdown in intangible intensity, driven by a slowdown in innovation intensity. We also find that the decline in innovation intensity was even more severe for firms that belonged to the highest percentiles of innovation intensity prior to the crisis, suggesting that the Great Recession did not have a cleansing effect in the Schumpeterian sense. We also find that firms switched between *R&D* and other intangible investments in the aftermath of the crisis, suggesting substitutability between the two categories and motivating further research on the mechanisms through which these affect production. Once we investigate

[4]See Ikeda and Kurozumi (2019), Anzoategui et al. (2019), Vinci and Licandro (2020) Garcia-Macia (2017), Caggese and Pérez-Orive (2020) or De Ridder (2016) for in depth discussion on this topic.

the drivers of these results, we find that higher sales growth in post recession years were associated with lower intangible intensity growth, suggesting that the most successful firms did not invest proportionally. Moreover, we find that *ex ante* intangible intensive firms did not grow proportionally more on average, thus our analysis does not support the hypothesis that recessions are cleansing periods where firms closer to the frontier outperform laggard competitors.

Overall, this paper contributes new evidence on the medium to long term scarring effects of recessions, by documenting a slowdown of intangible intensity, which may lead to the erosion of productive capacity and potential growth.

**Literature.** This paper relates to a wide range of literature spanning across endogenous growth, firm dynamics, industrial organization as well as business cycles.

In particular, we aim to offer insights to the recent theoretical literature exploring the complementarity and substitutability between innovation and other firm specific intangibles, over the long run and in the context of negative shocks.

Roldan and Cavenaile (2020) augment the Schumpeterian Growth framework proposed by Akcigit and Kerr (2018) to explicitly allow firms to invest in both $R\&D$ and advertising, and find that this improved the ability of the model to capture the relationship between firm size and firm growth. Moreover, they show that $R\&D$ and advertising can be substitutes, suggesting that firms pick optimally between the two categories of intangibles depending on their characteristics. De Ridder (2019) augments the Klette and Kortum (2004) framework and shows that considering software investment as a fixed cost can help explain firm choices regarding innovation spending and reconcile several facts concerning the decline in business dynamism in the United States. Caggese and Pérez-Orive (2020) explore the role of intangibles in driving the secular decline in corporate borrowing and the consequent decline in interest rates through the lens of a calibrated model. They argue that that intangible assets are hard to pledge as collateral, and thus firms have to rely on savings instead of loans to finance their investment, resulting in tighter credit constraints, hampering capital reallocation and slowing down growth. Focusing on recession periods, Garcia-Macia (2017) employs a rich dataset of Spanish firms to estimate a model of heterogeneous firms, to show that the lower value of intangibles as collateral plays a role in amplifying negative shocks during fi-

nancial crises. Schmitz (2017) focuses on innovation and adds that negative shocks have long lasting effects on $R\&D$ investment as small, radically innovative firms are disproportionately affected. Lastly, Sedláček and Sterk (2017) focus on the link between marketing investment, firm growth and business cycles. They argue that not all firms have the same growth potential at birth, as some specialize in mass goods and others in niche goods. Assuming that the former have a higher incentive to invest in marketing to build consumer capital and sustain demand, their estimated model predicts a reduction in the incentive to self-select into the production of mass goods in a downturn, resulting in a decline of new firms' growth potential.

The rest of the paper is organized as follows: Section 3.2 describes the data, Section 3.3 discusses the link between intangible intensity and firm growth, Section 3.4 focuses on the impact of the Great Recession on the rise of Intangible intensity, Section 3.5 presents our Robustness analysis, section 3.6 addresses the mechanics and and Section 3.7 concludes.

## 3.2 Data

We focus the analysis on the United States, using S&P's COMPUSTAT data. In line with common practice in this literature, we exclude firms with foreign headquarters, as well as firms in the utility sector, agriculture, public administration, finance, insurance are real estate, or unclassifiable sectors. Observations are further discarded if they have negative employment ($emp$), sales ($sale$), cost of goods sold ($cogs$), selling, administrative and general expenses ($xsga$), $R\&D$ ($xrd$), advertising expense ($xad$), property plant and equipment ($ppegt$), or total assets ($at$). We also excluded industries with less than 30 firms and observations where the market share at 3 digit NAICS level exceeded 90%.

We focus on the period 1980-2018 as these years encompass well the process of structural transformation towards a more intangible intensive economy. Figure 3.1 compares data for intangible intensity published by the Bureau of Economic Analysis (BEA), which tracks intellectual property products for private industries, and the equivalent series in our COMPUSTAT sample ($\frac{R\&D}{sales}$). Both figures show a clear upward trend since 1980, in line with Haskel and Westlake (2018). There is no clear break in conjunction with the Great Recession, motivating us to investigate weather the shock generated an acceleration or a slow down in the rate of growth. Moreover, throughout the paper we will investigate the dynamics of

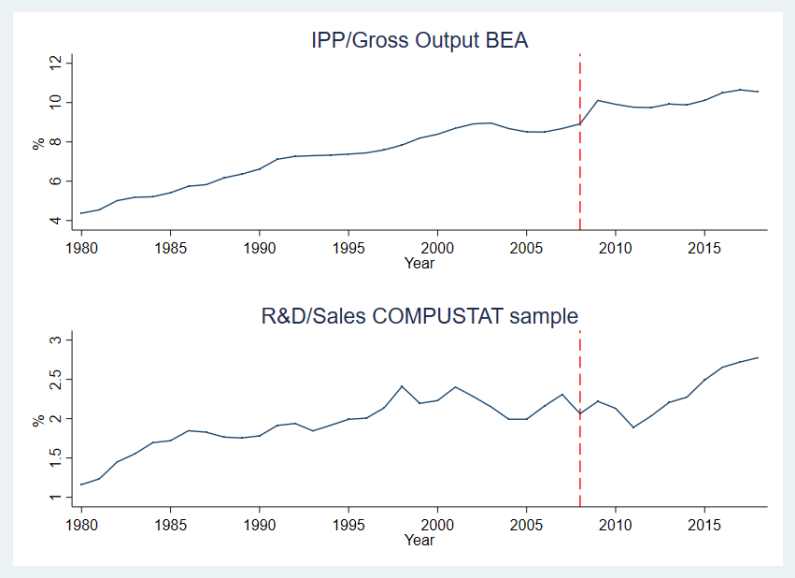



Figure 3.1: Innovation intensity over time: BEA vs COMPUSTAT sample.
IPP is Current-Cost Net Stock of Intellectual Property Products by private industries ( private fixed assets). Gross Output is nominal and for private firms. The COMPUSTAT measure is constructed as Total $R\&D$ expenditure on total sales.

intangible intensity beyond innovation intensity, considering firm specific intangibles more broadly.

The definition of firm specific intangibles ($FSI$) investment follows the approach of Peters and Taylor (2017), who estimate that 30% of general selling and administrative expenditures constitutes intangible investment. The COMPUSTAT measure is then $FSI = 0.3(xsga - xrd)$ where $xrd$ is investment in $R\&D$, which is typically included in the COMPUSTAT measure of $xsga$, as documented by Peters and Taylor (2017). $IntanInvest$ is simply the sum of the two intangible categories. These three measures are meant to capture a firm's effort to build intangible capital. Figure C.1 in the Appendix shows the rise of the two additional measures over time in COMPUSTAT. [5] In the sections that follow we analyse the behaviour or innovative as well as non innovative firms, defined as firms who reported positive $R\&D$ at least once in our sample vs firms that never did. Table C.3 shows that innovative firms tend

[5]We keep firms with values of intangible investment intensity below 100%, similarly to Roldan and Cavenaile (2020). Focusing on innovation intensity, Park (2011) argues that firms whose revenue lower than $R\&D$ investment are mostly in the technology and pharmaceutical sector and their business model is based on venture capital funding. We exclude them because we believe they are less likely to make investment choices in the same way as traditional, profit maximising firms and we apply the same logic to other intangible categories. The resulting sample still includes approximately 70% of Gross Private Domestic Investment in Research and Development, as shown in figure C.2 in the Appendix.

to be concentrated in the manufacturing sector and Table C.4 shows that there is a positive correlation between being innovative and investing in firm specific intangibles ($FSI$), as firms in the top 25% if $FSI$ intensity are more likely to be innovative.

## 3.3 Does intangible intensity matter for firm growth?

In this section, we describe the empirical analyses carried out to test the hypothesis that firms invest in intangible capital to sustain demand for their goods.

**Intensity and firm size.** As a first step, we investigate the relationship between intangible intensity and firm size, measured as the log of real sales, estimating the following specification for firm $i$:

$$IntanIntensity_{i,t} = \beta_0 + \beta_1 ln(sales)_{i,t} + \sum_{\kappa}^{N} \gamma_\kappa X_{i,t}^{\kappa} + \alpha_{j,t} + \alpha_i + \epsilon_{i,t} \tag{3.1}$$

$$IntanIntensity_{i,t} = \left[\frac{R\&D_{i,t}}{sales_{i,t}}, \frac{FSI_{i,t}}{sales_{i,t}}, \frac{IntanInvest_{i,t}}{sales_{i,t}}\right]$$

The control variables are:

$$X_{i,t}^{\kappa} = [age_{i,t}, leverage_{i,t}, equity_{i,t},]$$

Sales are defined as a firm's reported revenue divided by the BEA industry deflator. We control for age, which represents years since addition to COMPUSTAT, leverage, *i.e.* total debt on total assets, and equity, *i.e.* total equity on total assets. We introduce firm fixed effects in all specifications to account for unobserved firm characteristics and attenuate omitted variable bias. We also control for time-industry fixed effects at the NAICS 2 digit level, to allow for differences in industry dynamics, such as the rise of services and the decline of manufacturing as a share of value added and employment.[6]

Our results are in line with several studies focusing on innovation intensity, who find that firms with high innovation intensity tend to be smaller (see for example Akcigit (2009) and Akcigit and Kerr (2018)). Table 3.1 shows a strong negative correlation between intangible

[6]The industry classification is in table C.2 in the Appendix.

| | (1) $\frac{R\&D}{sales}$ b/se | (2) $\frac{FSI}{sales}$ b/se | (3) $\frac{IntanInvest}{sales}$ b/se |
|---|---|---|---|
| $ln(sales)$ | -0.013*** | -0.019*** | -0.031*** |
| | (0.001) | (0.001) | (0.001) |
| Number of obs. | 93,309 | 93,309 | 93,309 |
| $R^2$ | 0.039 | 0.106 | 0.094 |
| Firm fixed effects | YES | YES | YES |
| Industry-time fixed effects | YES | YES | YES |
| S.e. clustered at firm level | YES | YES | YES |
| Firm level controls | YES | YES | YES |

Table 3.1: Sales and intangible intensity.
Controls include age, leverage, and equity ratio.

intensity measures and revenue, suggesting that firms that invest relatively more in intangible assets tend to be smaller. Our analysis complements existing studies, as we document that the inverse relationship between innovation intensity and a firm's stance in the market also holds for $FSI$ and total intangibles. We repeat the analysis adopting the log of employment as a measure of size/ stance in the market and find comparable results (see Table C.14 in the Appendix).

We then check whether firms that use more intangible capital, *i.e.* have a higher share of intangible capital on total capital, have higher revenue.[7]

We estimate the following specification:

$$ln(sales)_{i,t} = \beta_0 + \beta_1 \frac{PurchasedIntan_{i,t}}{Capital_{i,t}} + \sum_{\kappa}^{N} \gamma_\kappa X^\kappa_{i,t} + \alpha_t + \alpha_i + \epsilon_{i,t} \tag{3.2}$$

$$X^\kappa_{i,t} = [ln(emp)_{i,t}, age_{i,t}, leverage_{i,t}, equity_{i,t}, ln(\mu)_{i,t}]$$

The regression includes firm and time effects and we also control for firm level mark-ups, constructed following De Loecker et al. (2020).[8] We also control for size, measured by the log of employment. To measure the stock of intangible capital, we exploit the variable *intan* in COMPUSTAT, which measures purchased intangibles. Intangible intensity is then constructed as purchased intangibles on total capital $\left(\frac{intan}{intan+ppegt}\right)$, as in Crouzet and Eberly (2019). This captures the stock of intangible capital that firms declare on their balance sheet, mostly resulting from acquisitions. The measure is far from ideal, as it misses the value of

[7] We also considered the relationship between intangible intensity and market share, but we found results to be mixed and dependent on how the market share measure was constructed, so we decided to exclude them from the paper. However, results are available upon request.

[8] A detailed description of the measure can be found in the Appendix.

| | (1) $ln(sales)$ (OLS) b/se | (2) $ln(sales)$ (IV) b/se |
|---|---|---|
| $\frac{PurchasedIntan}{Capital}$ | 0.178*** | 0.736*** |
| | (0.031) | (0.222) |
| Number of obs. | 137,803 | 126,497 |
| $R^2$ | 0.688 | 0.678 |
| Kleibergen-Paap Wald F-statistic | | 390.220 |
| Firm fixed effects | YES | YES |
| Time fixed effects | YES | YES |
| S.e. clustered at firm level | YES | YES |
| Firm level controls | YES | YES |

Table 3.2: Share of intangible capital in total capital and firm sales.
Controls include size(employment), mark-up, age, leverage and equity ratio. The instrument is $\frac{k_{know}+k_{org}}{k_{know}+k_{org}+ppegt}$ from Ewens et al. (2019).

internally built intangibles, but is nonetheless the most accurate representation available of the firm's valuation of its intangible capital.

This measure also raises measurement error concerns as firms might underestimate or over-estimate intangible assets at the acquisition stage, or over/under-estimate impairment over time. These errors could be correlated with our variables of interest, biasing our estimates. In order to address this issue, we use data on accumulated innovation and $FSI$ at the firm level made available by Ewens, Peters, and Wang (2019). They calculate the stock of internally built intangibles for U.S. publicly listed firms adopting perpetual inventory methods, but also adjusting structural parameters exploiting data on intangible assets transactions during acquisition and bankruptcy processes. The instrument is then $\frac{k_{know}+k_{org}}{k_{know}+k_{org}+ppegt}$, where $k_{org}$ is accumulated $FSI$ and $ppegt$ represents tangible capital.

The two measures represent different categories of intangibles, *i.e.* internally built vs externally acquired, but it is reasonable to expect them to be correlated. Moreover, the measure we use as an instrument is still subject to measurement error as perpetual inventory method does not take into account the fluctuations in the market value of assets, but this measurement error should be uncorrelated with the measurement error in balance sheet purchased intangibles. Table 3.2 shows that a higher share of intangible capital is associated with higher sales in the OLS regressions and the instrumental variable estimation confirms.[9]

[9]Using instead $k_{know}$ and $k_{org}$ from Peters and Taylor (2017), who follow a more traditional perpetual inventory method, yields comparable results.

**Intensity and firm growth.** From the previous results, we conclude that firms putting the most effort into intangible investment across both categories tend to be smaller. On the other hand, firms that have more intangible capital are larger. This motivates us to formulate the hypothesis that intangible investment could be a way to build up demand for smaller firms. To test this hypothesis, we employ the following specification:

$$y_{i,t} = \beta_0 + \beta_1 IntanIntensity + \beta_2 IntanIntensity * ln(e\bar{m}p)_{i,t} + \sum_{\kappa}^{N} \gamma_\kappa X_{i,t}^{\kappa} + \alpha_{j,t} + \alpha_i + \epsilon_{i,t} \quad (3.3)$$

Where the dependent variables are:

$$y_{i,t} = [SalesGrowth_{i,t}, EmploymentGrowth_{i,t}]$$

The measures of Intangible intensity are:

$$IntanIntensity = \left[\frac{R\&D_{i,t-1}}{sales_{i,t-1}}, \frac{FSI_{i,t-1}}{sales_{i,t-1}}, \frac{IntanInvest_{i,t-1}}{sales_{i,t-1}}\right]$$

The control variables are:

$$X_{i,t}^{\kappa} = [ln(e\bar{m}p)_{i,t}, age_{i,t}, leverage_{i,t}, equity_{i,t}, ln(\mu)_{i,t}]$$

Where employment and sales growth are computed as log difference of real sales and employment year on year. Size is measured as the logarithm of the average number of employees between t and t-1 ($ln(e\bar{m}p)_{i,t}$).[10] The specification controls for size and includes an interaction term of size and intangible intensity, to allow the elasticity of growth to changes in intangible intensity to vary along the firm-size distribution. We make this modelling choice because we found that smaller firms tend to invest relatively more in intangibles, and thus the return to intangible investment could be higher for smaller firms. Intangible intensity measures are lagged, to allow past investment to cumulate into intangible capital used in production, following the same logic behind standard perpetual inventory methods. Moreover this way the intangible investment choice is weakly exogenous to firm performance.

[10]This measure is widely used in the literature investigating the relationship between firm size and firm growth, as it allows to avoid regression to the mean bias. For a detailed discussion see Haltiwanger et al. (2013). Nonetheless, using employment at base year (t-1) or current employment yields similar estimates for our coefficient of interest.

| | (1) Sales growth b/se | (2) Sales growth b/se | (3) Sales growth b/se |
|---|---|---|---|
| $\frac{R\&D}{sales}(t-1)$ | | 1.114*** | |
| | | (0.055) | |
| $ln(e\bar{m}p)\frac{R\&D}{sales}(t-1)$ | | -0.124*** | |
| | | (0.022) | |
| $\frac{FSI}{sales}(t-1)$ | 3.105*** | | |
| | (0.114) | | |
| $ln(e\bar{m}p)\frac{FSI}{sales}(t-1)$ | 0.170*** | | |
| | (0.032) | | |
| $\frac{IntanInvest}{sales}(t-1)$ | | | 1.410*** |
| | | | (0.049) |
| $ln(e\bar{m}p)\frac{IntanInvest}{sales}(t-1)$ | | | -0.034** |
| | | | (0.017) |
| Number of obs. | 78,322 | 78,322 | 78,322 |
| $R^2$ | 0.292 | 0.238 | 0.298 |
| Firm fixed effects | YES | YES | YES |
| Industry-time fixed effects | YES | YES | YES |
| S.e. clustered at firm level | YES | YES | YES |
| Firm level controls | YES | YES | YES |

Table 3.3: Sales growth and intangible intensity.
Controls include size (average employment), mark-up, age, leverage, and equity ratio.

Table 3.3 shows that firms that invested relatively more in intangible capital, across all three categories, reported higher sales growth on average. In order to further investigate this result, we run the same regression for $FSI$ intensity, distinguishing between innovative and non-innovative firms, defining innovative firms as those that reported positive $R\&D$ at least once in the sample. Both coefficients of interest remain significant, suggesting that these firms can increase their revenue thanks solely to $FSI$, and that different categories on intangible could be substitutes (Table 3.4).

| | (1) Sales growth Innovative(≥once) b/se | (2) Sales growth Non-Innovative b/se |
|---|---|---|
| $\frac{FSI}{sales}(t-1)$ | 3.243*** | 2.124*** |
| | (0.115) | (0.321) |
| $ln(e\bar{m}p)\frac{FSI}{sales}(t-1)$ | 0.196*** | -0.015 |
| | (0.033) | (0.071) |
| Number of obs. | 63,929 | 14,393 |
| $R^2$ | 0.307 | 0.261 |
| Firm fixed effects | YES | YES |
| Industry-time fixed effects | YES | YES |
| S.e. clustered at firm level | YES | YES |
| Firm level controls | YES | YES |

Table 3.4: Sales growth: Innovative vs Non-Innovative.
Controls include size (average employment), mark-up, age, leverage, and equity ratio.

As a robustness check, we consider alternative measures of size and find that these results hold. In Tables C.17 and C.18 in the Appendix we take into account more inputs of production, *i.e.* all combinations of tangible capital ($ln(\frac{ppegt}{p^k})$) and labour, and show the impact of all control variables. We also tried adding tangible capital as a control, as well as when using total real assets as a measure of size.

From these results, we conclude that intangible intensity is associated with higher revenue growth. However, one shortcoming of COMPUSTAT data is that it does not disentangle prices and quantities sold, as firms only report revenue. Although this is a standard measure of firm growth in the empirical literature investigating the effects of innovative investments at the firm level (see for example Bloom et al. (2013) or Kogan et al. (2017)), it is possible for intangible capital to have an effect on the firm's ability to raise prices, rather than quantity. We partially addressed this concern by including firm mark-up as a control variable, thus controlling for the role of profit margins on revenue growth, resulting in a more precise estimate of the elasticity of firm performance to intangible investment intensity. Nonetheless, we also consider employment growth as a measure of firm performance, to better capture organic growth for the firm, as employment and quantity produced are likely to be highly correlated. [11]

Table 3.5 shows that intangible intensity is also associated with higher employment growth, suggesting that firms grow organically and produce more once that they have invested in intangible capital. In our baseline specification in Table 3.5 the coefficient of R&D intensity is positive but not significant, however once we consider alternative measures of size, such as capital and labour (Table C.18 in the Appendix) or the log of total real assets, the coefficient becomes significant. We thus conclude that there is a positive association between all categories of intangible intensity and employment growth, but not all results are highly robust. Note that mark-ups are also associated with higher employment growth, indicating that higher profit margins do not simply motivate firms to rise prices, but also production.

**Robustness.** As further robustness checks, we run the key regressions for sales growth and employment growth for each year (see Figures C.6 and C.7 in the Appendix), and find

[11] Note that when assessing the impact of intangible intensity on employment growth lagging measures of intangible intensity is even more important as contemporaneous rises in spending might stem from hiring choices. For example, the addition of a sales person would mechanically increase $xsga$ in COMPUSTAT as the wages of sales personnel are included.

| | (1) Employment growth b/se | (2) Employment growth b/se | (3) Employment growth b/se |
|---|---|---|---|
| $\frac{R\&D}{sales}(t-1)$ | 0.057 | | |
| | (0.045) | | |
| $ln(emp)\frac{R\&D}{sales}(t-1)$ | -0.052*** | | |
| | (0.017) | | |
| $\frac{FSI}{sales}(t-1)$ | | 0.865*** | |
| | | (0.157) | |
| $ln(emp)\frac{FSI}{sales}(t-1)$ | | 0.096** | |
| | | (0.039) | |
| $\frac{IntanInvest}{sales}(t-1)$ | | | 0.242*** |
| | | | (0.055) |
| $ln(emp)\frac{IntanInvest}{sales}(t-1)$ | | | -0.008 |
| | | | (0.017) |
| Number of obs. | 78,322 | 78,322 | 78,322 |
| $R^2$ | 0.074 | 0.079 | 0.077 |
| Firm fixed effects | YES | YES | YES |
| Industry-time fixed effects | YES | YES | YES |
| S.e. clustered at firm level | YES | YES | YES |
| Firm level controls | YES | YES | YES |

Table 3.5: Employment growth and Intangible intensity.
Controls include size(average employment), mark-up, age, leverage and equity ratio.

that intangible intensity coefficients tend to be stable over the whole period. We also follow Haltiwanger et al. (2013) and define sales growth and employment growth as $\frac{emp_t - emp_{t-1}}{0.5(emp_t + emp_{t-1})}$ and $\frac{RealSales_t - RealSales_{t-1}}{0.5(RealSales_t + RealSales_{t-1})}$. These measures are often used in the firm dynamics literature as they allow to smooth out entry and exit effects and they are bounded between -2 and 2. Results in Table C.20 and Table C.21 show that our results are robust to this specification. We also tried winsorizing the top and bottom 2% of sales and employment growth in Table C.15 and Table C.16, and our results are robust. We also consider the impact of survival bias and firm exit on our results. An in depth discussion can be found in in Appendix C.2, where we show that intangible firms are more likely to get acquired, but less likely to exit due to bankruptcy or other reasons.[12] This result suggests that intangible intensive firms are less likely to disappear from the market on average, thus our estimation of the relationship between intangible intensity and growth could be understated. Correcting for survival bias confirms this, as the coefficients of interest increase in magnitude for sales growth (see Table C.12). Results for employment growth are more mixed, but this is not surprising as we already found the positive correlation between intangible intensity and employment growth to be sensitive to the definition of firm size in benchmark regressions.

[12]We categorize as bankruptcy cases liquidation as well.

Overall, our analysis finds a positive relationship between intangible intensity and firm growth, which is highly robust when the latter is defined as sales growth and more tenuous when considering employment growth.

## 3.4 Did the Great Recession accelerate or slow down the rise of intangible intensity?

In this section we address our main research question: did the Great Recession accelerate or slow down the rise of intangible intensity?

Th empirical strategy draws from from Hershbein and Kahn (2018), and aims to separate the effects of the Great Recession from the underlying intangible intensity trend. In order to capture the Great Recession shock, we use two measures: GDP and exports. The first measure is available for the whole economy, as the BEA publishes estimates at the 3 digit NAICS level, and is a good indicator of the domestic demand shock. However it has the drawback of being affected by the performance of domestic firms. If firms in a given industry were more resilient to a negative shock for any given reason, the GDP measure would fall by less, thus not fully capturing the true magnitude of the shock. To address this concern, in the following section, we will repeat the analysis using export data from Schott, Fuest, and O'Rourke (2008), which represents a reliable indicator of external demand, drawing from the work of Aghion et al. (2020) and Gupta (2019). The drawback of the trade measure is that it does not capture the domestic demand shock, which was significant for the United States as the collapse of the housing market was a domestic event. Moreover, coverage is limited to the Manufacturing sector. Nevertheless, the combined results for both shocks help offer a comprehensive picture to answer our research question.

We estimate the following specification for firm $i$ in industry $j$:

$$INT_{i,j,t} - INT_{i,j,2007} = \beta_0 + \beta_1 IntanIntensity_{i,j,2007} + \beta_2 * Shock_j * I^t + \beta_3 * I^t + \sum_{\kappa}^{N} \gamma_\kappa X^\kappa_{i,j,2007} + \epsilon_{i,j,t} \tag{3.4}$$

$$INT_{i,j,t} = \left[ \frac{R\&D_{i,t}}{sales_{i,t}} * 100, \frac{FSI_{i,t}}{sales_{i,t}} * 100, \frac{IntanInvest_{i,t}}{sales_{i,t}} * 100 \right]$$

$$X^{\kappa}_{i,j,2007} = [ln(emp)_{i,j,2007}, age_{i,j,2007}, leverage_{i,j,2007}, equity_{i,j,2007}, ln(\mu)_{i,j,2007}, GDPgrowth_{j,2007}]$$

The GDP shock variable is defined as $Shock_j = -(ln(GDP_{j,2009}) - ln(GDP_{j,2007})) * 100$, for t=2010-2018 and industry $j$ and is held constant at the industry level for the whole sample.[13]. The intensity of the GDP shock for each 3 digit NAICS industry in our sample are displayed in Figure C.8 in the Appendix. We pick 2007 and 2009 as these represent the peak and through of the recession, and control for *ex ante* firm characteristics by including control variables pre-recession. These include age, employment (log), leverage, equity ratio, mark-up (log) as well as industry GDP growth (log difference). This specification allows us to identify the effect of the shock on the path of intangible intensity, disentangling between the underlying trend, captured by the time dummies $I_t$ and the effect of the shock, captured by the interaction between the shock variable and the time fixed effects. Tables C.22, C.23 and C.24 show the time profile of the shock and time fixed effects for the key specifications.

**Innovation Intensity.** Figure 3.2 shows the results of our estimation for innovation intensity. The graph in the top left shows that firms in industries worst hit by the shock reduced their innovation intensity in the aftermath of the Great Recession, compared to the underlying trend. Moreover, the decline is significant and long lasting, as Innovation intensity remains 4 percentage points below trend at the end of the sample for a firm in an industry hit by a 1% shock to GDP.

To better understand this result, we classify firms according to their pre-Great Recession $R\&D$ intensity, captured in 2006 and 2007 to avoid picking up the aftermath of the Dot-com bubble. A firm is classified as having high innovation intensity if its $\frac{R\&D}{sales}$ is above the $75^{th}$ percentile in its 3 digit NAICS industry, medium if it is between the $25^{th}$ and the $75^{th}$ percentile, and low if it belongs to the bottom $25^{th}$ percentile.[14] Repeating the analysis for each of the three categories yields the remaining plots in figure 3.2. These show that the aggregate decline in innovation intensity was the result of a widespread decline across all

[13]BEA industry classification (3 digit NAICS)

[14]Industries with less than 10 firms were excluded when computing Low-Medium-High intensity categories. The overall Innovation intensity displayed is consistent with this sample restriction, but the full sample is comparable.

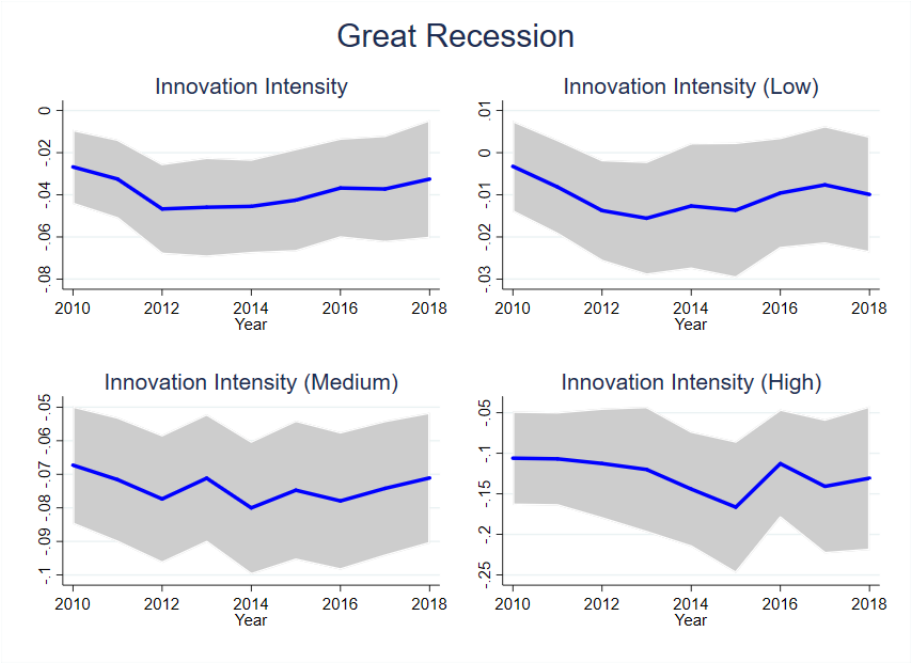



Figure 3.2: The effects of the Great Recession shocks on intangible intensity.
The graph plots the coefficins of Time-fixed-effects*GDPshock from equation 3.4, with 90% confidence intervals.

firms, but the slowdown was particularly severe for firms that had *ex ante* medium and high intensity, suggesting that the shock had long lasting effects on the most innovative firms in the economy, as a 1% reduction in GDP is associated with a reduction of innovation intensity of 7 to 10 percentage points.

**FSI Intensity.** Next, we investigate the effects of the recession on firm specific intangibles ($FSI$). Figure 3.3 shows that the Great Recession shock had no effect on $FSI$ intensity overall, but once we distinguish between innovative and non innovative firms we see a different pattern. Firms that never reported $R\&D$ saw an increase in their $FSI$ intensity in the aftermath of the Great Recession, which accelerated the rise of intangible intensity for these firms. [15]

**Intangible intensity.** We then estimate the overall impact of the Great Recession shock on Intangible intensity, and figure 3.4 shows a long lasting, significant decline. Our estimation suggests that the economy's intangible intensity associated with a 1% GDP shock was 4

[15] The number of observations for non innovative firms is low, motivating caution when interpreting this result.

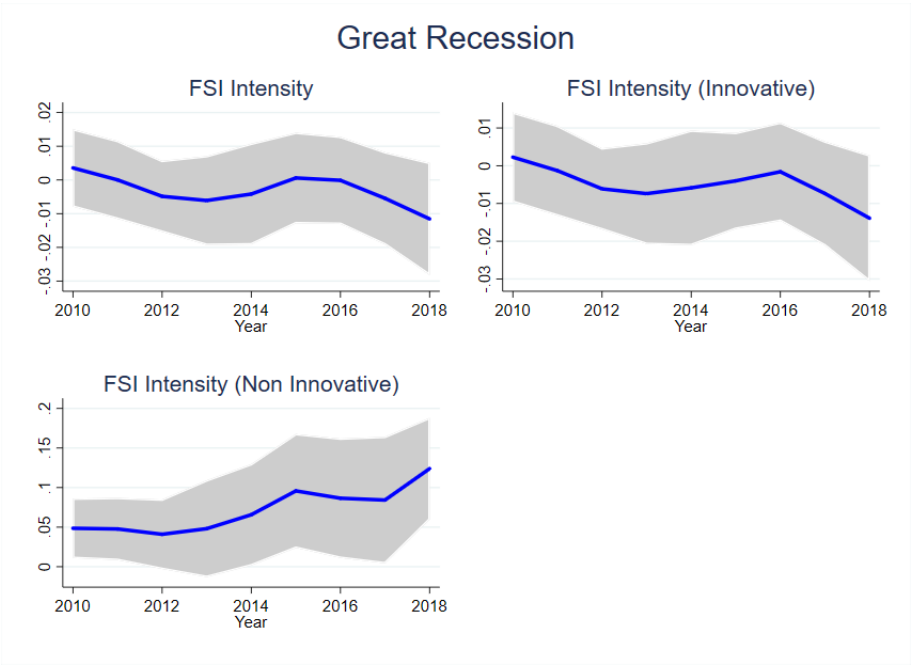



Figure 3.3: GDP Shock and $FSI$ Intensity.
Timefixed effects*GDPshock

percentage points lower compared to the time trend.

**Switching between intangibles.** The fact that innovation intensity declined whilst $FSI$ intensity remained on trend for the aggregate economy raises the question: did innovative firms switch from $R\&D$ to $FSI$ investment? It is possible that investments such as marketing or software may become more attractive following a negative shock, as their return might be more immediate and less uncertain with respect to $R\&D$.

To test this hypothesis we follow the same methodology, but considering the deviation of the share of $R\&D$ in $xsga$ from 2007 as the dependent variable. This allows us to measure the relative importance of $R\&D$ compared of other intangibles at the firm level. Figures 3.5 shows a significant and long lasting decline in this ratio in the aftermath of the Great Recession, suggesting that firms switched from $R\&D$ to other intangibles. The estimated decline improves after 2014, suggesting that the effect might be temporary, although long lived.

**Investment effort.** It is well known in the literature that the Great Recession had profound impact on total investment, which plummeted during the crisis and never recovered to

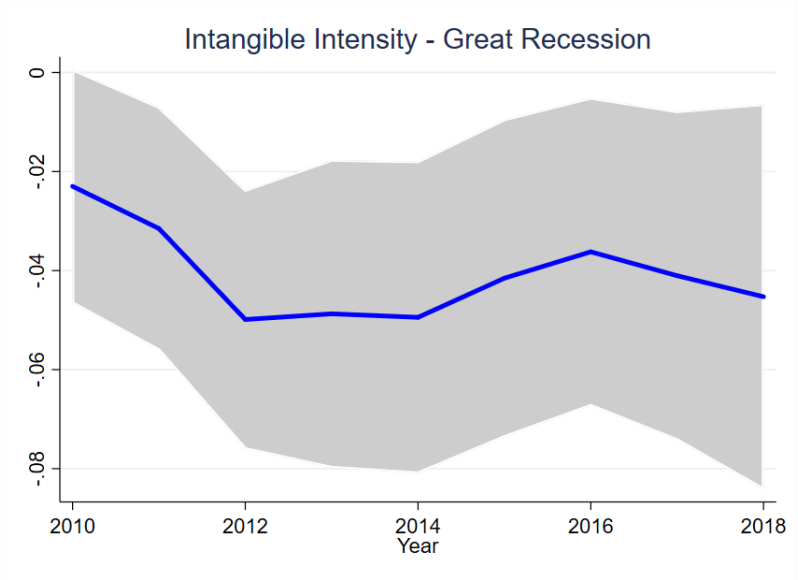



Figure 3.4: GDP Shock and Intangible Intensity.
Timefixed effects*GDPshock

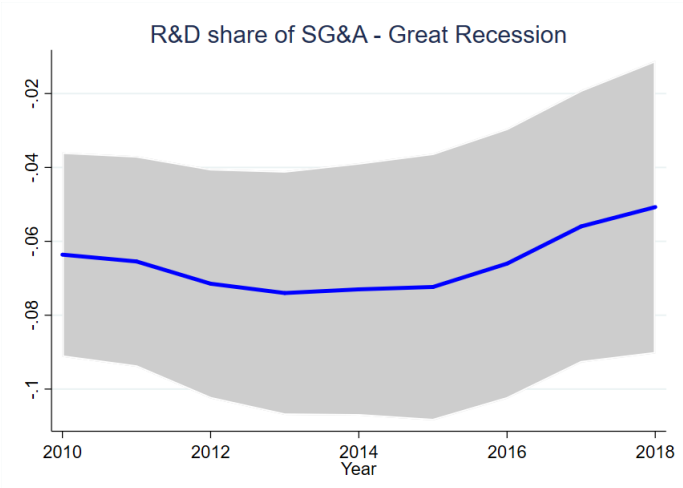



Figure 3.5: GDP Shock and $R\&D$ share of $SG\&A$.
Timefixed effects*GDPshock

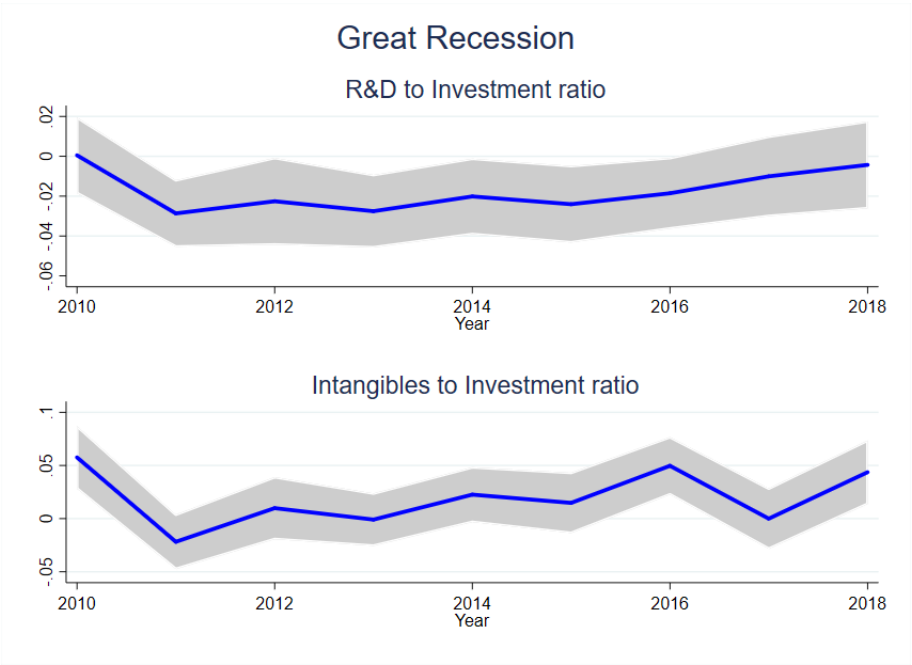



Figure 3.6: GDP Shock and Investment ratios.
Timefixed effects*GDPshock

its previous growth trajectory. We thus investigate weather firms changed the composition of their investment efforts, weather they reduced their $R\&D$ or total intangible investment as a share of total investment ($ppent+ xrd+ FSI$). Figure 3.6 shows that the share of $R\&D$ in total investment declined, but recovered towards the end of the sample, whilst the share of total intangibles was barely affected.

These results suggest that the Great Recession had a significant impact on firm's propensity to invest in intangibles, but did not play an important role in their choice between intangible and tangible capital, on average.

## 3.5 Robustness

The previous results suggest that firms in sectors worst hit by the Great Recession reduced their intangible intensity, and innovation intensity in particular. However this result could be driven by underlying trends specific to those industries, and not to Great Recession. To test this hypothesis, we run the same specification, but considering 1999 as the base year.[16] If the decline in intensity was driven exclusively by the Great Recession shock, we should find that

[16]We did the same using 2003 and 2004, with comparable results.

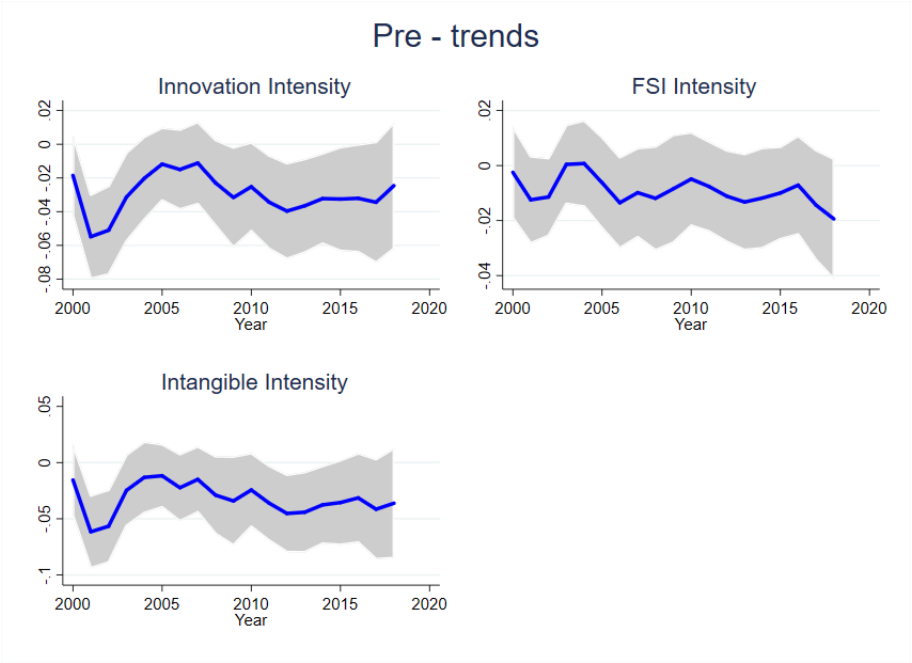



Figure 3.7: GDP Shock: Pre-trends.
Timefixed effects*GDPshock

the interaction of the shock variable and the time dummies to be insignificant. This is not the case, the coefficients remain negative and significant, especially for innovation intensity, but the magnitude varies with the business cycle. Figure 3.7 shows that decline in intensity was pronounced between 2000 and 2003, the coefficient became smaller in 2004 to 2006, is insignificant in 2007 and then negative again in 2008, gradually recovering at the end of the sample. This shows that periods of downturn, *i.e.* the Dot-com recession and the Great Recession, were both associated with declines in intangible intensity in the industries worst hit by the Great Recession.

These results are not surprising, as the burst of the dot-com bubble involved intangible intensive firms. Moreover, the results of year on year regressions presented in the previous section (figures C.6 and C.7) already indicated that the dot-com period mattered for intangible intensity in COMPUSTAT.

**Dot-com bubble shock.** To check the hypothesis that downturns affect intangible intensity, we repeat the exercise, considering the impact of the dot-com shock on the economy, calculating the GDP shock as the difference between 2001 and 2000. We find that the bursting of the dot-com bubble was also associated with a decline in Innovation intensity, and to a

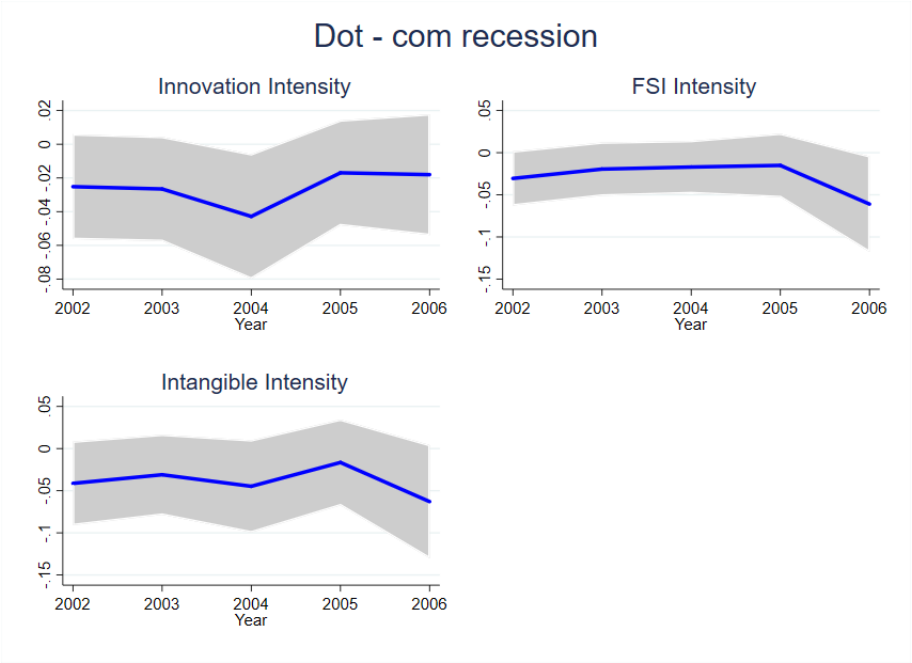



Figure 3.8: Dot-com recession.
Timefixed effects*GDPshock

lesser extent $FSI$ investment (Figure 3.8). The dot-com recession, although milder in terms of its impact on GDP, slowed down the rise of intangible intensity. [17] However, our estimation suggests that the effect is not as long lived compared to the Great Recession. The reason for this difference could lie in the unprecedented L-shaped recovery that followed the Great Recession, both in terms of GDP and investment.

These results suggest that all downturns have the potential to affect the intangible intensity trend, but the size of the shock and the shape of the recovery are also likely to play a role.

**Export Shock (Manufacturing only).** In order to build a measure of the export shock we employ data for exports at the 3 digit NAICS level made available from Schott et al. (2008), which is almost exclusively focused on the manufacturing sector.[18] We aggregate nominal exports to the 3 digit level and then deflate them by 3-digit NAICS deflators from BEA. Our methodology to build the shock measure aims to capture the fall in exports in conjunction with the Great Recession, so we de-trend the data to exclude the impact of some underlying trade dynamics, drawing from Gupta (2019) and Aghion et al. (2020). The

[17] This was likely due to a large decline in equity financing, which is a key source of funding for intangibles. For a detailed discussion see Bianchi et al. (2019).

[18] We also tried aggregating a the 4-digit level, but the number of firms per sector is very small for many of those finer sectors.

benchmark shock is then defined as the change in export growth between 2008 and 2009 relative to the average growth rate of the previous five years. Each growth rate is smoothed by averaging exports over two years.[19]

$$ln(x_t) - ln(x_{t-1}) \equiv g^{trend} + g^{shock}, \qquad \Rightarrow \qquad g^{shock} = ln(x_t) - ln(x_{t-1}) - g^{trend}$$

In Figure 3.9 and 3.10 we compare results for innovation intensity, for the GDP shock and the Export shock. The two shock measures yield broadly comparable results, as Innovation intensity is between 4 and 5 percentage points below trend for a 1% shock to GDP or exports.[20] Differently from results for the whole economy, the negative impact of the recession is not as long-lived, as both figures show a slow recovery, with the effect becoming insignificant towards the end of the sample. The negative impact of the shock is also common across all innovation intensity levels, although the effect on highly innovative firms is not as precisely identified when considering the export shock. Nevertheless, both regressions indicate a large and long-lasting decline in innovation intensity, particularly severe for the highest percentiles, in line with our benchmark results.

In Figures 3.11 and 3.12 we show that results are also similar for the overall decline in intangible intensity, although the recovery is stronger when we consider the export shock. When estimating the impact on $FSI$ intensity, the export shock predicts a muted impact. Lastly, both regressions find a decline in the share of $R\&D$ in $xsga$, comparably with the benchmark.

Overall, these robustness checks confirm the results presented in the previous section.

[19] We also construct shock measures based on a three year average trend, stopping the trend in 2006 instead of 2007, and defining the shock as a relative growth rate as in (Aghion et al., 2020) and results are largely robust.

[20] Full results can be found in Table C.25 in the Appendix.

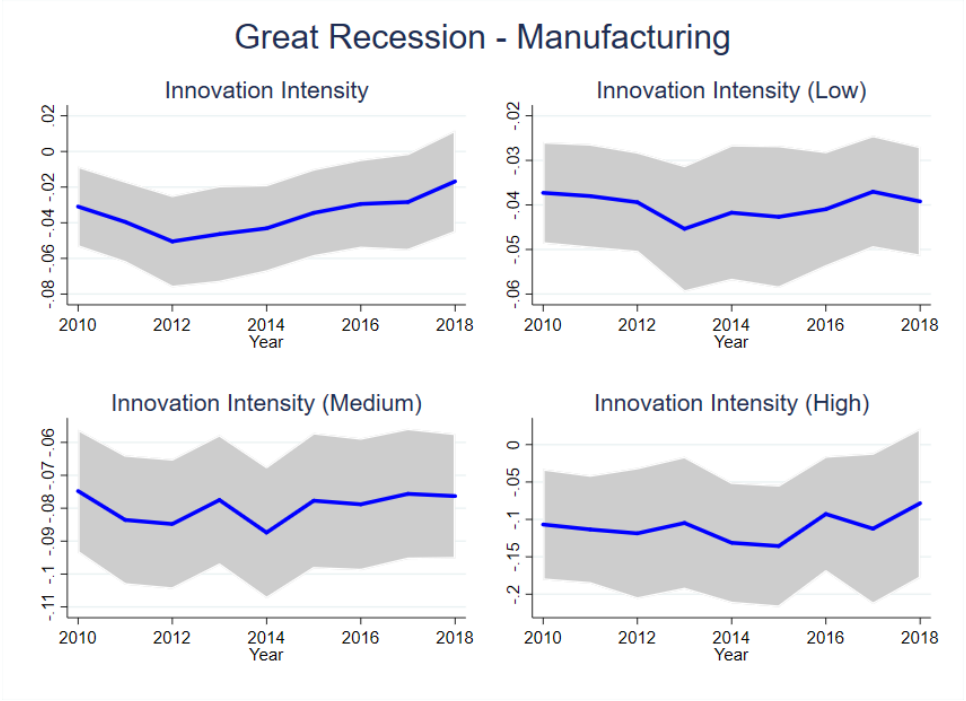



Figure 3.9: GDP Shock in Manufacturing.
Timefixed effects*GDPshock

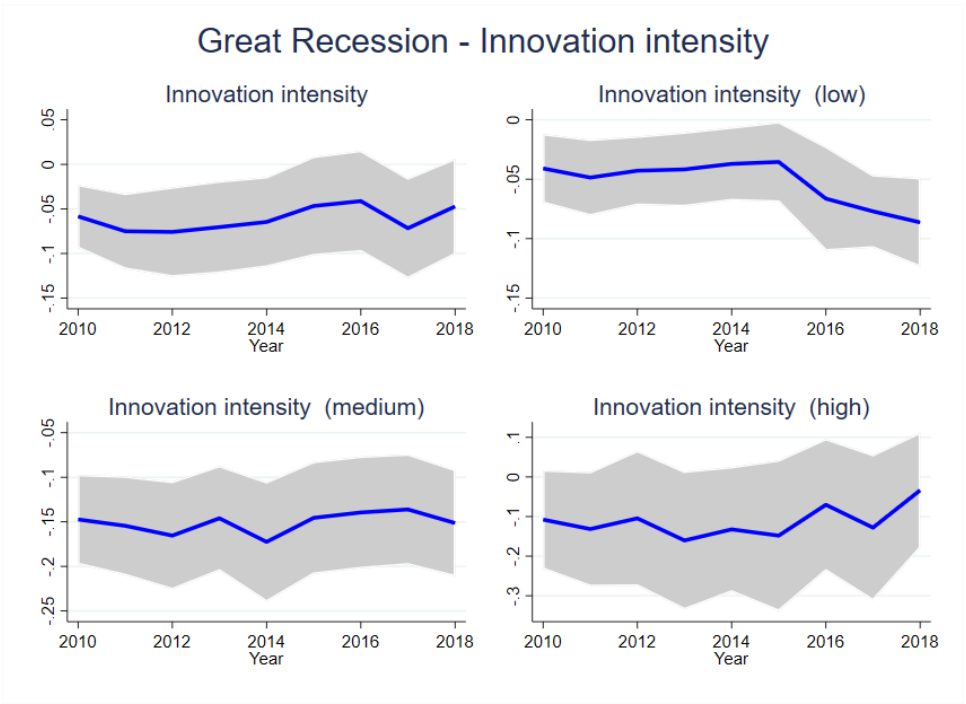



Figure 3.10: Export Shock and Innovation Intensity.
Timefixed effects*Exportshock

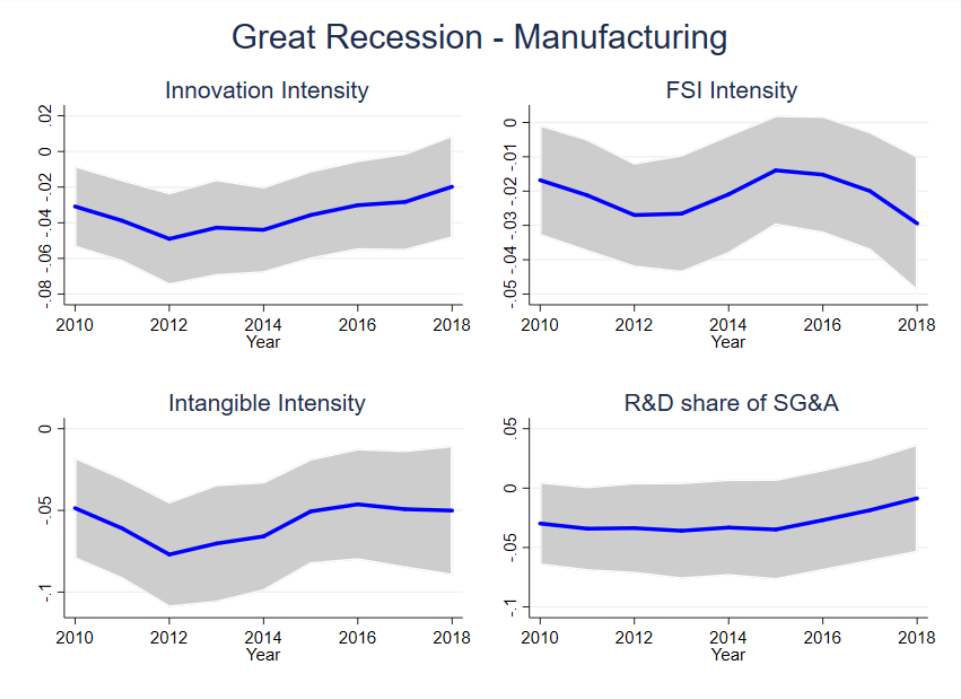



Figure 3.11: Manufacturing results.
Timefixed effects*GDPshock

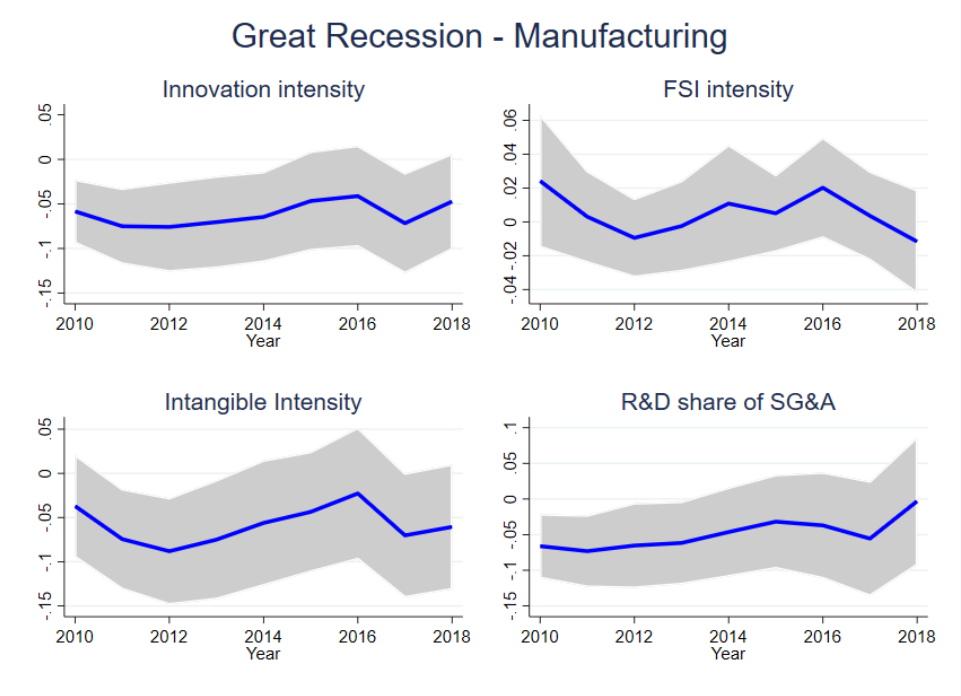



Figure 3.12: Great Recession Results: Export shock.
Timefixed effects*Exportshock

## 3.6 Mechanics

In the previous sections, we found that the Great Recession was associated with a slow down in the rise of intangible intensity across the whole economy. To further investigate the drivers of this result, we ask the following question: did firms that were *ex ante* more intangible intensive grow faster? If this was the case, our findings would sustain the hypothesis that recessions are cleansing, and firms closer to the frontier can outperform laggard firms.

To test this hypothesis, we estimate the following specification for firm $i$ in industry $j$:

$$OutcomeSales_{i,j,t} = \beta_0 + \beta_1 IntanIntensity_{i,j,2007} * Shock_j * I^t + \beta_2 * Shock_j * I^t + \beta_3 * I^t + \\ + \sum_{\kappa}^{N} \gamma_\kappa X^\kappa_{i,j,2007} + \epsilon_{i,j,t} \quad (3.5)$$

$$OutcomeSales_{i,j,t} = 100 * (ln(sales_{i,j,t}) - ln(sales)_{i,j,2007})$$

$$IntanIntensity_{i,j,2007} = \left[\frac{R\&D_{i,j,2007}}{sales_{i,j,2007}}, \frac{FSI_{i,j,2007}}{sales_{i,j,2007}}, \frac{IntanInvest_{i,j,2007}}{sales_{i,j,2007}}\right]$$

$$X^\kappa_{i,j,2007} = [ln(emp)_{i,j,2007}, leverage_{i,j,2007}, equity_{i,j,2007}, ln(\mu)_{i,j,2007}, GDPgrowth_{j,2007}]$$

We measure sales growth in real terms, relatively to 2007. We use the GDP shock measure, as defined in the previous section, *i.e.* $Shock_j = -(ln(GDP_{j,2009}) - ln(GDP_{j,2007})) * 100$, for t=2010-2018 and industry $j$, held constant at the industry level for the whole sample. Tables C.26, C.26 and C.28 in the Appendix show that the GDP shock had a negative impact on sales growth in the aftermath of the recession, but we find no significant difference considering *ex ante* intangible intensity, across all definitions.

Our analysis thus rejects the hypothesis that more intangible intensive firms *ex-ante* gained prominence in the aftermath of the shock, reinforcing the idea that the recession did not accelerate the process of structural transformation towards a more intangible production process.

We then check whether firms that grew faster relatively to pre-Great Recession levels increased their intangible intensity in the aftermath of the recession.

| | (1) $\frac{R\&D}{sales}$ b/se | (2) $\frac{FSI}{sales}$ b/se | (3) $\frac{IntanInvest}{sales}$ b/se |
|---|---|---|---|
| $ln(sales) - ln(sales)_{2007}$ | -0.015*** | -0.019*** | -0.034*** |
| | (0.003) | (0.001) | (0.003) |
| Number of obs. | 9,851 | 9,851 | 9,851 |
| $R^2$ | 0.215 | 0.455 | 0.365 |
| Firm-industry fixed effects | YES | YES | YES |
| S.e. clustered at firm level | YES | YES | YES |

Table 3.6: Sales growth and intangible intensity growth.
Controls include employment, intangible intensity, leverage, equity and mark-up, all measured in 2007.

The specification is:

$$INT_{i,j,t} - INT_{i,j,2007} = \beta_0 + \beta_1 OutcomeSales_{i,j,t} + \sum_{\kappa}^{N} \gamma_\kappa X^{\kappa}_{i,j,2007} + \alpha_{j,t} + \epsilon_{i,j,t} \quad (3.6)$$

$$OutcomeSales_{i,j,t} = 100 * (ln(sales_{i,j,t}) - ln(sales)_{i,j,2007})$$

$$INT_{i,j,t} = \left[ \frac{R\&D_{i,t}}{sales_{i,t}} * 100, \frac{FSI_{i,t}}{sales_{i,t}} * 100, \frac{IntanInvest_{i,t}}{sales_{i,t}} * 100 \right]$$

$$X^{\kappa}_{i,j,2007} = [ln(emp)_{i,j,2007}, leverage_{i,j,2007}, equity_{i,j,2007}, ln(\mu)_{i,j,2007}]$$

Table 3.6 shows that the fastest growing firms chose not to invest proportionally in intangibles, as higher sales growth is associated with lower growth in intangible intensity. This is not surprising, as investment choices are likely lumpy and subject to adjustment costs.

Overall, these results suggest that firms reduced their investment efforts in the aftermath of the recession, and signal that the reallocation of economic activity in favour of *ex-ante* intangible intensive firms was lacking. As a result, the rise of intangible intensity was slowed down by the Great Recession.

## 3.7 Conclusion

This paper contributes to the literature by providing empirical evidence on the positive link between intangible intensity and firm growth, distinguishing between $R\&D$ and firm specific intangibles, as well as considering their combined effect. We find that intangible investment matters for growth even for non innovative firms, suggesting that different categories of

intangibles could be substitutes, as suggested by Roldan and Cavenaile (2020).

However, the main contribution of this paper is to document a slowdown in intangible intensity as a consequence of the Great Recession, across the whole U.S. economy. Our results suggest that this downward deviation from the intangible intensity trend was the result of a sizeable reduction in innovation effort, especially driven by firms who had the highest innovation intensity prior to the financial crisis. Our paper hence does not support the Schumpeterian view suggesting that recessions are cleansing periods accelerating technological progress. Our results are more in line with the recent literature emphasising the negative and permanent effects of recessions on the productive capacity of the economy, driven by a rise in destruction, without a proportional rise in creation (Anzoategui et al., 2019) (Vinci & Licandro, 2020). Nevertheless, a limitation of our empirical strategy is that it does not take into account the role played by entrants in the aftermath of the recession, as we condition the analysis on firms that were in the sample before the Great Recession, in order to disentangle the effects of the shocks from the underlying intangible intensity trend. As Begenau and Palazzo (2020) point out, entrants in COMPUSTAT tend to be more innovation intensive then incumbents, thus our estimated decline in intangible intensity could represent a lower-bound. These considerations motivate further investigation.

We also find that the decline in $R\&D$ spending was partially compensated by a rise in firm specific intangibles intensity, reinforcing the notion that different types of intangibles might be substitutes in bad times as well. Lastly, our analysis indicates that *ex ante* intangible intensive firms did not outperform others and that even the most successful firms reduced their investment effort, on average.

This paper opens several avenues for future research. Firstly, we ought to shed light on the root cause of the slowdown in innovation intensity. Many factors have been highlighted by the literature are likely to influence a firm's decision to invest in innovation, including credit constraints, uncertainty or pessimistic expectations over future demand. It would also be interesting to explore the role of investment off-shoring for multinational firms, as the decline in domestic investment could be the result or reallocation of expenditure in foreign subsidiaries. We were unable to evaluate this hypothesis because COMPUSTAT does not include information on investment off-shoring. Nonetheless, data for innovation investment provided by the BEA suggests that this channel could potentially play a role in explaining the

slowdown in intangible investment in the United States. Figure C.9 shows that the proportion of $R\&D$ conducted domestically by multinational firms across industries remained high in the last 20 years, averaging around 85%, but data also shows a slight downward trend.

Secondly, this paper also offers motivation to dig deeper into the mechanisms through which different categories of intangibles affect the productivity of the firm, its market power and the production process as a whole.

# Chapter 4

# Conclusion and Research Agenda

This thesis was the result of four years of research work and represents the starting point of my future research agenda, to be developed in two main directions.

Firstly, I am keen to continue investigating the mechanics of growth, by looking for further evidence in favour or against a representation of the economy as an endogenous growth model and whether this is the result of structural transformation: has the economy evolved from a neoclassical technology to an AK model? Moreover, I think it is important to evaluate which model of endogenous growth better represents economic dynamics, once incorporated into a DSGE framework. The learning-by-doing framework has the advantage of allowing for the smallest deviation from the standard technology, making it easier to understand the role played by the AK technology and monetary policy, but a more complex model could offer richer dynamics that might be quantitatively relevant.

Secondly, if the economy behaves as an endogenous growth model, how should policy be designed? The first paper shows that in such a context monetary policy has the power to influence the level of economic activity permanently. This result generates important questions for policy making, such as under which conditions is this optimal? What is the role of unconventional monetary policy in this framework? Furthermore, there is room to explore the impact of macroprudential and fiscal policies in this framework. These questions are worth answering, especially in the context of the COVID-19 crisis, to guide the actions of policy-makers in what looks like uncharted territory.

Thirdly, the second paper served as an initial exploration of the relationship between differ-

ent categories of intangibles, that I carried out to build motivation for theoretical work. The idea that I am keen to explore is weather $FSI$ and $R\&D$ play different roles in sustaining firm demand, one affecting market power, the other efficiency. There are noteworthy theoretical contributions advocating this channels separately, such as Sedláček and Sterk (2017), who introduces customer capital as a demand shifter, and the Schumpeterian literature, linking innovation investment and efficiency (see Klette and Kortum (2004) for example). Roldan and Cavenaile (2020) are the first to explicit model both channels, allowing firms to invest in both $R\&D$ and advertising. The latter adopt a long run perspective, whilst I would like to focus on business cycles, by looking at how firms respond to negative shocks when they have the option to invest in innovation as well as $FSI$. How does the distribution of innovation and $FSI$ intensity change over the business cycle and what effect does this have on the recovery process? This aspect is interesting because, as my work on the sluggish recovery that followed the Great Recession pointed out, changes in technology, *i.e.* the aggregate production function, play an important role in shaping the recovery. Moreover, studies explicitly modelling growth through innovation and business cycle dynamics, such as Anzoategui et al. (2019) and Ikeda and Kurozumi (2019), show that economies who growth through $R\&D$ investment are more likely to display slow and incomplete recoveries.

I am planning to dig further into the data, to estimate weather these channels are quantitatively relevant. For example, what is the relationship between intangible investments, TFPR and TFPQ? Can we find empirical support for the hypothesis that $FSI$ impact market power whilst $R\&D$ affects productivity? I was not able to answer these questions in the second paper due to data limitations, but I am actively looking for alternative datasets. Building on the resulting motivation, I would integrate firms' choice of innovation investment in a firm dynamics model with endogenous growth, *ex ante* heterogeneity and endogenous $FSI$ accumulation. The resulting paper could shed light on the optimal choices of intangible intensive firms over the business cycle, and the consequences for aggregate dynamics.

In conclusion, this thesis offers several contributions to the literature and constitutes what I hope will be the starting point of my research journey.

# Appendix A

# Switching-track after the Great Recession: Appendix

## A.1 Equilibrium

### A.1.1 Baseline model

Note: All variables are expressed in real terms, but we do not add hats in order to keep notation simple.

$$\lambda_t = (c_t - \chi c_{t-1})^{-1}\epsilon_t^c - \beta\chi E_t(c_{t+1} - \chi c_t)^{-1}\epsilon_{t+1}^c \tag{A.1}$$

$$r_t^k = \alpha s_t a_t k_t^{\alpha+\eta-1} h_t^{1-\alpha} \tag{A.2}$$

$$w_t = (1-\alpha) s_t a_t (k_t)^{\alpha+\eta} h_t^{-\alpha} \tag{A.3}$$

$$\lambda_t = \beta R_t E_t[\lambda_{t+1}\pi_{t+1}^{-1}] \tag{A.4}$$

$$R_{t+1}^k = \frac{\pi_{t+1}\left(r_{t+1}^k + (1-\hat{\delta}_{t+1})\hat{q}_{t+1}\right)}{\hat{q}_t} \tag{A.5}$$

$$R_{t+1}^F = \frac{\pi_{t+1}\left(r_{t+1}^k + (1-\hat{\kappa}_{t+1})\hat{q}_{t+1}\right)}{\hat{q}_t} \tag{A.6}$$

$$1 - \delta_t = (1-\hat{\kappa}_t)\,\mathrm{F}_{t-1}(\bar{\omega}_t) + (1-\hat{\delta}_t)\big(1 - \mathrm{F}_{t-1}(\bar{\omega}_t)\big). \tag{A.7}$$

$$\hat{\kappa}_t = \kappa\left(\frac{\mathrm{F}_{t-2}(\bar{\omega}_{t-1})}{\mathrm{F}(\bar{\omega})}\right)^{a_{\bar{\omega}}} \tag{A.8}$$

$$\hat{\delta}_t = \delta\left(\frac{\mathrm{F}_{t-2}(\bar{\omega}_{t-1})}{\mathrm{F}(\bar{\omega})}\right)^{a_{\bar{\omega}}} \tag{A.9}$$

$$k_{t+1} = i_t\left(1 - S\left(\frac{i_t}{i_{t-1}}\right)\right) + (1-\delta_t)k_t \tag{A.10}$$

$$log\left(\frac{\sigma_t}{\bar{\sigma}}\right) = \rho_\sigma log\left(\frac{\sigma_{t-1}}{\bar{\sigma}}\right) + \epsilon_{\sigma_t} \tag{A.11}$$

$$log(a_t) = \rho_a log(a_{t-1}) + \epsilon_{a,t} \tag{A.12}$$

$$log(\epsilon_t^c) = \rho_c log(\epsilon_{t-1}^c) + \epsilon_{c,t} \tag{A.13}$$

$$\frac{1-\mathrm{F}_t(\bar{\omega}_{t+1})}{1-\Gamma_t(\bar{\omega}_{t+1})} = \frac{\frac{R_{t+1}^k}{R_t}[1-\mathrm{F}_t(\bar{\omega}_{t+1}) - \mathrm{G}_t'(\bar{\omega}_{t+1})\big(1-\frac{R_{t+1}^F}{R_{t+1}^k}(1-\mu)-\xi\big)]}{1-\frac{R_{t+1}^k}{R_t}\Big(\bar{\omega}_{t+1}(1-\mathrm{F}_t(\bar{\omega}_{t+1})) + (1-\mu)H_t(\bar{\omega}_{t+1}) + \xi G_t(\bar{\omega}_{t+1})\Big)}. \tag{A.14}$$

$$\bar{N}_{t+1} = \gamma[1-\Gamma_{t-1}(\bar{\omega}_t)]R_t^k\frac{\hat{q}_{t-1}}{\pi_t}k_t + w^e k_t \tag{A.15}$$

$$\hat{q}_t k_{t+1} = \frac{1}{1-\frac{R_{t+1}^k}{R_t}\Big(\bar{\omega}_{t+1}(1-\mathrm{F}_t(\bar{\omega}_{t+1})) + (1-\mu)\mathrm{H}_t(\bar{\omega}_{t+1}) + \xi G_t(\bar{\omega}_{t+1})\Big)}\bar{N}_{t+1} \tag{A.16}$$

$$(1-\theta) + \theta s_t - \pi_t\phi_p(\pi_t - 1) + \beta E_t\left[\frac{\lambda_{t+1}}{\lambda_t}\pi_{t+1}\phi_p(\pi_{t+1}-1)\frac{Y_{t+1}}{Y_t}\right] = 0 \tag{A.17}$$

$$w_t = \frac{\varepsilon}{\varepsilon-1}\frac{\psi h_t^\nu \epsilon_t^c}{\lambda_t} + E_t\left[\beta\frac{\lambda_{t+1}}{\lambda_t}\Omega_{t+1}Y_{t+1}\frac{1}{h_t}\right] - \Omega_t\pi_t\frac{Y_t}{h_t} \tag{A.18}$$

$$\Omega_t = \frac{\chi^w}{\epsilon_w - 1}(\pi_t^w - 1)\pi_t^w \tag{A.19}$$

$$\frac{w_t}{w_{t-1}} = \frac{\pi_t^w}{\pi_t} \tag{A.20}$$

$$S\left(\frac{i_t}{i_{t-1}}\right) = \left[exp\left(\left(\sqrt{\frac{S''}{2}}\right)\left(\frac{i_t}{i_{t-1}}-1\right)\right) + exp\left(\left(-\sqrt{\frac{S''}{2}}\right)\left(\frac{i_t}{i_{t-1}}-1\right)\right) - 2\right] \tag{A.21}$$

$$1 = \hat{q}_t\left(-S'\left(\frac{i_t}{i_{t-1}}\right)\left(\frac{i_t}{i_{t-1}}\right) + 1 - S\left(\frac{i_t}{i_{t-1}}\right)\right) + \beta E_t\frac{\lambda_{t+1}}{\lambda_t}\hat{q}_{t+1}S'\left(\frac{i_{t+1}}{i_t}\right)\left(\frac{i_{t+1}}{i_t}\right)^2 \tag{A.22}$$

$$S'\left(\frac{i_t}{i_{t-1}}\right) = \sqrt{\frac{S''}{2}}\left[exp\left(\left(\sqrt{\frac{S''}{2}}\right)\left(\frac{i_t}{i_{t-1}}-1\right)\right) - exp\left(\left(-\sqrt{\frac{S''}{2}}\right)\left(\frac{i_t}{i_{t-1}}-1\right)\right)\right] \tag{A.23}$$

$$S'\left(\frac{i_{t+1}}{i_t}\right) = \sqrt{\frac{S''}{2}}\left[exp\left(\left(\sqrt{\frac{S''}{2}}\right)\left(\frac{i_{t+1}}{i_t}-1\right)\right) - exp\left(\left(-\sqrt{\frac{S''}{2}}\right)\left(\frac{i_{t+1}}{i_t}-1\right)\right)\right] \tag{A.24}$$

$$Y_t = a_t k_t^{\alpha+\eta}(h_t)^{1-\alpha} \tag{A.25}$$

$$Y_t = c_t + i_t + \mu\int_0^{\bar{\omega}_t}\omega d\mathrm{F}(\omega)R_t^F\frac{\hat{q}_{t-1}}{\pi_t}k_t + \frac{\phi_p}{2}(\pi_t-1)^2 Y_t + \frac{\chi^w}{2}(\pi_t^w-1)^2 Y_t \tag{A.26}$$

$$GDP_t = c_t + i_t \tag{A.27}$$

$$R_t^m = \bar{R}^m + \rho_\pi(\pi_t - \bar{\pi}^m) + \rho_y log\left(\frac{G\hat{D}P_t}{y_t^p}\right) \tag{A.28}$$

$$R_t = max(1, R_t^m) \tag{A.29}$$

$$y_t^p = y_{t-1}^p + \rho(\frac{1}{n}\sum_{j=1}^{n}G\hat{D}P_{t-4-j} - y_{t-1}^p) \tag{A.30}$$

### A.1.2 The stationarized AK case

$$\tilde{\lambda}_t = (\tilde{c}_t - \frac{\chi}{1+g_z}\tilde{c}_{t-1})^{-1}\epsilon_t^c - \beta\chi E_t(\tilde{c}_{t+1}(1+g_z) - \chi\tilde{c}_t)^{-1}\epsilon_{t+1}^c \tag{A.31}$$

$$r_t^k = \alpha s_t a_t h_t^{1-\alpha} \tag{A.32}$$

$$\tilde{w}_t = (1-\alpha)s_t a_t \tilde{k}_t h_t^{-\alpha} \tag{A.33}$$

$$\tilde{\lambda_t} = \frac{\beta}{(1+g_z)} R_t E_t[\tilde{\lambda}_{t+1}\pi_{t+1}^{-1}] \tag{A.34}$$

$$log\left(\frac{\sigma_t}{\bar{\sigma}}\right) = \rho_\sigma log\left(\frac{\sigma_{t-1}}{\bar{\sigma}}\right) + \epsilon_\sigma \tag{A.35}$$

$$log(\epsilon_t^c) = \rho_c log(\epsilon_{t-1}^c) + \epsilon_{c,t} \tag{A.36}$$

$$\tilde{y}_t = a_t \tilde{k}_t h_t^{1-\alpha} \tag{A.37}$$

$$log(a_t) = \rho_a log(a_{t-1}) + \epsilon_{a,t} \tag{A.38}$$

$$R_{t+1}^k = \frac{\pi_{t+1}\left(r_{t+1}^k + (1-\hat{\delta}_{t+1})\hat{q}_{t+1}\right)}{\hat{q}_t} \tag{A.39}$$

$$R_{t+1}^F = \frac{\pi_{t+1}\left(r_{t+1}^k + (1-\hat{\kappa}_{t+1})\hat{q}_{t+1}\right)}{\hat{q}_t} \tag{A.40}$$

$$1-\delta_t = (1-\hat{\kappa}_t)\,\mathrm{F}_{t-1}(\bar{\omega}_t) + (1-\hat{\delta}_t)\big(1-\mathrm{F}_{t-1}(\bar{\omega}_t)\big). \tag{A.41}$$

$$\hat{\kappa}_t = \kappa\left(\frac{\mathrm{F}_{t-2}(\bar{\omega}_{t-1})}{\mathrm{F}(\bar{\omega})}\right)^{a_{\bar{\omega}}} \tag{A.42}$$

$$\hat{\delta}_t = \delta\left(\frac{\mathrm{F}_{t-2}(\bar{\omega}_{t-1})}{\mathrm{F}(\bar{\omega})}\right)^{a_{\bar{\omega}}} \tag{A.43}$$

$$\frac{1-\mathrm{F}_t(\bar{\omega}_{t+1})}{1-\Gamma_t(\bar{\omega}_{t+1})} = \frac{\frac{R_{t+1}^k}{R_t}[1-\mathrm{F}_t(\bar{\omega}_{t+1}) - \mathrm{G}_t'(\bar{\omega}_{t+1})\big(1-\frac{R_{t+1}^F}{R_{t+1}^k}(1-\mu)-\xi\big)]}{1-\frac{R_{t+1}^k}{R_t}\Big(\bar{\omega}_{t+1}(1-\mathrm{F}_t(\bar{\omega}_{t+1})) + (1-\mu)H_t(\bar{\omega}_{t+1}) + \xi G_t(\bar{\omega}_{t+1})\Big)}. \tag{A.44}$$

$$\tilde{\bar{N}}_{t+1} = (\gamma[1-\Gamma_{t-1}(\bar{\omega}_t)]R_t^k\frac{\hat{q}_{t-1}}{\pi_t}\tilde{k}_t + \tilde{w}^e\tilde{k}_t)\frac{1}{1+g_z} \tag{A.45}$$

$$\hat{q}_t\tilde{k}_{t+1} = \frac{1}{1-\frac{R_{t+1}^k}{R_t}\Big(\bar{\omega}_{t+1}(1-\mathrm{F}_t(\bar{\omega}_{t+1})) + (1-\mu)\mathrm{H}_t(\bar{\omega}_{t+1}) + \xi G_t(\bar{\omega}_{t+1})\Big)}\tilde{\bar{N}}_{t+1} \tag{A.46}$$

$$\tilde{y}_t = \tilde{c}_t + \tilde{i}_t + \frac{\phi_p}{2}(\pi_t-1)^2\tilde{y}_t + \frac{\chi^w}{2}(\pi_t^w-1)^2\tilde{y}_t + \mu\int_0^{\bar{\omega}_t}\omega d\mathrm{F}(\omega)R_t^F\frac{\hat{q}_{t-1}}{\pi_t}\tilde{k}_t \tag{A.47}$$

$$G\tilde{D}P_t = \tilde{c}_t + \tilde{i}_t \tag{A.48}$$

$$\tilde{S}\left(\frac{\tilde{i}_t}{\tilde{i}_{t-1}}\right) = \\ = \left[exp\left(\left(\sqrt{\frac{S''}{2}}\right)\left(\frac{\tilde{i}_t}{\tilde{i}_{t-1}}(1+g_z) - g_z - 1\right)\right) + exp\left(\left(-\sqrt{\frac{S''}{2}}\right)\left(\frac{\tilde{i}_t}{\tilde{i}_{t-1}}(1+g_z) - g_z - 1\right)\right) - 2\right] \tag{A.49}$$

$$\tilde{k}_{t+1} = \left( i_t \left( 1 - S\left( \frac{\tilde{i}_t}{\tilde{i}_{t-1}} \right) \right) + (1-\delta_t)\tilde{k}_t \right) \frac{1}{1+g_z} \tag{A.50}$$

$$1 = \hat{q}_t \left( -S'\left( \frac{\tilde{i}_t(1+g_z)}{\tilde{i}_{t-1}} \right) \left( \frac{\tilde{i}_t(1+g_z)}{\tilde{i}_{t-1}} \right) + 1 - S\left( \frac{\tilde{i}_t(1+g_z)}{\tilde{i}_{t-1}} \right) \right) + \\ + \frac{\beta}{1+g_z} E_t \frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t} \hat{q}_{t+1} S'\left( \frac{\tilde{i}_{t+1}(1+g_z)}{\tilde{i}_t} \right) \left( \frac{\tilde{i}_{t+1}(1+g_z)}{\tilde{i}_t} \right)^2 \tag{A.51}$$

$$S'\left( \frac{\tilde{i}_t(1+g_z)}{\tilde{i}_{t-1}} \right) = \\ = \sqrt{\frac{S''}{2}} \left[ exp\left( \left( \sqrt{\frac{S''}{2}} \right) \left( \frac{\tilde{i}_t}{\tilde{i}_{t-1}}(1+g_z) - g_z - 1 \right) \right) - exp\left( \left( -\sqrt{\frac{S''}{2}} \right) \left( \frac{\tilde{i}_t}{\tilde{i}_{t-1}}(1+g_z) - g_z - 1 \right) \right) \right] \tag{A.52}$$

$$S'\left( \frac{\tilde{i}_{t+1}(1+g_z)}{\tilde{i}_t} \right) = \\ = \sqrt{\frac{S''}{2}} \left[ exp\left( \left( \sqrt{\frac{S''}{2}} \right) \left( \frac{\tilde{i}_{t+1}}{\tilde{i}_t}(1+g_z) - g_z - 1 \right) \right) - exp\left( \left( -\sqrt{\frac{S''}{2}} \right) \left( \frac{\tilde{i}_{t+1}}{\tilde{i}_t}(1+g_z) - g_z - 1 \right) \right) \right] \tag{A.53}$$

$$(1-\theta) + \theta s_t - \pi_t \phi_p(\pi_t - 1) + \beta E_t \left[ \frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t} \pi_{t+1} \phi_p(\pi_{t+1} - 1) \frac{\tilde{y}_{t+1}}{\tilde{y}_t} \right] = 0 \tag{A.54}$$

$$\tilde{w}_t = \frac{\varepsilon}{\varepsilon - 1} \frac{\psi h_t^{\nu} \epsilon_t^c}{\tilde{\lambda}_t} + E_t \left[ \beta \frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t} \Omega_{t+1} \tilde{Y}_{t+1} \frac{1}{h_t} \right] - \Omega_t \pi_t \frac{\tilde{Y}_t}{h_t} \tag{A.55}$$

$$\Omega_t = \frac{\chi^w}{\epsilon_w - 1} (\pi_t^w - 1) \pi_t^w \tag{A.56}$$

$$\frac{\tilde{w}_t}{\tilde{w}_{t-1}} = \frac{\pi_t^w}{\pi_t} \tag{A.57}$$

$$R_t^m = \bar{R}^m + \rho_\pi (\pi_t - \bar{\pi}^m) + \rho_y log\left( \frac{G\hat{D}P_t}{{y_t}^p} \right) \tag{A.58}$$

$$R_t = max(1, R_t^m) \tag{A.59}$$

$$\tilde{y}_t^p = \tilde{y}_{t-1}^p + \rho\left( \frac{1}{n} \sum_{j=1}^{n} G\hat{D}P_{t-4-j} - y_{t-1}^p \right) \tag{A.60}$$

### A.1.3 Steady state

The routine used to compute the steady state is a modified version of the one proposed by Christiano et al. (2014), to accommodate the differences in technology as well as the variations in financial frictions. Here we describe the main differences and refer to the original paper

for more details. For a given level of capital $k_{ss} > 0$ and the parameters listed in previous sections, we start from:

$$R^k_{ss} = \alpha s_{ss} h^{1-\alpha}_{ss} + 1 - \delta$$

$$R^f_{ss} = \alpha s_{ss} h^{1-\alpha}_{ss} + 1 - \kappa$$

We then build a guess for $R_{ss} = R^k_{ss} - \epsilon$, $\epsilon > 0$ and input into:

$$\frac{1 - \mathrm{F}_s(\bar{\omega}_{ss})}{1 - \Gamma_{ss}(\bar{\omega}_{ss})} = \frac{\frac{R^k_{ss}}{R_{ss}}[1 - \mathrm{F}_{ss}(\bar{\omega}_{ss}) - \mathrm{G}'_{ss}(\bar{\omega}_{ss})\big(1 - \frac{R^F_{ss}}{R^k_{ss}}(1-\mu) - \xi\big)]}{1 - \frac{R^k_{ss}}{R_{ss}}\Big(\bar{\omega}_{ss}(1 - \mathrm{F}_{ss}(\bar{\omega}_{ss})) + (1-\mu)H_{ss}(\bar{\omega}_{ss}) + \xi G_{ss}(\bar{\omega}_{ss})\Big)}.$$

and

$$N_{ss} = (\gamma[1 - \Gamma_{ss}(\bar{\omega}_{ss})]R^k_{ss} k_{ss} + w^e_{ss})\frac{1}{1+g_z}$$

and iterate until

$$k_{ss} = \frac{1}{1 - \frac{R^k_{ss}}{R_{ss}}\Big(\bar{\omega}_{ss}(1 - \mathrm{F}_{ss}(\bar{\omega}_{ss})) + (1-\mu)\mathrm{H}_t(\bar{\omega}_{ss}) + \xi G_{ss}(\bar{\omega}_{ss})\Big)} N_{ss}$$

Where $s_{ss} = \frac{\theta-1}{\theta}$, $\alpha = 1 - \frac{w_{ss}h_{ss}}{s_{ss}}$ , $(1+g_z) = \beta R_{ss}$, $\xi = (1-\mu)(1 - \frac{R_f}{R_k})$.

## A.2 Model-data comparison and data sources

**Taylor rule**: GDP is Real Gross Domestic Product, Billions of Chained 2012 Dollars, Seasonally Adjusted Annual Rate, inflation is Gross Domestic Product: Implicit Price Deflator, Index 2012=100, Seasonally Adjusted (percentage change from a year ago), FFR is the Effective Federal Funds Rate, Percent, Not Seasonally Adjusted. Potential output historical estimates were retrieved from the Congressional Budget Office website.

**Data for model simulation comparison**: all data was retrieved from the FRED database. GDP is Real Gross Domestic Product, consumption is Real Personal Consumption Expenditures, investment is Real Gross Private Domestic Investment and private non-residential investment is Private Nonresidential Fixed Investment, divided by its deflator (retrieved from BEA). All variables are expressed in billions of chained 2012 dollars, quarterly, seasonally adjusted annual rates and in per capita terms. The bankruptcy probability is the estimated risk shock in Christiano et al. (2014). Credit is Total Credit to the Non-Financial Corporations, adjusted for breaks, in billions of U.S. Dollars, divided by the GDP deflator. The nominal interest rate is the Effective Federal Funds Rate (quarterly averages).

**Data for model steady state comparison**: All values are averages over the period 1980-2008Q2 or 2008 when data was available annually. The labour share is the average of the share of labour Compensation in GDP, and labour hours are the average of

the time series average annual hours worked by persons engaged for United States, calculated as a percentage of total hours in the year. GDP growth per capita was retrieved from FRED (BEA data) and the investment to GDP ratio is calculated in real terms from BEA data. The real interest rate data was retrieved from the World Bank database. The interest spread is the corporate bond credit spread constructed by Gilchrist and Zakrajšek (2012), who calculate the difference between each loan obtained by firms in COMPUSTAT with the rate the U.S. government would have paid for a comparable maturity. The credit to capital ratio $\frac{B}{K}$ is proxied by the average of real debt over real assets for the Non-financial private sector in COMPUSTAT, where total assets were deflated using the BEA investment deflator, whilst total debt was deflated using the GDP deflator.

| Moment | Model | U.S. Data |
|---|---|---|
| Labour share (1980-2008) | 60.8% | 61% |
| Labour hours (1980-2008) | 20% | 20.5% |
| Quarterly GDP growth pc (1980-2008Q2) | 0.6% | 0.5% |
| $\frac{I}{GDP}$ (1980-2008) | 12% | 15% |
| Real interest rate (1980-2008) | 1.6% | 1.37% |
| Interest Spread $400(\frac{Z}{R}-1)$ (1980-2008Q2) | 1.19% | 1.56% |
| $\frac{B}{K}$ (1980-2008) | 0.5 | 0.5 |

Table A.1: Aggregate data and model steady state values.

## A.3 Taylor rule mechanics

With a positive weight in the output gap, the Taylor rule implies that a negative output gap will put pressure on the nominal interest rate to fall. However, in our simulations we find that a positive weight on the output gap generates a higher nominal interest rate in equilibrium, compared to pure inflation targeting (see Figures 2.9 and 2.10). This appears to be a puzzle. In order to understand how a positive weight on the output gap can generate an increase in both the nominal interest rate and inflation, we propose a simple exercise of comparative statics. In our model, as in the standard New Keynesian model, the nominal interest rate and inflation are determined by the intersection of the Euler equation and the Taylor rule. These can be represented as linear relationships between inflation and the nominal interest rate, so that their intersection represents the steady state, *i.e.* the point in which $\pi_t = \bar{\pi} = 1$ and the nominal interest rate is $R_t = \bar{R} = \frac{1+gz}{\beta}$: Ignoring the ZLB constraint, the two equations can

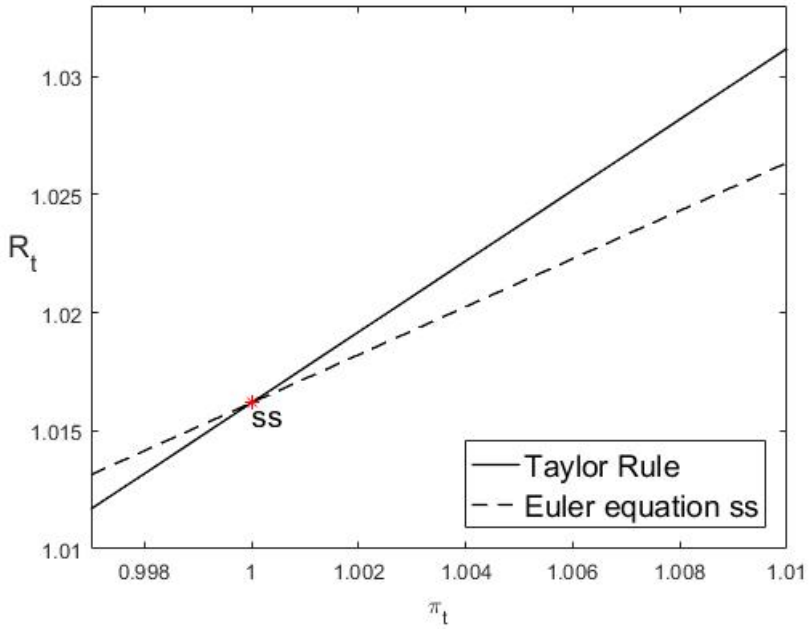



Figure A.1: Euler equation and Taylor Rule in Steady State.

be can be written as:

$$\text{Taylor Rule} : R_t = \frac{1+gz}{\beta} + 1.5(\pi_t - \bar{\pi}) + 0.125log\left(\frac{G\hat{D}P_t}{G\bar{\hat{D}P}}\right) \tag{A.61}$$

$$\text{Euler equation } : R_t = \frac{1+gz}{\beta}\frac{\hat{\lambda}_t}{\hat{\lambda}_{t+1}}\frac{\pi_{t+1}}{\pi_t}\pi_t \tag{A.62}$$

Figure A.1 plots them for a grid of $\pi_t$ and $R_t$ close to the steady state. We then ask: how would the equilibrium change if we considered the response of the economy to a TFP shock? We use values of $\frac{\hat{\lambda}_t}{\hat{\lambda}_{t+1}}$ and $\frac{\pi_{t+1}}{\pi_t}$ from our baseline TFP shock at time 1, 2, 5 and 10, with no weight on the output gap. Figure A.2 shows that the Euler equation rotates upwards as the shock hits, and then gradually comes back to the initial value. The transition is consistent with the IRFs in figure 2.9, as the TFP shock results in a temporary increase in the nominal interest rate and inflation.

Then we repeat the exercise for the scenario in which the weight on the output gap is positive, considering data for $\frac{\hat{\lambda}_t}{\hat{\lambda}_{t+1}}, \frac{\pi_{t+1}}{\pi_t}$ and $\frac{G\hat{D}P_t}{G\bar{\hat{D}P}}$ from our simulation. Figure A.3 shows that in this case the Taylor rule shifts to the right as the output gap pushes the intercept down, so that $R_t$ and $\pi_t$ are higher in equilibrium at time 1, compared to the pure inflation targeting case, consistently with our results in Figure 2.9. This simple exercise shows that a positive weight on the output makes the the monetary authority offer a lower nominal interest rate for each level of inflation, stimulating substitution from savings to consumption through the Euler equation. The equilibrium will be the result of the interaction of the Taylor rule and the Euler equation, in turn effected by aggregate shocks.

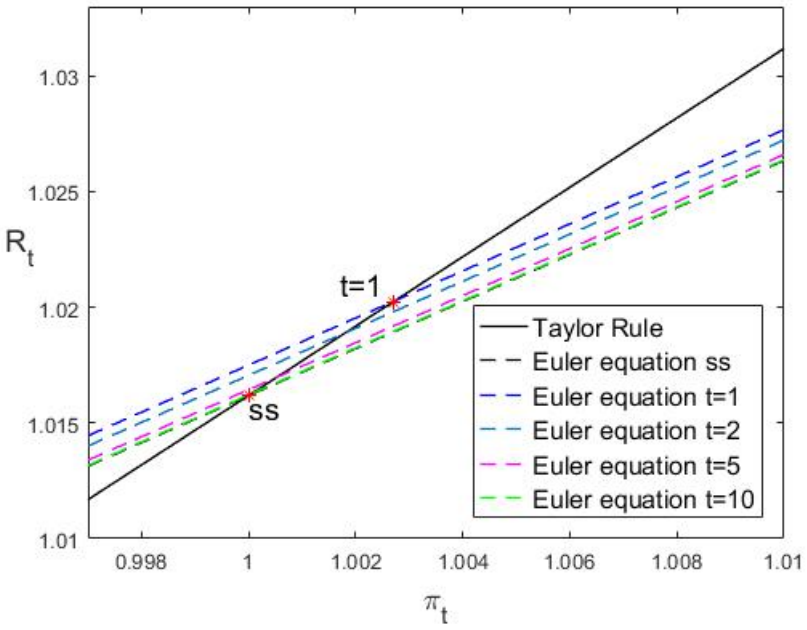



Figure A.2: TFP shock mechanics with no weight on the output gap.

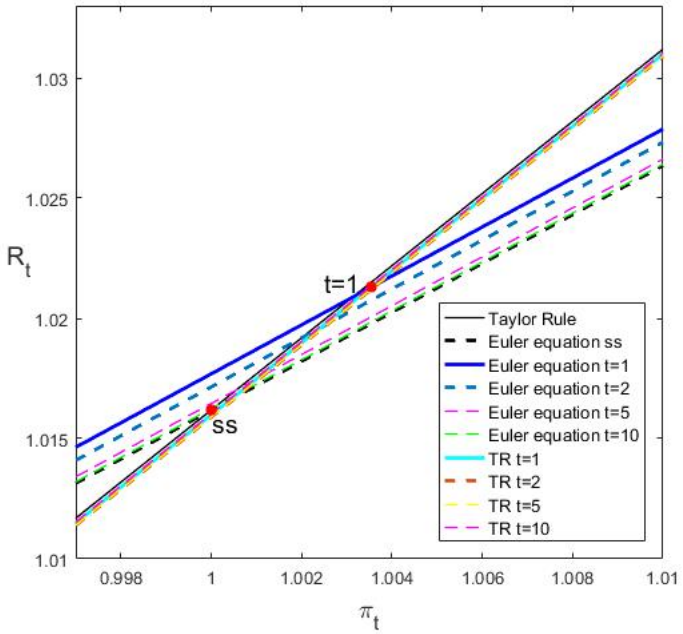



Figure A.3: TFP shock mechanics with positive weight on the output gap.

## A.4 Capital quality

In this section we compare the depreciation rate in our model for the Great Recession to a measure of capital quality constructed by Kozlowski et al. (2020). They employ the FED's Flow of Funds data for non-financial assets held by corporations, at market value (MV) and historical cost (HC). We replicate their methodology with quarterly series, assuming the depreciation rate to be at our steady state value. They define a capital quality shock as a decline in the productive value of installed capital, which is equivalent to a rise in depreciation in our model. Assuming: $k_t = \phi_t \hat{k}_t$, the capital used in production $k_t$ depends on the installed capital $\hat{k}_t$ and the shock $\phi_t$, equal to 1 in normal times.

Let us denote by $k_t$ the stock of capital at the end of period $t$, and by $x_t$ and $p_t$ real investment and the price of capital at time $t$, respectively. Past capital (net of depreciation) and current investment cumulate in $\hat{k}_t$ that suffers a quality shock $\phi_t$ before becoming the end of period capital $k_t$, *i.e.*:

$$\hat{k}_t = x_t + (1-\delta)k_{t-1} \qquad \text{and} \qquad k_t = \phi_t \hat{k}_t. \tag{A.63}$$

Kozlowski et al. (2020) assume that historical capital is measured following

$$\text{HC}_t = p_{t-1}x_t + (1-\delta)\text{HC}_{t-1} \tag{A.64}$$

Then, assuming $p_t k_t = \text{MV}_t$, from (A.63) and (A.64) we can recover

$$p_{t-1}\hat{k}_t = (1-\delta)p_{t-1}k_{t-1} + p_{t-1}x_t = (1-\delta)\text{MV}_{t-1} + \text{HC}_t - (1-\delta)\text{HC}_{t-1}. \tag{A.65}$$

then using the non-residential investment deflator from BEA:

$$\phi_t = \frac{k_t}{\hat{k}_t} = \frac{p_t k_t}{p_{t-1}\hat{k}_t}\frac{PriceIndex_{t-1}}{PriceIndex_t} \tag{A.66}$$

The resulting measure has an average value of 1.01 in the interval we consider, and displays a large negative realization in conjunction with the Great Recession. This mostly captures variations in the market value of structures, as the methodology behind the data adjusts the market value of commercial real estate. In this sense, this series complements Lanteri (2018)'s data, which was informative as to the value of equipment.

Mapping into our model, $\phi_t = \frac{1-\delta_t}{1-\delta}$. We normalise the data to average 1 to ease comparison, and figure A.4 shows that our model is consistent with the dynamics of the data. The magnitude of the model's fall in capital value is considerably smaller compared to the constructed measure, confirming our conservative approach.

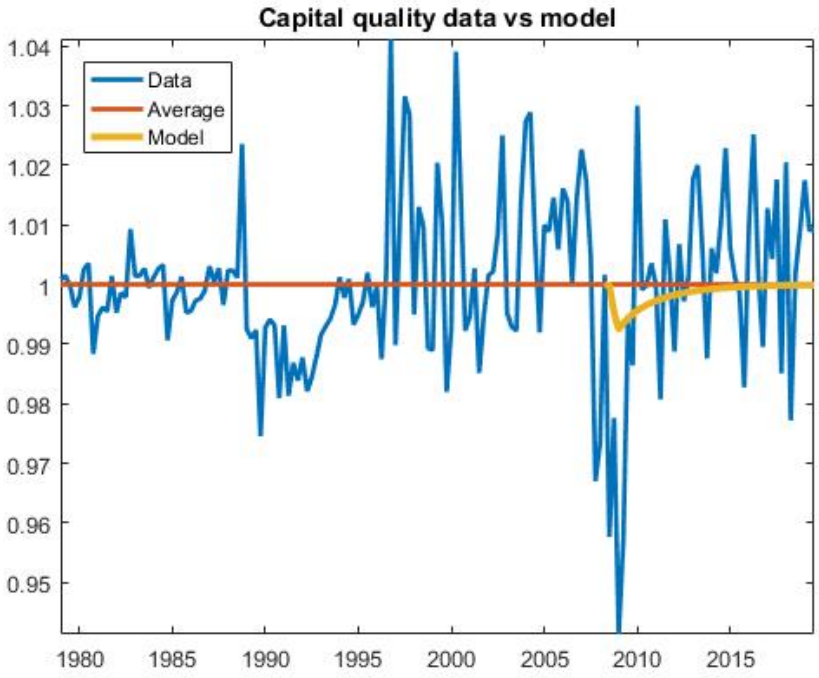



Figure A.4: Capital quality measure from Kozlowski et al. (2020) $\phi_t$ in the data and in our model.

## A.5 Figures

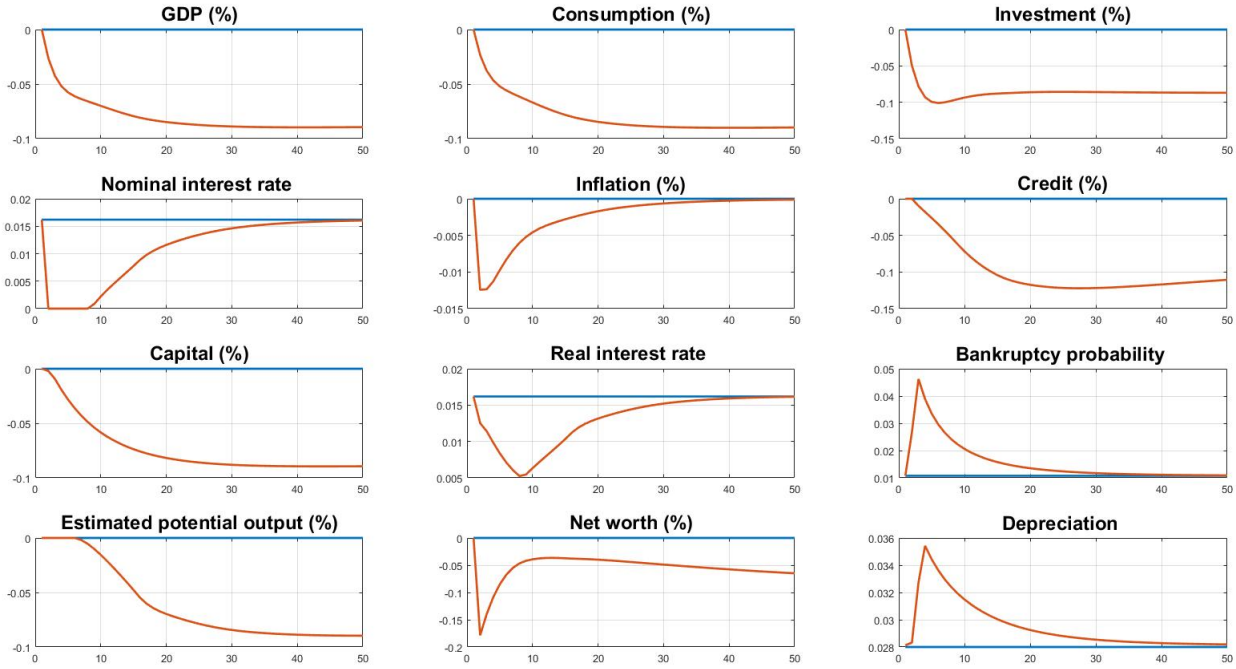



Figure A.5: The Great Recession (baseline): quarterly model simulations.

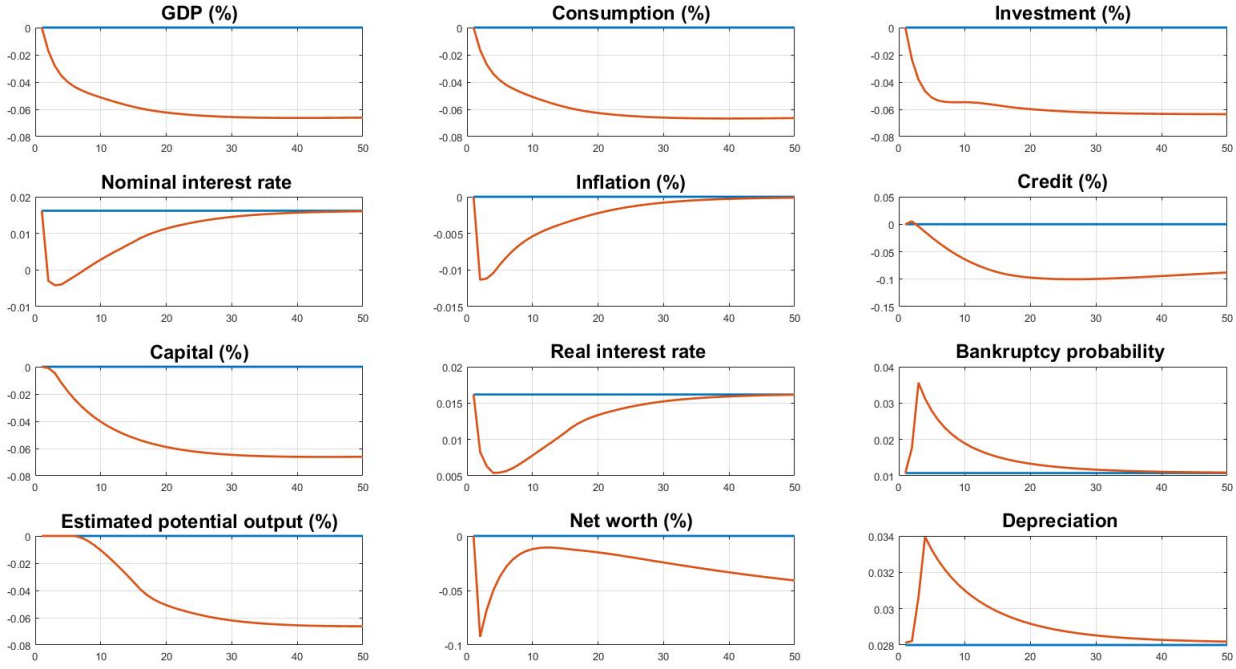



Figure A.6: The Great Recession: quarterly model simulations, without the ZLB constraint.

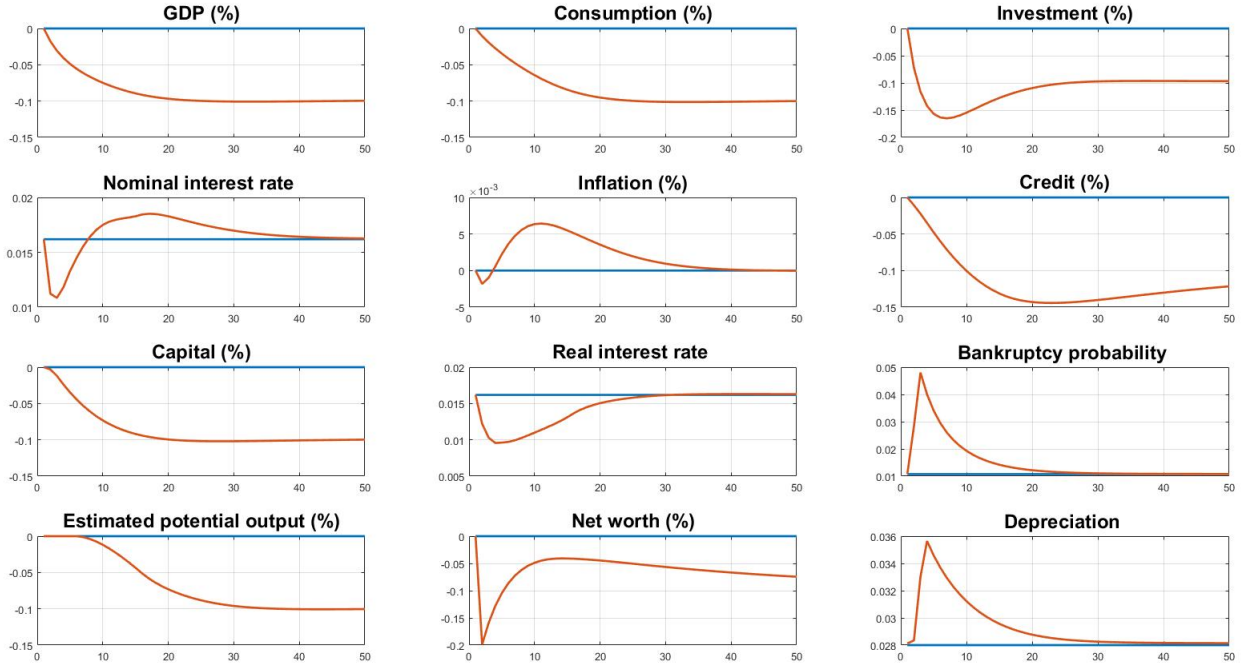



Figure A.7: The risk shock: quarterly model simulations.

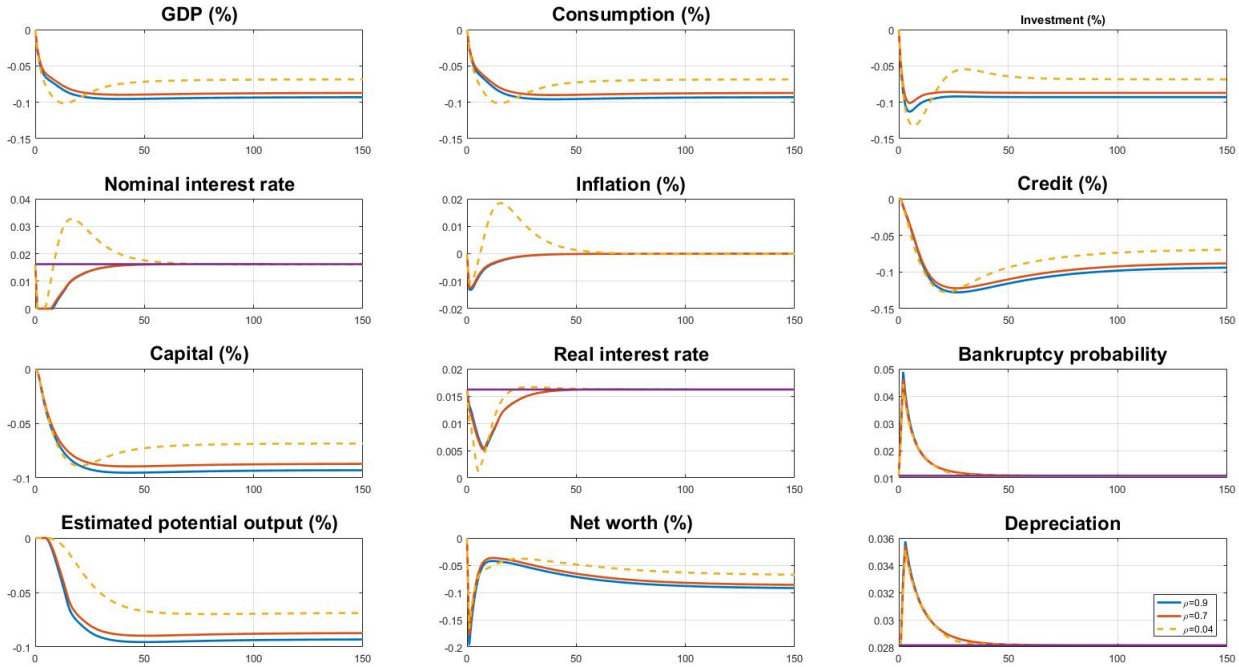



Figure A.8: The Great Recession for different values of potential output revision intensity.

Note that GDP, consumption and investment fall more as the shock hits when the revision of potential output is slower than baseline, *i.e.* the policy intervention is stronger. This is a consequence of the ZLB binding, as stronger demand stimulus generates higher inflation compared to the baseline, resulting in a sharp fall in the real interest rate with a binding ZLB. The latter provides stimulus to the marginal utility of consumption, but results in a sharper contraction in the labour supply, negatively affecting the level of economic activity. As soon as the nominal interest rate leaves the ZLB, the real interest rate re-bounces and monetary policy generates a partial recovery.

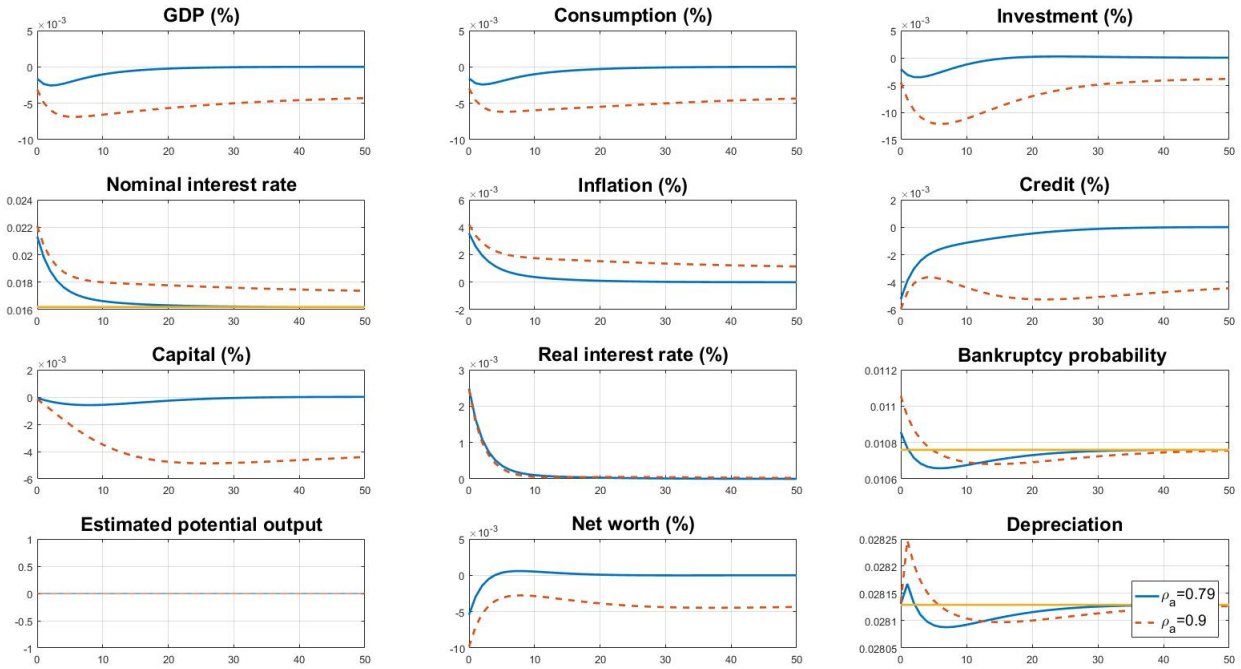



Figure A.9: TFP shock for different values of persistence, baseline calibration.

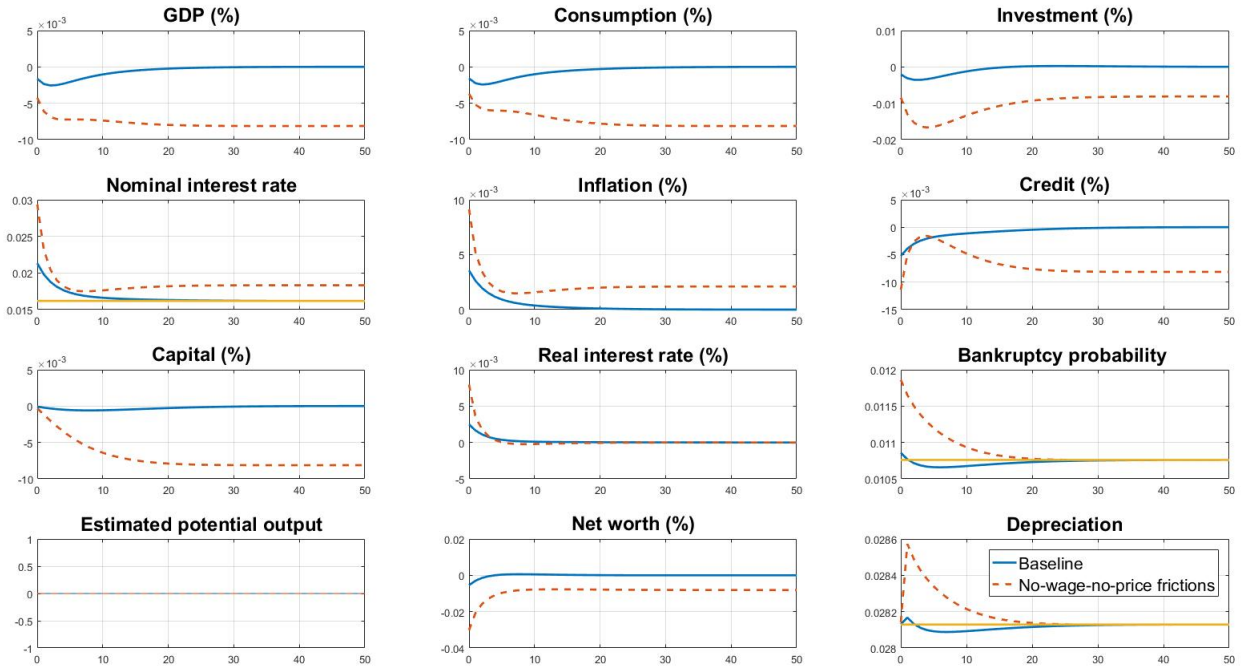



Figure A.10: TFP shock: Baseline vs No-wage-no-price frictions.

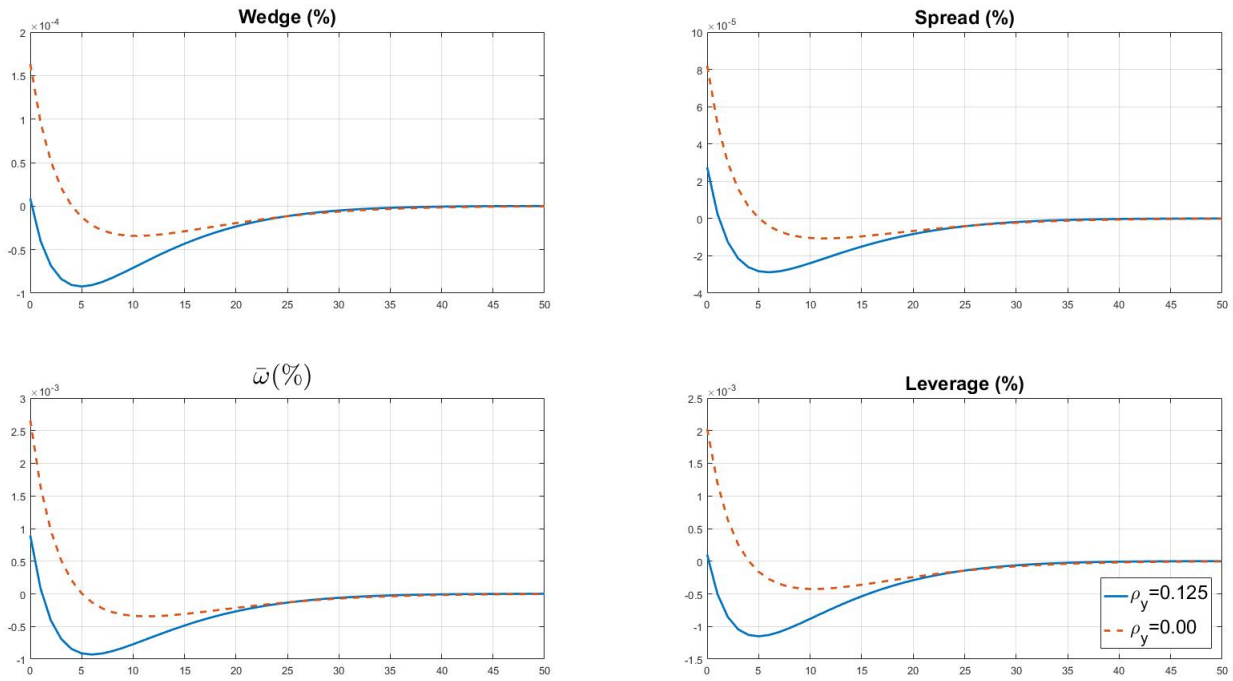



Figure A.11: TFP shock: additional variables.

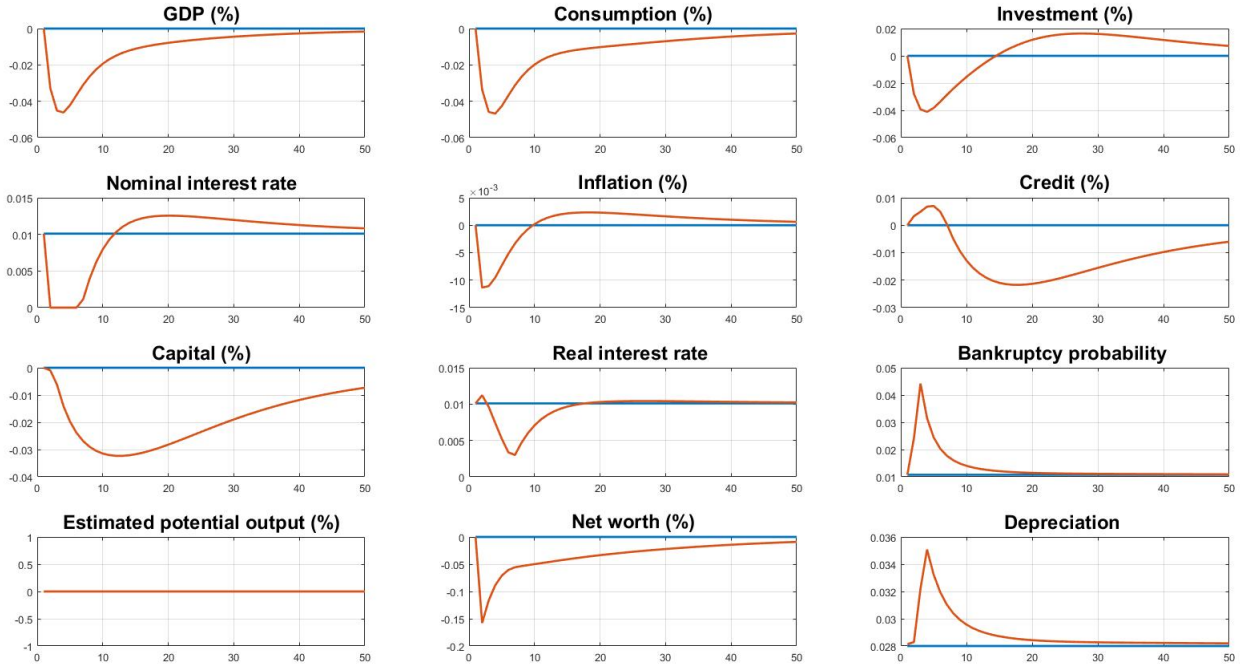



Figure A.12: The Great Recession shocks with a quasi standard Cobb-Douglas technology and no potential output revisions.

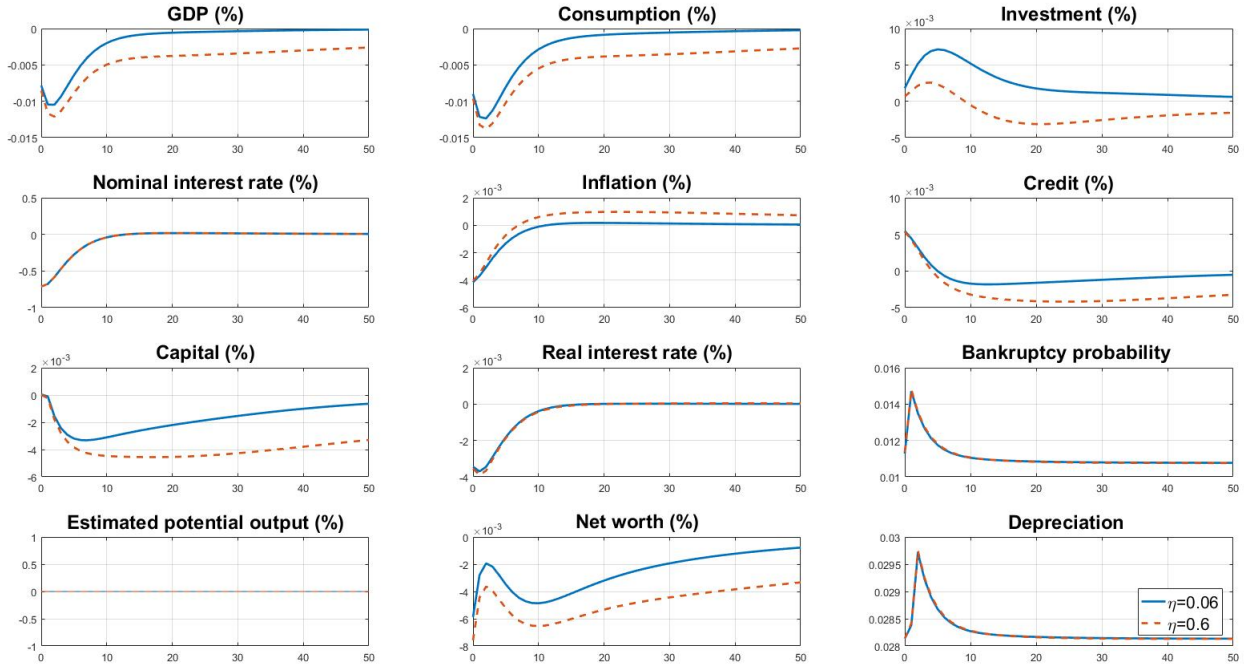



Figure A.13: Relaxing the AK assumption: small demand shock for different intensities of knowledge spillovers.

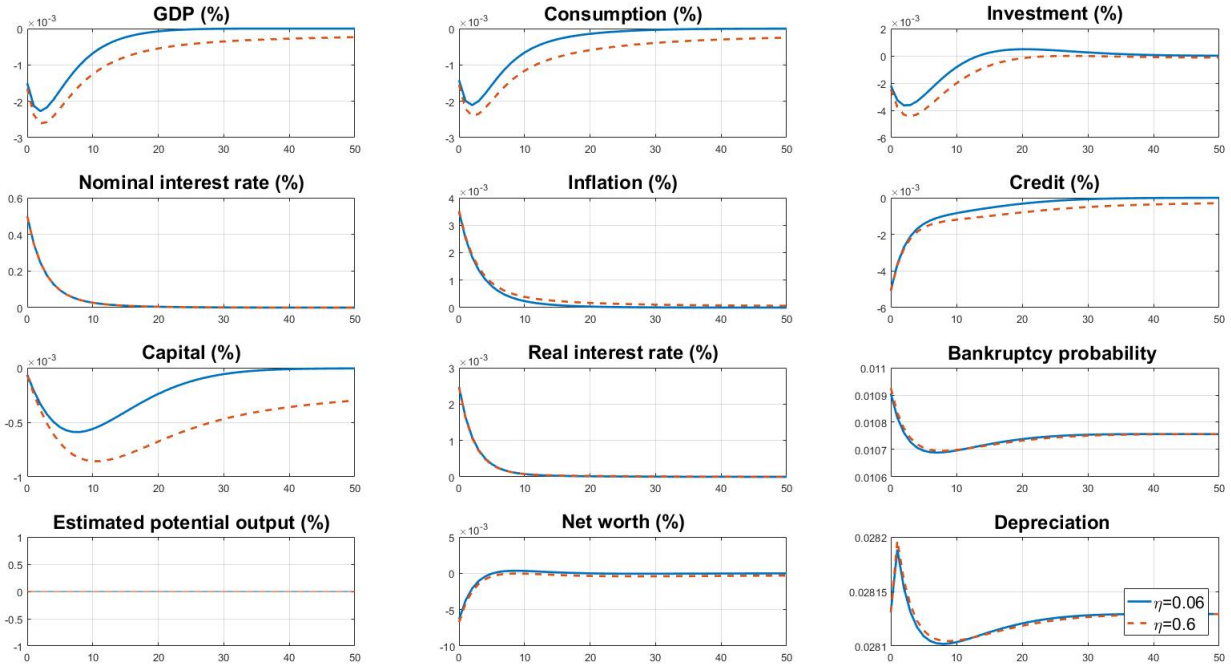



Figure A.14: Relaxing the AK assumption: TFP shock for different intensities of knowledge spillovers.

# Appendix B

# Annex: a simple DSGE model of endogenous growth

## B.1 Model

This annex illustrates the first version on the model described in the first paper, to better explain the motivation behind the modelling choices that followed. This model is a simplified DSGE with price frictions, with the additions of a learning-by-doing technology, drawing from Annicchiarico and Rossi (2013). We introduce a capital destruction shock, meant to shift the level of GDP downwards, generating a L-shaped recovery.

### B.1.1 The household problem

The representative household maximises utility subject to its budget constraints:

$$\max_{c_t, k_{t+1}, i_t, B_t} \quad U_t = E_t \left[ \sum_{j=0}^{\infty} \beta^j \frac{(c_{t+j} - \phi c_{t+j-1})^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} \right] \tag{B.1}$$

$$s.t. \quad B_t + P_t c_t + P_t i_t = R_{t-1} B_{t-1} + P_t w_t h + P_t r_t^k k_t + D_t - P_t \tau_t \tag{B.2}$$

$$s.t. \quad k_{t+1} = \left[ \left( 1 - \frac{\epsilon}{2} \left( \frac{i_t}{i_{t-1}} - 1 \right)^2 \right) i_t + (1-\delta) k_t \right] d_t \tag{B.3}$$

Where $\beta < 1$ is the time discount factor, $c$ is consumption, $\phi$ is a habit formation parameter. $B_t$ represent risk-less one period nominal bonds, purchased at time $t$, that earn the nominal interest rate $R_t$ the following period. $r_t^k$ represents the real rental rate of capital $k_t$, $w_t$ is the real wage, whilst $\tau$ is a lump sum tax. $P_t$ is the price of the final good and $D_t$ are profits redistributed to households by firms. Finally, the capital stock grows with investment, net of depreciation. The parameter $\epsilon$ represents the intensity of investment adjustment costs, which depend on the growth rate of investment. In the spirit of Gourio (2012), we introduce a capital destruction shock $d_t$, taking the value of 1 in normail times and following an AR(1)

process:

$$log(d_t) = \rho_d log(d_{t-1}) + \epsilon_t^d \tag{B.4}$$

with $\epsilon_t^d \sim$ i.i.d. $N(0, \sigma_d^2)$.

The household's FOCs are:

$$\Lambda_t P_t = (c_t - \phi c_{t-1})^{-\frac{1}{\sigma}} - \beta\phi E_t (c_{t+1} - \phi c_t)^{-\frac{1}{\sigma}} \tag{B.5}$$

$$\mu_t = \beta E_t (\Lambda_{t+1} P_{t+1} r_{t+1}^k + \mu_{t+1}(1-\delta)) d_{t+1} \tag{B.6}$$

$$\Lambda_t P_t = \mu_t \left[ 1 - \frac{\epsilon}{2} \left( \frac{i_t}{i_{t-1}} - 1 \right)^2 - \epsilon \frac{i_t}{i_{t-1}} \left( \frac{i_t}{i_{t-1}} - 1 \right) \right] d_t + \\ + \beta E_t \mu_{t+1} \left[ \epsilon \left( \frac{i_{t+1}}{i_t} - 1 \right) \left( \frac{i_{t+1}}{i_t} \right)^2 \right] d_{t+1} \tag{B.7}$$

$$\Lambda_t = R_t \beta E_t \Lambda_{t+1} \tag{B.8}$$

### B.1.2 The final good sector

The final good, $Y_t$, is produced in perfect competition and can be turned into consumption good or investment, as well as government consumption. Production employs intermediate goods as inputs according to the following technology:

$$Y_t = \left( \int_0^1 y_t(i)^{\frac{\theta-1}{\theta}} di \right)^{\frac{\theta}{\theta-1}} \tag{B.9}$$

Final good firm's problem:

$$\max_{y_t(i)} \quad D_t = P_t Y_t - \int_0^1 p_t(i) y_t(i) di \tag{B.10}$$

$$s.t. \quad Y_t = \left( \int_0^1 y_t(i)^{\frac{\theta-1}{\theta}} di \right)^{\frac{\theta}{\theta-1}} \tag{B.11}$$

Which yields the demand function for intermediate goods:

$$y_t(i) = \left( \frac{p_t(i)}{P_t} \right)^{-\theta} Y_t \tag{B.12}$$

and the price index:

$$P_t = \left( \int_0^1 p_t(i)^{1-\theta} di \right)^{\frac{1}{1-\theta}} \tag{B.13}$$

### B.1.3 The intermediate good sector

Each intermediate firm $(i)$, $i \in (0,1)$ operates in monopolistic competition. It employs capital and labour, which is supplied inelastically by households, with the following technology:

$$y_t(i) = a_t \left(k_t(i)\right)^{\alpha} \left(h(i)\right)^{1-\alpha} K_t^{\eta} \qquad \alpha \in (0,1), a > 0 \tag{B.14}$$

Where $B_t$ represents a measure of knowledge, freely available to all firms and acquired through learning-by-doing. We assume that $K_t = k_t$, where $k_t = \int_0^1 k_t(i)di$. This implies that $K$ is a pure externality, proportional to the aggregate level of capital employed in the economy, and $0 \leq \eta \leq 1-\alpha$ represents the strength of the spillovers. $a_t$ is an aggregate productivity shock, following: $log(a_t) = \rho_a log(a_{t-1}) + \epsilon_{a,t}$, where $\rho_a \in (0,1)$ and $\epsilon_{a,t} \sim$i.i.d. $N(0,\sigma^2)$. This is a moderate shock, typical of business cycle dynamics.

Firms in the intermediate sector minimize real costs subject to the technology:

$$\min_{k_t(i),h(i)} \quad w_t h(i) + r_t^k k_t(i) \tag{B.15}$$

$$s.t. \quad y_t(i) = a_t \left(k_t(i)\right)^{\alpha} \left(h(i)\right)^{1-\alpha} K_t^{\eta} \tag{B.16}$$

FOCs:

$$w_t = \kappa_t \frac{(1-\alpha) y_t(i)}{h(i)} \tag{B.17}$$

$$r_t^k = \kappa_t \frac{\alpha y_t(i)}{k_t(i)} \tag{B.18}$$

Where $\kappa_t$ is the Lagrange multiplier. Using the conditions above:

$$k_t(i) = \frac{\alpha}{1-\alpha} \frac{w_t}{r_t^k} h(i) \tag{B.19}$$

Then real costs become:

$$w_t h(i) (\frac{1}{1-\alpha}) \tag{B.20}$$

Since the firm has constant returns to scale, we can find the real marginal cost $s_t$ by using:

$$1 = a_t \left(k_t(i)\right)^{\alpha} \left(h(i)\right)^{1-\alpha} K_t^{\eta} \tag{B.21}$$

where capital and labour represent the inputs required to produce one unit of output. Plugging in (B.19) and rearranging:

$$h(i) = \frac{1}{a_t^{\alpha} K_t^{\eta}} \left( \frac{w_t}{r_t^k} \frac{\alpha}{1-\alpha} \right)^{-\alpha} \tag{B.22}$$

Plugging (B.22) into (B.20) we find the real marginal cost function:

$$s_t = \frac{1}{\alpha^{\alpha}(1-\alpha)^{1-\alpha}} \frac{1}{a_t K_t^{\eta}} w_t^{1-\alpha} (r_t^k)^{\alpha} \tag{B.23}$$

Since the Lagrange multiplier is the cost the firm incurs when it increases production by one unit, $\kappa_t = s_t$. The FOCs become:

$$w_t = s_t \frac{(1-\alpha)y_t(i)}{h(i)} \tag{B.24}$$

$$r_t^k = s_t \frac{\alpha y_t(i)}{k_t(i)} \tag{B.25}$$

Intermediate good producers are monopolistically competitive , however they face an adjustment cost when changing prices. Following Rotemberg (1982), the adjustment cost increases with the magnitude of the change in prices and the size of the economy and is given by:

$$\frac{\phi_p}{2}\left(\frac{P_t(i)}{P_{t-1}(i)} - 1\right)^2 Y_t \tag{B.26}$$

Where $\phi_p \geq 0$ is a measure of price rigidities.

The firm maximises its profit given all its costs:

$$\max_{P_t(i)} \quad E_t\left[\sum_{j=0}^{\infty} \Phi_{t,t+j}\left(P_{t+j}(i)y_{t+j}(i) - P_{t+j}s_{t+j}y_{t+j}(i) - P_{t+j}\frac{\phi_p}{2}\left(\frac{P_t(i)}{P_{t-1}(i)} - 1\right)^2 Y_{t+j}\right)\right] \tag{B.27}$$

Where $\Phi_{t,t+j} \approx \beta^j \frac{\Lambda_{t+j}}{\Lambda_t}$ is the household's discount factor. Using the demand function for intermediate goods, the first order condition of the problem is:

$$\begin{aligned}(1-\theta)\left(\frac{P_t(i)}{P_t}\right)^{-\theta} Y_t + \theta \frac{P_t}{P_t(i)} s_t \left(\frac{P_t(i)}{P_t}\right)^{-\theta} Y_t - \left(\frac{P_t}{P_{t-1}(i)}\right)\phi_p\left(\frac{P_t(i)}{P_{t-1}(i)} - 1\right)Y_t \\ + \beta E_t\left[\frac{\Lambda_{t+1}}{\Lambda_t}\frac{P_{t+1}P_{t+1}(i)}{P_t(i)^2}\phi_p\left(\frac{P_{t+1}(i)}{P_t(i)} - 1\right)Y_{t+1}\right] = 0\end{aligned} \tag{B.28}$$

### B.1.4 The Government

In this economy, the government consumes a fixed portion of private output, levies lump-sum taxes and issues debt, which pays the nominal interest rate $R_t^m = 1 + r_t$, which is set by the central bank. The government budget constraint in real terms is then:

$$g_t + r_t \frac{d_{t-1}}{P_t} = \tau_t + \frac{d_t - d_{t-1}}{P_t} \tag{B.29}$$

Its spending and cost of debt must be equal to the taxes collected and the issuance of new debt.

### B.1.5 Aggregate economy

All firms face the same wage and capital cost, therefore, by symmetry:

$$\frac{k_t(i)}{h(i)} = \frac{k_t}{h} \tag{B.30}$$

Also, market clearing for capital and labour implies $\int_0^1 k_t(i)di = k_t$ and $\int_0^1 h(i)di = h$. Firms face the same costs and can change their price in every period, so they will chose the same price and produce the same quantity. Therefore $P_t(i) = P_t$ and $Y_t(i) = Y_t$, hence aggregate production in this economy is:

$$Y_t = a_t k_t^{\alpha+\eta} h^{1-\alpha} \tag{B.31}$$

Therefore, if $\eta = 1 - \alpha$ the technology presents an AK structure.

The first order condition for the intermediate firm problem becomes:

$$(1-\theta)Y_t + \theta s_t Y_t - \pi_t \phi_p(\pi_t - 1)Y_t + \beta E_t \left[ \frac{\lambda_{t+1}}{\lambda_t} \pi_{t+1} \phi_p(\pi_{t+1} - 1) Y_{t+1} \right] = 0 \tag{B.32}$$

Where $\lambda_t = \Lambda_t P_t$. Dividing by $Y_t$, we find:

$$(1-\theta) + \theta s_t - \pi_t \phi_p(\pi_t - 1) + \beta E_t \left[ \frac{\lambda_{t+1}}{\lambda_t} \pi_{t+1} \phi_p(\pi_{t+1} - 1) \frac{Y_{t+1}}{Y_t} \right] = 0 \tag{B.33}$$

Using the aggregate production function and $K_t = k_t$:

$$r_t^k = \alpha s_t a_t k_t^{\alpha+\eta-1} h^{1-\alpha} \tag{B.34}$$

$$w_t = (1-\alpha) s_t a_t k_t^{\alpha+\eta} h^{-\alpha} \tag{B.35}$$

All government debt must be held by households in aggregate, so that $d_t = B_t$ Then, the government budget constraint becomes:

$$\tau_t = g_t + R_{t-1}^m \frac{B_{t-1}}{P_t} - \frac{B_t}{P_t} \tag{B.36}$$

Plugging (B.36) into the household's budget constraint yields:

$$B_t + P_t c_t + P_t i_t = R_{t-1}^m B_{t-1} + P_t w_t h + P_t r_t^k k_t + P_t D_t - P_t (g_t + R_{t-1}^b \frac{B_{t-1}}{P_t} - \frac{B_t}{P_t}) \tag{B.37}$$

This simplifies to :

$$P_t c_t + P_t i_t + P_t g_t = P_t w_t h + P_t r_t^k k_t + P_t D_t \tag{B.38}$$

And $D_t$ represents aggregate dividends of intermediate firms:

$$D_t = \int_0^1 D_t(i) di \tag{B.39}$$

with

$$D_t(i) = \frac{P_t(i)}{P_t} y_t(i) - w_t h(i) - r_t^k k_t(i) - \frac{\phi_p}{2}\left(\frac{P_t(i)}{P_{t-1}(i)} - 1\right)^2 Y_t \tag{B.40}$$

Using market clearing conditions for the labour market and capital, $P_t(i) = P_t$ and $Y_t(i) = Y_t$:

$$D_t = Y_t - w_t h - r_t^k k_t - \frac{\phi_p}{2}\left(\pi_t - 1\right)^2 Y_t \tag{B.41}$$

Plugging into (38) and simplifying we find that output is allocated across consumption, investment and public spending, but a portion of it is wasted due to the price adjustment cost.

$$Y_t = c_t + i_t + g_t + \frac{\phi_p}{2}\left(\pi_t - 1\right)^2 Y_t \tag{B.42}$$

### B.1.6 The monetary authority

The monetary authority sets a Taylor rule of the following form:

$$\frac{R_t^m}{\bar{R}^m} = \left(\frac{\pi_t}{\bar{\pi}^m}\right)^{\rho_\pi} \left(\frac{Y_t}{\bar{Y}^m}\right)^{\rho_y} \tag{B.43}$$

Where $\bar{y}$, $\bar{R}$, $\bar{\pi}$ are target values and $\rho_\pi$, $\rho_y$, $\rho_r$ are policy parameters. This formulation implies that the current nominal interest rate is determined by the deviation of inflation and output from their targets. We will set $\bar{Y}^m$ to be equal to the steady state of total output.

### B.1.7 Equilibrium conditions

Define $q_t = \frac{\mu_t}{\lambda_t}$. The household conditions become:

$$\lambda_t = (c_t - \phi c_{t-1})^{-\frac{1}{\sigma}} - \beta\phi E_t (c_{t+1} - \phi c_t)^{-\frac{1}{\sigma}} \tag{B.44}$$

$$r_t^k = \alpha s_t a_t k_t^{\alpha+\eta-1} h^{1-\alpha} \tag{B.45}$$

$$w_t = (1-\alpha) s_t a_t (k_t)^{\alpha+\eta} h^{-\alpha} \tag{B.46}$$

$$q_t = \beta E_t \left[\frac{\lambda_{t+1}}{\lambda_t}\left(r_{t+1}^k + (1-\delta) q_{t+1} d_{t+1}\right)\right] \tag{B.47}$$

$$1 = q_t \left[1 - \frac{\epsilon}{2}\left(\frac{i_t}{i_{t-1}} - 1\right)^2 - \epsilon \frac{i_t}{i_{t-1}}\left(\frac{i_t}{i_{t-1}} - 1\right)\right] d_t + \\ + \beta E_t q_{t+1} \frac{\lambda_{t+1}}{\lambda_t}\left[\epsilon\left(\frac{i_{t+1}}{i_t} - 1\right)\left(\frac{i_{t+1}}{i_t}\right)^2\right] d_{t+1} \tag{B.48}$$

$$\lambda_t = \beta R_t E_t [\lambda_{t+1} \pi_{t+1}^{-1}] \tag{B.49}$$

The production side:

$$k_{t+1} = \left[\left(1 - \frac{\epsilon}{2}\left(\frac{i_t}{i_{t-1}} - 1\right)^2\right) i_t + (1-\delta)k_t\right] d_t \tag{B.50}$$

$$log(a_t) = \rho_a log(a_{t-1}) + \epsilon_{a,t} \tag{B.51}$$

$$log(d_t) = \rho_d log(d_{t-1}) + \epsilon_{d,t} \tag{B.52}$$

$$(1-\theta) + \theta s_t - \pi_t \phi_p(\pi_t - 1) + \beta E_t\left[\frac{\lambda_{t+1}}{\lambda_t}\pi_{t+1}\phi_p(\pi_{t+1}-1)\frac{Y_{t+1}}{Y_t}\right] = 0 \tag{B.53}$$

$$Y_t = a_t k_t^{\alpha+\eta}(h)^{1-\alpha} \tag{B.54}$$

$$Y_t = c_t + i_t + g_t + \frac{\phi_p}{2}\left(\pi_t - 1\right)^2 Y_t \tag{B.55}$$

$$g_t = g_y Y_t \tag{B.56}$$

$$\frac{R_t^m}{\bar{R}^m} = \left(\frac{\pi_t}{\bar{\pi}^m}\right)^{\rho_\pi}\left(\frac{Y_t}{\bar{Y}^m}\right)^{\rho_y} \tag{B.57}$$

### B.1.8 The AK case

When $\eta = 1 - \alpha$, the economy is on a balanced growth path, growing at the rate $g_z$ and needs to be made stationary. Defining: $\tilde{c}_t = \frac{c_t}{(1+g_z)^t}$, $\tilde{y}_t = \frac{Y_t}{(1+g_z)^t}$, $\tilde{k}_t = \frac{k_t}{(1+g_z)^t}$, $\tilde{i}_t = \frac{i_t}{(1+g_z)^t}$, $\tilde{w}_t = \frac{w_t}{(1+g_z)^t}$ and $\tilde{\lambda}_t = \lambda_t(1+g_z)^t$, and setting $\sigma = 1$, the equilibrium becomes:

The equilibrium becomes:

$$\tilde{\lambda}_t = \left(\tilde{c}_t - \phi\frac{\tilde{c}_{t-1}}{1+g_z}\right)^{-1} - \beta\phi E_t\left(\tilde{c}_{t+1}(1+g_z) - \phi\tilde{c}_t\right)^{-1} \tag{B.58}$$

$$r_t^k = \alpha s_t a_t h^{1-\alpha} \tag{B.59}$$

$$\tilde{w}_t = (1-\alpha)s_t a_t \tilde{k}_t h^{-\alpha} \tag{B.60}$$

$$q_t = \frac{\beta}{1+g_z}E_t\left[\frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t}\left(r_{t+1}^k + (1-\delta)q_{t+1}d_{t+1}\right)\right] \tag{B.61}$$

$$\begin{aligned} 1 = q_t\Bigg[1 - \frac{\epsilon}{2}\left(\frac{\tilde{i}_t}{\tilde{i}_{t-1}}(1+g_z) - 1 - g_z\right)^2 - \epsilon\frac{\tilde{i}_t}{\tilde{i}_{t-1}}(1+g_z)\left(\frac{\tilde{i}_t}{\tilde{i}_{t-1}}(1+g_z) - 1 - g_z\right)\Bigg] d_t + \\ + \frac{\beta}{1+g_z}E_t q_{t+1}\frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t}\left[\epsilon\left(\frac{\tilde{i}_{t+1}}{\tilde{i}_t}(1+g_z) - 1 - g_z\right)\left(\frac{\tilde{i}_{t+1}}{\tilde{i}_t}(1+g_z)\right)^2\right] d_{t+1} \end{aligned} \tag{B.62}$$

$$\tilde{\lambda_t} = \frac{\beta}{1+g_z}R_t E_t[\tilde{\lambda}_{t+1}\pi_{t+1}^{-1}] \tag{B.63}$$

$$\tilde{k}_{t+1} = \left[\left(1 - \frac{\epsilon}{2}\left(\frac{\tilde{i}_t}{\tilde{i}_{t-1}}(1+g_z) - 1 - g_z\right)^2\right)\tilde{i}_t + (1-\delta)\tilde{k}_t\right]\frac{d_t}{1+g_z} \tag{B.64}$$

$$log(d_t) = \rho_d log(d_{t-1}) + \epsilon_t^d \tag{B.65}$$

$$\tilde{y}_t = a_t \tilde{k}_t(h)^{1-\alpha} \tag{B.66}$$

$$log(a_t) = \rho_a log(a_{t-1}) + \epsilon_{a,t} \tag{B.67}$$

$$\tilde{y}_t = \tilde{c}_t + \tilde{i}_t + \tilde{g}_t + \frac{\phi_p}{2}(\pi_t - 1)^2 \tilde{y}_t \tag{B.68}$$

$$\tilde{g}_t = g_y \tilde{y}_t \tag{B.69}$$

$$(1-\theta) + \theta s_t - \pi_t \phi_p(\pi_t - 1) + \beta E_t \left[ \frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t} \pi_{t+1} \phi_p(\pi_{t+1} - 1) \frac{\tilde{y}_{t+1}}{\tilde{y}_t} \right] = 0 \tag{B.70}$$

$$\frac{R_t^m}{\bar{R}^m} = \left(\frac{\pi_t}{\bar{\pi}^m}\right)^{\rho_\pi} \left(\frac{\tilde{y}_t}{\tilde{\bar{Y}}^m}\right)^{\rho_y} \tag{B.71}$$

Steady state:

$$s_{ss} = \frac{\theta - 1}{\theta} \tag{B.72}$$

$$r_{ss}^k = \alpha s_{ss} h_{ss}^{1-\alpha} \tag{B.73}$$

$$g_z = \beta(r_{ss}^k + 1 - \delta) - 1 \tag{B.74}$$

$$R_{ss} = \frac{\pi_{ss}(1 + g_z)}{\beta} \tag{B.75}$$

$$k_{ss} = \alpha s_{ss} \left( \frac{\beta}{1 + g_z - \beta(1-\delta)} \right) y_{ss} \tag{B.76}$$

$$i_{ss} = (\delta + g_z) k_{ss} \tag{B.77}$$

$$c_{ss} = y_{ss} - i_{ss} - g_{ss} \tag{B.78}$$

$$k_{ss} > 0 \tag{B.79}$$

$$y_{ss} = k_{ss} h_{ss}^{1-\alpha} \tag{B.80}$$

$$\lambda_{ss} = \left( \tilde{c}_{ss} - \eta \frac{\tilde{c}_{ss}}{1 + g_z} \right)^{-1} - \beta \left( \tilde{c}_{ss}(1 + g_z) - \eta \tilde{c}_{ss} \right)^{-1} \tag{B.81}$$

### B.1.9 Calibration and Results

We calibrate the model and solve it with perturbation methods, in line with the main paper.[1] We then simulate the Great Recession as a a 10% capital destruction shock, lasting four quarters, to explore the mechanics of the model. Figure B.1 shows that this shock pushes the nominal interest rate below zero and generates a L-shaped recovery, in line with what happened in the United States. The model thus embeds the key properties needed to reproduce the Great Recession. The Taylor rule also plays an important role, as a higher weight on the output gap is associated with a smaller level affect and a slow recovery.

[1] We set habit formation and investment adjustment costs to zero for the purpose of this exercise to illustrate the key dynamics of the model, as they do not play a crucial role for the aspects we want to highlight.

| Parameter | value | |
|---|---|---|
| $\beta$ | 0.99 | discount factor |
| $\delta$ | 0.03 | depreciation rate |
| $\theta$ | 5 | substitution in final good |
| $\pi_{ss}$ | 1 | inflation |
| $\phi$ | 0 | habit formation |
| $\alpha$ | 0.24 | labour share |
| $g_y$ | 0.2 | government spending share |
| $h$ | 0.2 | labour hours |
| $\epsilon$ | 0 | investment adjustment costs |
| $\phi_p$ | 46.6 | Rotemberg price adjustment parameter |
| $\rho_\pi$ | 1.5 | policy response to inflation |
| $\rho_d$ | 0.1 | capital destruction shock persistence |

In particular, the blue line represents the case in which the central bank does not respond to the output gap. In this case, the economy moves to a lower path, with a permanent level effect on output and a change in the steady state for output, consumption, investment and capital: a pure L-shaped recovery. As we increase $\rho_y$, the output stabilization efforts reduce the negative effects on output. The mechanics behind this are driven by the consumption/saving decision of households. The larger the weight on the output gap, the lower interest rate the central bank will offer for any given level of inflation. As a consequence, households will demand higher consumption for a given level of supply, resulting in higher inflation and nominal interest rate. In equilibrium, the real interest rate, and in parallel the return to capital, will also rise more (although the effect is small), keeping investment demand higher compared to pure inflation targeting and allowing a slow recovery.

To better understand these dynamics, and also how our model differs from the standard New Keynesian literature, let us consider the arbitrage conditions for bonds and capital.

$$\lambda_t = \beta R_t E_t[\lambda_{t+1}\pi_{t+1}^{-1}] \tag{B.82}$$

Standard New Keynesian (Cobb Douglas production function):

$$\lambda_t = \beta E_t\left[\lambda_{t+1}\left(\alpha s_t a_t k_t^{\alpha-1} h^{1-\alpha} + 1 - \delta\right)\right] \tag{B.83}$$

AK case:

$$\lambda_t = \beta E_t\left[\lambda_{t+1}\left(\alpha s_t a_t h^{1-\alpha} + 1 - \delta\right)\right] \tag{B.84}$$

In the standard case, as the central bank reduces the nominal interest rate, investment rises in order for the arbitrage condition to hold, due to diminishing marginal returns to capital. Conversely, with the AK technology, in order for the conditions to hold marginal costs ($s_t$)

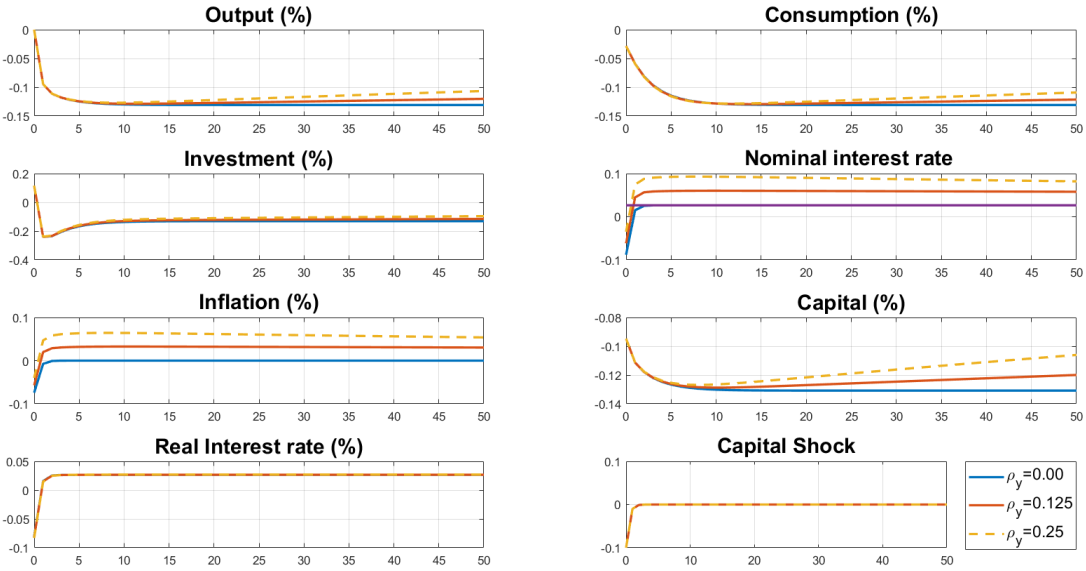



Figure B.1: Capital destruction shock response.

must drop. This implies that the investment choice remains anchored to the savings choice, so that a higher demand for savings due to an increase in the interest rate will lead to an increase in investment as well. This implies that this model cannot replicate the negative relationship between investment and the interest rate. Nonetheless, these results show that a recovery can potentially be induced by a policy intervention in an AK model.

Following these considerations, we modified the model to add financial frictions on capital, allowing us to restore the negative relationship between investment and the interest rate. Moreover, the additional frictions increased the effectiveness of monetary policy, bringing us closer to generating V-shaped recoveries.

# Appendix C

# The Economy after the Fall: Less Innovative, Less Intangible: Appendix

## C.1 Sample Characteristics

| | Mean | SD | Min. | Max. | N |
|---|---|---|---|---|---|
| Sales (Millions of 2012 USD) | 1917.47 | 12589.44 | 0 | 747299 | 164499 |
| Employees (Thousands) | 6.94 | 34.31 | 0 | 2300 | 153765 |
| Mark-up | 1.01 | 0.20 | 0 | 2 | 164499 |
| PPE (MIllions of 2012 USD) | 974.85 | 7284.76 | 0 | 467297 | 164499 |
| Sales growth YoY | 0.10 | 0.38 | -6 | 6 | 145584 |
| Employment growth YoY | 0.04 | 0.36 | -6 | 7 | 134967 |
| $\frac{FSI}{sales}$ | 0.10 | 0.09 | 0 | 1 | 94592 |
| $\frac{R\&D}{sales}$ | 0.07 | 0.11 | 0 | 1 | 94592 |
| $\frac{IntanInvest}{sales}$ | 0.17 | 0.16 | 0 | 1 | 94592 |
| Observations | 164499 | | | | |

Table C.1: Summary statistics COMPUSTAT.

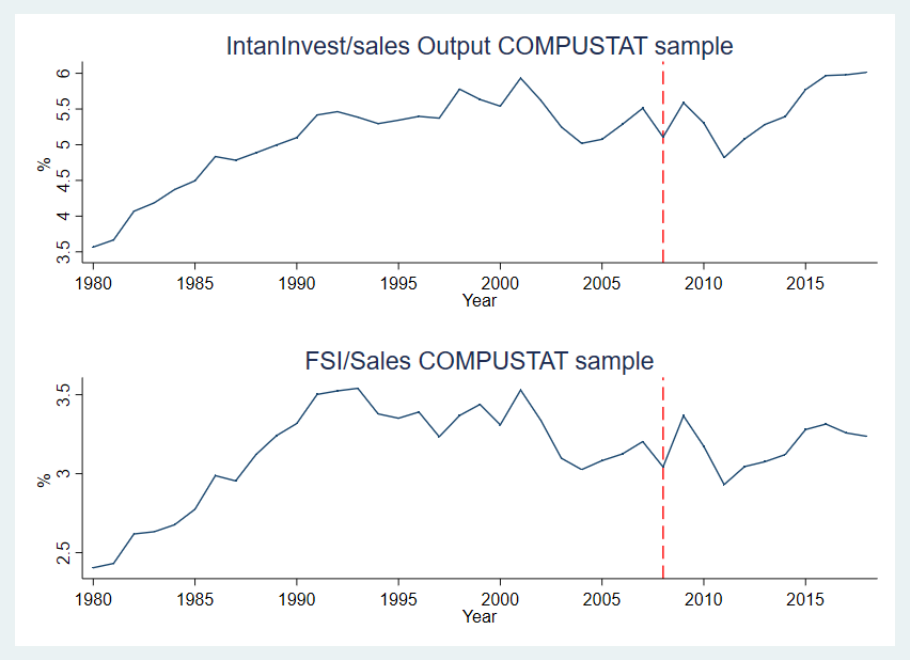



Figure C.1: $FSI$ and IntanInvest intensity over time in our COMPUSTAT sample. The COMPUSTAT measure is constructed as Total $FSI$ expenditure on total sales and total $FSI$ + total $R\&D$ on sales.

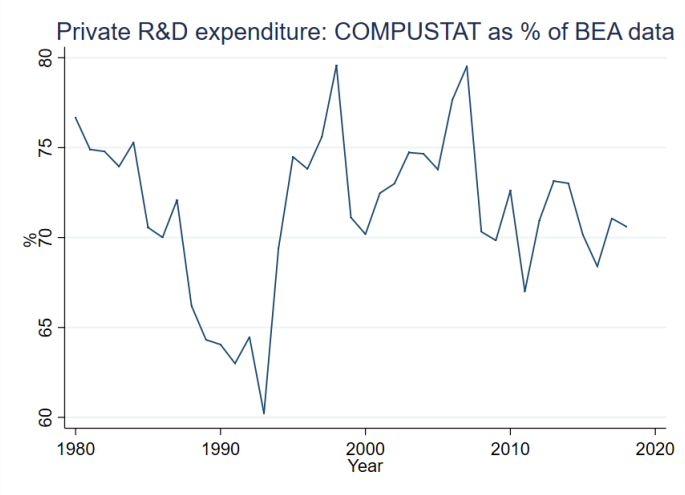



Figure C.2: Representativeness of R&D Investment in COMPUSTAT sample. Source: BEA data series Gross Private Domestic Investment: Fixed Investment: Nonresidential: Intellectual Property Products: Research and Development.)

| Industry | Number | Percent |
|---|---|---|
| Mining | 9,151.0 | 5.7 |
| Construction | 2,954.0 | 1.8 |
| Manufacturing | 82,404.0 | 51.0 |
| Wholesale trade | 8,645.0 | 5.4 |
| Retail trade | 11,311.0 | 7.0 |
| Transportation and warehousing | 3,155.0 | 2.0 |
| Services | 43,836.0 | 27.2 |
| Total | 161,456.0 | 100.0 |

Table C.2: Sectoral coverage at 2 digit NAICS level.
BEA Service industries aggregated in single category. Note that the sample size differs from Table 1 because in the early yers of the sample some firms do not report NAICS codes.

| | (Innovative) | | (NonInnovative) | | (Difference) | |
|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | b | t |
| Mining | 0.01 | 0.12 | 0.11 | 0.31 | 0.09*** | (75.93) |
| Construction | 0.01 | 0.07 | 0.03 | 0.18 | 0.03*** | (40.03) |
| Manufacturing | 0.72 | 0.45 | 0.25 | 0.44 | -0.47*** | (-212.45) |
| Wholesale trade | 0.02 | 0.15 | 0.09 | 0.29 | 0.07*** | (58.94) |
| Retail trade | 0.01 | 0.09 | 0.14 | 0.35 | 0.13*** | (101.05) |
| Transportation and warehousing | 0.00 | 0.05 | 0.04 | 0.20 | 0.04*** | (51.51) |
| Services | 0.22 | 0.42 | 0.33 | 0.47 | 0.11*** | (47.03) |
| Observations | 88325 | | 73131 | | 161456 | |

Table C.3: Industry groups of Innovative vs NonInnovative firms.
A firm is considered innovative if it reported positive $R\&D$ at least once in the whole sample.

## C.2 Exit and Survival Bias

COMPUSTAT provides information on the deletion reasons for firms, allowing us to check weather intangible intensive firms are also more likely to exit. The exit rates due to bankruptcy are low in COMPUSTAT compared to BDS data, as public firms are less likely to exit, but there is still moderate churning due to acquisitions and other deletion reasons, such as going private or leveraged buyouts for example.

We are going to focus on Acquisitions and Bankruptcy, attempting to shed light on whether our results are driven by selection bias. In particular if intangible investment aides success

| | (Innovative) | | (NonInnovative) | | (Difference) | |
|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | b | t |
| Low FSI Intensity | 0.23 | 0.42 | 0.32 | 0.47 | 0.08*** | (21.53) |
| Medium FSI Intensity | 0.49 | 0.50 | 0.54 | 0.50 | 0.04*** | (10.71) |
| High FSI Intensity | 0.27 | 0.45 | 0.15 | 0.35 | -0.13*** | (-40.66) |
| Observations | 76713 | | 17879 | | 94592 | |

Table C.4: FSI Intensity, Innovative vs Non-Innovative firms.
A firm is considered innovative if it reported positive $R\&D$ at least once in the whole sample. Low, Medium and High FSI intensity are defines as firms with FSI intensity below the $25^{th}$ percentile, between $25^{th}$ and $75^{th}$ and above $75^{th}$, respectively.

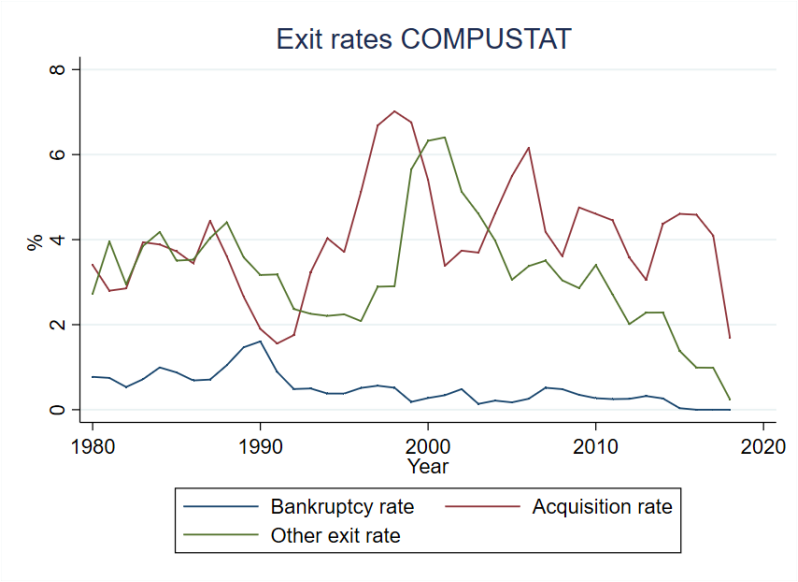



Figure C.3: Exit rates COMPUSTAT

| | (Bankrupt) | | (NonBankrupt) | | (Difference) | |
|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | b | t |
| $\frac{R\&D}{sales}$ | 0.05 | 0.09 | 0.07 | 0.11 | 0.02*** | (12.95) |
| $\frac{FSI}{sales}$ | 0.10 | 0.09 | 0.10 | 0.09 | -0.00 | (-1.56) |
| $\frac{IntanInvest}{sales}$ | 0.15 | 0.15 | 0.17 | 0.16 | 0.02*** | (7.06) |
| Observations | 3286 | | 91306 | | 94592 | |

Table C.5: Intangible Intensity and Bankruptcy rates.

and growth for a firm, but also increases the probability of bankruptcy our results would suffer from selection bias. Moreover, the acquisition of intangible intensive firms could also play a role in the aggregate degree of intangible intensity, as merged companies could behave differently ex-post. Tables C.5 and C.6 compare characteristics of firms that get acquired or go bankrupt in our sample. Groups are defined according to weather the firm went bankrupt or was acquired over the the period we consider. In this sense, we are comparing the treatment group and the control group. Innovative firms are less likely to go bankrupt and more likely to get acquired.

Next, we investigate the drivers of the probability of bankruptcy and acquisition through the lens of a probit model:

$$P(x=1)_{i,j,t} = \beta_1 IntanIntensity_{i,j,t-1} + \beta_2 ln(emp)_{i,j,t} + \beta_3 SalesGrowth_{i,j,t} + \beta_4 leverage_{i,j,t} + \\ + \beta_5 equity_{i,j,t} + \beta_6 ln(\mu)_{i,j,t} + \epsilon_{j,t} + \epsilon_{i,j,t} \quad \text{(C.1)}$$

Where x:(Acquired, Bankrupt, Other exit), and the dependent variable takes the value of 1 if the firm exited due to acquisition, bankruptcy or other reason in a given year. We find

| | (Acquired) | | (NonAcquired) | | (Difference) | |
|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | b | t |
| $\frac{R\&D}{sales}$ | 0.08 | 0.11 | 0.07 | 0.11 | -0.02*** | (-21.94) |
| $\frac{FSI}{sales}$ | 0.09 | 0.07 | 0.10 | 0.10 | 0.01*** | (15.68) |
| $\frac{IntanInvest}{sales}$ | 0.17 | 0.15 | 0.17 | 0.17 | -0.01*** | (-6.99) |
| Observations | 39437 | | 55155 | | 94592 | |

Table C.6: Intangible Intensity and Acquisition rates.

| | (1) Bankruptcy b/se | (2) Bankruptcy b/se | (3) Bankruptcy b/se |
|---|---|---|---|
| $\frac{R\&D}{sales}_{t-1}$ | -0.423 | | |
| | (0.258) | | |
| $\frac{FSI}{sales}_{t-1}$ | | -1.022*** | |
| | | (0.352) | |
| $\frac{IntanInvest}{sales}_{t-1}$ | | | -0.585*** |
| | | | (0.204) |
| Number of obs. | 65,042 | 65,042 | 65,042 |
| Industry-Year Fixed Effects | YES | YES | YES |
| Firm level controls | YES | YES | YES |
| S.e. clustered at firm level | YES | YES | YES |
| Log Likelihood | -1722.1483 | -1718.9468 | -1718.7509 |

Table C.7: Probit model results: Bankruptcy.
Controls include size (employment), sales growth, mark-up, age, leverage and equity ratio.

that intangible firms are less likely to go bankrupt in our sample, attenuating the selection bias concern. We also find that intangible firms are more likely to get acquired. This is likely part of the structural transformation process towards intangibles and higher concentration documented by Crouzet and Eberly (2019), as intangible firms gain prominence over time and industries consolidate. We investigate this result in the context of the Great Recession, and find that intangible intensive firms in sectors worst hit in the recession were not more significantly more likely to get acquired in the aftermath of the shock (Table C.10).[1]

[1] A detailed description of the shock measure can be found in section 2.4.

| | (1) Other Exit b/se | (2) Other Exit b/se | (3) Other Exit b/se |
|---|---|---|---|
| $\frac{R\&D}{sales}_{t-1}$ | -1.402*** | | |
| | (0.144) | | |
| $\frac{FSI}{sales}_{t-1}$ | | -0.191 | |
| | | (0.175) | |
| $\frac{IntanInvest}{sales}_{t-1}$ | | | -0.868*** |
| | | | (0.103) |
| Number of obs. | 76,382 | 76,382 | 76,382 |
| Industry-Year Fixed Effects | YES | YES | YES |
| Firm level controls | YES | YES | YES |
| S.e. clustered at firm level | YES | YES | YES |
| Log Likelihood | -7024.1461 | -7092.8212 | -7045.7486 |

Table C.8: Probit model results: Other exit.
Controls include size (average employment), sales growth, mark-up, age, leverage and equity ratio.

| | (1) Acquisition b/se | (2) Acquisition b/se | (3) Acquisition b/se |
|---|---|---|---|
| $\frac{R\&D}{sales}_{t-1}$ | 0.842*** | | |
| | (0.082) | | |
| $\frac{FSI}{sales}_{t-1}$ | | 0.575*** | |
| | | (0.133) | |
| $\frac{IntanInvest}{sales}_{t-1}$ | | | 0.668*** |
| | | | (0.066) |
| Number of obs. | 73,831 | 73,831 | 73,831 |
| Industry-Year Fixed Effects | YES | YES | YES |
| Firm level controls | YES | YES | YES |
| S.e. clustered at firm level | YES | YES | YES |
| Log Likelihood | -13211.788 | -13251.198 | -13212.695 |

Table C.9: Probit model results: Acquisitions.
Controls include size (employment average), sales growth, mark-up, age, leverage and equity ratio.

| | (1) Acquisition b/se | (2) Acquisition b/se | (3) Acquisition b/se | (4) Acquisition b/se |
|---|---|---|---|---|
| shockGDP | -0.002 | | | |
| | (0.001) | | | |
| $\frac{R\&D}{sales}_{t-1}$ | 1.118*** | 1.059*** | | |
| | (0.238) | (0.241) | | |
| shockGDP* $\frac{R\&D}{sales}_{t-1}$ | | -0.015 | | |
| | | (0.011) | | |
| shockGDP* $\frac{FSI}{sales}_{t-1}$ | | | -0.004 | |
| | | | (0.015) | |
| $\frac{FSI}{sales}_{t-1}$ | | | -0.042 | |
| | | | (0.522) | |
| shockGDP* $\frac{IntanInvest}{sales}_{t-1}$ | | | | -0.006 |
| | | | | (0.007) |
| $\frac{IntanInvest}{sales}_{t-1}$ | | | | 0.727*** |
| | | | | (0.199) |
| Number of obs. | 9,779 | 9,632 | 9,632 | 9,632 |
| Time-Industry Fixed effects | | Yes | Yes | Yes |
| Firm level controls | Yes | Yes | Yes | Yes |
| S.e. clustered at firm level | Yes | Yes | Yes | Yes |
| Log Likelihood | -1867.8119 | -1837.8323 | -1850.0458 | -1842.2829 |

Table C.10: Probit model for acquisitions, intangible intensity and GDP shock.
Controls include size (employment), sales growth, mark-up, age, leverage and equity ratio.

Results on the impact of intangibles on firm performance might be biased due to firm exit. Smaller firms are more likely to exit, thus not accounting for exit would generate an upward bias in the relationship between firm size and firm growth. However, small firms also invest relatively more on intangibles and intangible intensive firms are less likely to exit. Not capturing exit could thus produce a downward bias in our estimation of the relationship between intangible intensity and firm growth.[2]

We verify this by running a similar regression as Akcigit (2009), setting the growth rate of sales in the period of exit to -100%. As an auxiliary step, we also change the timing in the regressions in Table 3.3 and Table 3.5. The positive link between intangible intensity and growth persists (see Table C.11).[3] In table C.12 we show that the results are robust to allowing for exiting firms as well.[4] We also check robustness of all results when observations with significant acquisition expenses are excluded, *i.e.* we exclude firms with acquisition expenses over 5% of total assets.

[2]For a similar discussion of selection bias see Akcigit (2009).

[3]This avoids making an assumption about all other variables in the period of exit.

[4]Firms that are acquired are not included in this experiment. We are focusing on firms exiting due to bankruptcy or other reasons.

| | (1) Sales growth b/se | (2) SG b/se | (3) SG b/se | (4) SG b/se | (5) SG b/se | (6) SG b/se |
|---|---|---|---|---|---|---|
| $\frac{R\&D}{sales}(t-1)$ | | | | | 1.114*** | 0.057 |
| | | | | | (0.055) | (0.057) |
| $\frac{FSI}{sales}(t-1)$ | 3.105*** | 0.410*** | | | | |
| | (0.114) | (0.120) | | | | |
| $\frac{IntanInvest}{sales}(t-1)$ | | | 1.410*** | 0.212*** | | |
| | | | (0.049) | (0.053) | | |
| $ln(e\bar{m}p)$ | -0.022*** | | -0.007* | | -0.019*** | |
| | (0.004) | | (0.004) | | (0.004) | |
| $ln(e\bar{m}p_{t-1})$ | | -0.074*** | | -0.072*** | | -0.092*** |
| | | (0.004) | | (0.004) | | (0.004) |
| Number of obs. | 78,322 | 70,530 | 78,322 | 70,530 | 78,322 | 70,530 |
| $R^2$ | 0.292 | 0.127 | 0.298 | 0.126 | 0.238 | 0.117 |
| Time-Industry Fixed effects | YES | YES | YES | YES | YES | YES |
| Firm level controls | YES | YES | YES | YES | YES | YES |
| S.e. clustered at firm level | YES | YES | YES | YES | YES | YES |

Table C.11: Benchmark regressions vs versions with with lagged contemporaneous controls.

| | (1) Sales growth b/se | (2) SG(S) b/se | (3) SG b/se | (4) SG(S) b/se | (5) SG b/se | (6) SG(S) b/se |
|---|---|---|---|---|---|---|
| $\frac{R\&D}{sales}(t-1)$ | | | | | 0.057 | 0.120* |
| | | | | | (0.057) | (0.063) |
| $\frac{FSI}{sales}(t-1)$ | 0.410*** | 0.448*** | | | | |
| | (0.120) | (0.132) | | | | |
| $\frac{IntanInvest}{sales}(t-1)$ | | | 0.212*** | 0.282*** | | |
| | | | (0.053) | (0.058) | | |
| $ln(e\bar{m}p_{t-1})$ | -0.074*** | -0.060*** | -0.072*** | -0.058*** | -0.092*** | -0.075*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Number of obs. | 70,530 | 72,493 | 70,530 | 72,493 | 70,530 | 72,493 |
| $R^2$ | 0.127 | 0.101 | 0.126 | 0.102 | 0.117 | 0.095 |
| Time-Industry F.E. | YES | YES | YES | YES | YES | YES |
| Firm level controls | YES | YES | YES | YES | YES | YES |
| S.e. clustered (firm) | YES | YES | YES | YES | YES | YES |

Table C.12: Survival bias.

Odd columns reproduce benchmark regressions with lagged controls, whilst even columns include an additional observation for exiting firms, as we set the growth rate of sales in the period of exit to -100%.

## C.3 Mark-up

Mark-ups are unobserved, but we draw from the work of De Loecker et al. (2020) to estimate them at the firm level. In an economy with N firms, indexed by $i$, we can define the production function as:

$$Q_{it} = Q_{it}(\Omega_{it}, V_{it}, K_{it}, X_{it}) \tag{C.2}$$

and firm's profits are:

$$Q_{it} - P_{it}^{V} V_{it} - r V_{it}^{K} K V_{it} - P^{X} V_{it} X_{it} \tag{C.3}$$

Where, $\Omega_{it}$ is productivity, $V_{it}$ is a variable input bundle, $K_{it}$ is tangible capital and $X_{it}$ are other overhead costs.[5] The Lagrangian objective function associated with the firm's cost minimization problem can be expressed as:

$$\ell(V_{it}, K_{it}, X_{it}, \lambda_{it}) = P_{it}^{V} V_{it} + r^{K} K_{it} + P^{X} X_{it} - \lambda_{it}(Q_{it}(.) - \bar{Q}) \tag{C.4}$$

where $P_{it}^{V}$ is the price of the variable input, $r^{K}$ is the user cost of capital, $Q_{it}(.)$ is the technology and $\bar{Q}$ is a scalar and $\lambda_{it}$ is the Lagrange multiplier. The FOC w.r.t. V is then:

$$P_{it}^{V} - \lambda_{it} \frac{\partial Q_{it}(.)}{\partial V_{it}} = 0 \tag{C.5}$$

Where $\lambda_{it}$ is measure of marginal cost. Multiplying by $\frac{V_{it}}{Q_{it}}$ and rearranging yields the definition of the elasticity of production to the variable input:

$$\theta_{it} = \frac{\partial Q_{it}(.)}{\partial V_{it}} \frac{V_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^{V} V_{it}}{Q_{it}} \tag{C.6}$$

And defining the mark-up $\mu_{it}$ as the wedge between output price and marginal cost ($\mu = \frac{P}{\lambda}$), we find:

$$\mu_{it} = \theta_{it} \frac{P_{it} Q_{it}}{P_{it}^{V} V_{it}} \tag{C.7}$$

We then use this expression to calculate mark-ups at the firm level in COMPUSTAT, which provides data on sales ($P_{it}Q_{it}$) as well as variable input costs ($P_{it}^{V}V_{it}$) directly. To measure the variable input, we use the cost of goods sold variable ($cogs$), which includes costs for materials and intermediate inputs, labour costs, energy costs and expenses linked to production of the firm's output. As for $\theta_{it}$, De Loecker et al. (2020) suggest two alternative approaches that yield comparable results. We choose their non-parametric approach, which allows us to remain agnostic concerning the shape of the production function.[6] We thus use the cost

[5] An alternative, more traditional specification in the industrial organization literature would treat costs such as $R\&D$ and advertising expenditure as fixed costs. However, as stressed by De Loecker et al. (2020) among others, the significant rise in the magnitude of these expenditure across firms suggests that they matter to determine units produced and sold, and should hence enter the production function. For example, a well designed advertising campaign can increase units sold by reaching more consumers, and innovation expenditure can raise the quality of products and their demand.

[6] The alternative approach relies on the estimation of a Cobb-Douglas production function to identify the elasticity of the variable input. The mark-ups we estimate in our sample with the non-

| | (1) $\mu$ growth b/se | (2) $\mu$ growth b/se | (3) $\mu$ growth b/se | (4) $\mu$ growth b/se |
|---|---|---|---|---|
| $\frac{FSI}{Sales}_{t-1}$ | 1.493*** | | | |
| | (0.032) | | | |
| $\frac{R\&D}{Sales}_{t-1}$ | | 0.719*** | | |
| | | (0.020) | | |
| $\frac{Advertising}{Sales}_{t-1}$ | | | 0.797*** | |
| | | | (0.058) | |
| $\frac{IntanInvest}{Sales}_{t-1}$ | | | | 0.783*** |
| | | | | (0.016) |
| Number of obs. | 83,567 | 83,567 | 37,949 | 83,567 |
| $R^2$ | 0.210 | 0.089 | 0.049 | 0.196 |
| $R^2$ | 0.211 | 0.088 | 0.050 | 0.196 |
| Firm fixed effects | YES | YES | YES | YES |
| Industry-time fixed effects | YES | YES | YES | YES |
| S.e. clustered at firm level | YES | YES | YES | YES |

Table C.13: Intangible Intensity and Mark-up growth.

share of the variable input as a measure of $\theta_{it}$, such that:

$$\theta_{it} = \frac{P_{it}^V V_{it}}{P_{it}^V V_{it} + + r^K K_{it} + P^X X_{it}} \tag{C.8}$$

Where $r^K$ is the user cost of capital, calculated following De Loecker et al. (2020), $K_{it}$ is property plant and equipment (*ppegt* in COMPUSTAT), and $P^X X_{it}$ is selling, general and administrative expenses ($xsga$), which include advertising expenditure and $R\&D$, as well as salaries of sales personnel, advertising, executive salaries, and administrative support.

We trim the resulting mark-up measure at the top and bottom 1%, and investigate how intangible capital investment intensity affects mark-up growth by running regressions with firm and industry-year fixed effects for our whole sample. We find that all measures of past intangible intensity, i.e. $R\&D$, Advertising, $FSI$ and total intangibles, are positively correlated to mark-up-growth, suggesting that intangibles have the potential to affect profit margins. However, these results are simplistic, and this topic deserves in depth analysis to investigate the channels at play, which is beyond the scope of this paper. We thus interpret these results as support for the inclusion of the mark-up measure as a control in the main analysis, to take into account the potential role of intangible investment on the firm's ability to charge higher prices.

parametric-approach are comparable to the estimation of De Loecker et al. (2020) using the production function approach. We show this for the traditional case as well, i.e. when $P^X X_{it}$ is considered a fixed cost. See Figure C.4 and C.5.

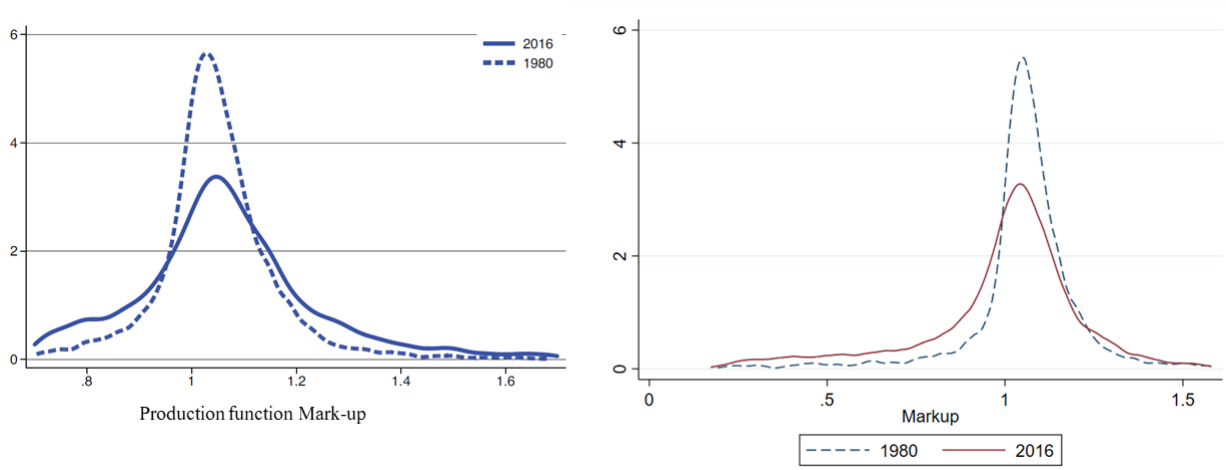



Figure C.4: Distribution of Mark-ups:De Loecker et al. (2020) production function results vs baseline.

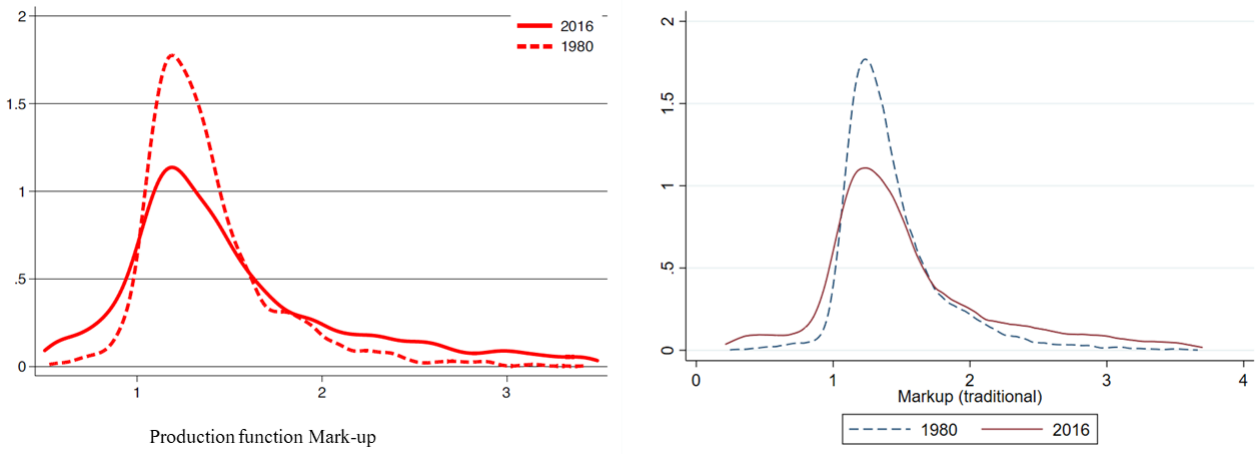



Figure C.5: Distribution of Mark-ups: De Loecker et al. (2020) traditional production function results vs baseline.

## C.4 Intangible Intensity and Firm Growth

| | (1) $\frac{R\&D}{sales}$ b/se | (2) $\frac{FSI}{sales}$ b/se | (3) $\frac{IntanInvest}{sales}$ b/se |
|---|---|---|---|
| $ln(emp)$ | -0.008*** | -0.015*** | -0.022*** |
| | (0.001) | (0.001) | (0.001) |
| Number of obs. | 88,170 | 88,170 | 88,170 |
| $R^2$ | 0.020 | 0.054 | 0.043 |
| Firm fixed effects | YES | YES | YES |
| Industry-time fixed effects | YES | YES | YES |
| S.e. clustered at firm level | YES | YES | YES |
| Firm level controls | YES | YES | YES |

Table C.14: Employment and Intangible intensity.
Controls include age, leverage, and equity ratio.

| | (1) Sales growth_w b/se | (2) Sales growth_w b/se | (3) Sales growth_w b/se |
|---|---|---|---|
| $\frac{R\&D}{sales}(t-1)$ | | 0.885*** | |
| | | (0.043) | |
| $ln(e\bar{m}p)\frac{R\&D}{sales}(t-1)$ | | -0.111*** | |
| | | (0.018) | |
| $\frac{FSI}{sales}(t-1)$ | 2.268*** | | |
| | (0.075) | | |
| $ln(e\bar{m}p)\frac{FSI}{sales}(t-1)$ | 0.100*** | | |
| | (0.022) | | |
| $\frac{IntanInvest}{sales}(t-1)$ | | | 1.075*** |
| | | | (0.035) |
| $ln(e\bar{m}p)\frac{IntanInvest}{sales}(t-1)$ | | | -0.039*** |
| | | | (0.012) |
| Number of obs. | 78,322 | 78,322 | 78,322 |
| $R^2$ | 0.290 | 0.253 | 0.302 |
| Firm fixed effects | YES | YES | YES |
| Industry-time fixed effects | YES | YES | YES |
| S.e. clustered at firm level | YES | YES | YES |

Table C.15: Sales growth regression after winsoring top and bottom 2% of the dependent variable.
Controls include size (employees), mark-up, age, leverage, and equity ratio.

| | (1) Employment growth_w b/se | (2) Employment growth_w b/se | (3) Employment growth_w b/se |
|---|---|---|---|
| $\frac{R\&D}{sales}(t-1)$ | -0.016 | | |
| | (0.035) | | |
| $ln(emp)\frac{R\&D}{sales}(t-1)$ | -0.055*** | | |
| | (0.014) | | |
| $\frac{FSI}{sales}(t-1)$ | | 0.347*** | |
| | | (0.066) | |
| $ln(emp)\frac{FSI}{sales}(t-1)$ | | 0.004 | |
| | | (0.018) | |
| $\frac{IntanInvest}{sales}(t-1)$ | | | 0.071** |
| | | | (0.030) |
| $ln(emp)\frac{IntanInvest}{sales}(t-1)$ | | | -0.033*** |
| | | | (0.010) |
| Number of obs. | 78,322 | 78,322 | 78,322 |
| $R^2$ | 0.096 | 0.098 | 0.097 |
| Firm fixed effects | YES | YES | YES |
| Industry-time fixed effects | YES | YES | YES |
| S.e. clustered at firm level | YES | YES | YES |

Table C.16: Employment growth regression (winsorizing).
Winsorizing top and bottom 2% of the dependent variable. Controls include size (employees), mark-up, age, leverage, and equity ratio.

| | (1) Sales growth b/se | (2) Sales growth b/se | (3) Sales growth b/se |
|---|---|---|---|
| $\frac{R\&D}{sales}(t-1)$ | | 1.339*** | |
| | | (0.054) | |
| $ln(e\bar{m}p)ln(K)\frac{R\&D}{sales}(t-1)$ | | 0.004 | |
| | | (0.005) | |
| $\frac{FSI}{sales}(t-1)$ | 3.148*** | | |
| | (0.099) | | |
| $ln(e\bar{m}p)ln(K)\frac{FSI}{sales}(t-1)$ | -0.038*** | | |
| | (0.005) | | |
| $\frac{IntanInvest}{sales}(t-1)$ | | | 1.538*** |
| | | | (0.044) |
| $ln(e\bar{m}p)ln(K)\frac{IntanInvest}{sales}(t-1)$ | | | -0.003 |
| | | | (0.003) |
| age | 0.006** | -0.001 | 0.003 |
| | (0.003) | (0.003) | (0.003) |
| $ln(e\bar{m}p)ln(K)$ | 0.001 | -0.000 | -0.002** |
| | (0.001) | (0.001) | (0.001) |
| leverage | 0.001 | 0.002 | 0.002 |
| | (0.002) | (0.002) | (0.002) |
| equity | 0.002 | 0.002 | 0.002 |
| | (0.002) | (0.001) | (0.002) |
| $ln(\mu)$ | 1.081*** | 0.952*** | 1.117*** |
| | (0.018) | (0.018) | (0.017) |
| Number of obs. | 78,322 | 78,322 | 78,322 |
| $R^2$ | 0.294 | 0.234 | 0.298 |
| Firm fixed effects | YES | YES | YES |
| Industry-time fixed effects | YES | YES | YES |
| S.e. clustered at firm level | YES | YES | YES |

Table C.17: Intangible Intensity and Sales growth, full results.

| | (1) Employment growth b/se | (2) Employment growth b/se | (3) Employment growth b/se |
|---|---|---|---|
| $\frac{R\&D}{sales}(t-1)$ | | 0.179*** | |
| | | (0.045) | |
| $ln(e\bar{m}p)ln(K)\frac{R\&D}{sales}(t-1)$ | | -0.001 | |
| | | (0.004) | |
| $\frac{FSI}{sales}(t-1)$ | 0.920*** | | |
| | (0.125) | | |
| $ln(e\bar{m}p)ln(K)\frac{FSI}{sales}(t-1)$ | -0.022*** | | |
| | (0.006) | | |
| $\frac{IntanInvest}{sales}(t-1)$ | | | 0.330*** |
| | | | (0.046) |
| $ln(e\bar{m}p)ln(K)\frac{IntanInvest}{sales}(t-1)$ | | | -0.005 |
| | | | (0.003) |
| age | -0.004 | -0.006* | -0.005 |
| | (0.003) | (0.003) | (0.003) |
| $ln(e\bar{m}p)ln(K)$ | 0.000 | -0.001 | -0.001 |
| | (0.001) | (0.001) | (0.001) |
| leverage | -0.005* | -0.004* | -0.004* |
| | (0.003) | (0.002) | (0.002) |
| equity | 0.002 | 0.002 | 0.002 |
| | (0.002) | (0.002) | (0.002) |
| $ln(\mu)$ | 0.489*** | 0.438*** | 0.478*** |
| | (0.018) | (0.017) | (0.018) |
| Number of obs. | 78,322 | 78,322 | 78,322 |
| $R^2$ | 0.079 | 0.073 | 0.076 |
| Firm fixed effects | YES | YES | YES |
| Industry-time fixed effects | YES | YES | YES |
| S.e. clustered at firm level | YES | YES | YES |

Table C.18: Intangible Intensity and Employment growth, full results.

| | (1) Employment growth Innovative(≥once) b/se | (2) Employment growth Non-Innovative b/se |
|---|---|---|
| $\frac{FSI}{sales}(t-1)$ | 0.934*** | 0.349 |
| | (0.164) | (0.311) |
| $ln(emp)\frac{FSI}{sales}(t-1)$ | 0.108** | -0.001 |
| | (0.042) | (0.055) |
| Number of obs. | 63,929 | 14,393 |
| $R^2$ | 0.090 | 0.087 |
| Firm fixed effects | YES | YES |
| Industry-time fixed effects | YES | YES |
| S.e. clustered at firm level | YES | YES |
| Firm level controls | YES | YES |

Table C.19: Employment growth: Innovative vs Non-Innovative.
Controls include size (average employment), mark-up, age, leverage, and equity ratio. Note that the significance of the FSI coefficient in column 2 is sensitive to the definition of size.

| | (1) Sales growth_avg b/se | (2) Sales growth_avg b/se | (3) Sales growth_avg b/se |
|---|---|---|---|
| $\frac{R\&D}{sales}(t-1)$ | 0.998*** | | |
| | (0.047) | | |
| $ln(emp)\frac{R\&D}{sales}(t-1)$ | -0.117*** | | |
| | (0.019) | | |
| $\frac{FSI}{sales}(t-1)$ | | 2.628*** | |
| | | (0.085) | |
| $ln(emp)\frac{FSI}{sales}(t-1)$ | | 0.118*** | |
| | | (0.025) | |
| $\frac{IntanInvest}{sales}(t-1)$ | | | 1.226*** |
| | | | (0.039) |
| $ln(emp)\frac{IntanInvest}{sales}(t-1)$ | | | -0.041*** |
| | | | (0.014) |
| Number of obs. | 78,322 | 78,322 | 78,322 |
| $R^2$ | 0.253 | 0.299 | 0.309 |
| Firm fixed effects | YES | YES | YES |
| Industry-time fixed effects | YES | YES | YES |
| S.e. clustered at firm level | YES | YES | YES |
| Firm level controls | YES | YES | YES |

Table C.20: Intangible intensity and sales growth (average base).
Sales growth is defined as $\frac{RealSales_t - RealSales_{t-1}}{0.5(RealSales_t + RealSales_{t-1})}$. Controls include size (employment), sales growth, mark-up, age, leverage and equity ratio.

| | (1) Employment growth_avg b/se | (2) Employment growth_avg b/se | (3) Employment growth_avg b/se |
|---|---|---|---|
| $\frac{R\&D}{sales}(t-1)$ | 0.027 | | |
| | (0.039) | | |
| $ln(emp)\frac{R\&D}{sales}(t-1)$ | -0.055*** | | |
| | (0.015) | | |
| $\frac{FSI}{sales}(t-1)$ | | 0.555*** | |
| | | (0.090) | |
| $ln(emp)\frac{FSI}{sales}(t-1)$ | | 0.037 | |
| | | (0.023) | |
| $\frac{IntanInvest}{sales}(t-1)$ | | | 0.148*** |
| | | | (0.036) |
| $ln(emp)\frac{IntanInvest}{sales}(t-1)$ | | | -0.024** |
| | | | (0.011) |
| Number of obs. | 78,322 | 78,322 | 78,322 |
| $R^2$ | 0.084 | 0.087 | 0.086 |
| Firm fixed effects | YES | YES | YES |
| Industry-time fixed effects | YES | YES | YES |
| S.e. clustered at firm level | YES | YES | YES |
| Firm level controls | YES | YES | YES |

Table C.21: Robustness: Intangible intensity and employment growth.
Employment growth is defined as $\frac{emp_t - emp_{t-1}}{0.5(emp_t + emp_{t-1})}$, following Haltiwanger et al. (2013). Controls include size (employment), sales growth, mark-up, age, leverage and equity ratio.

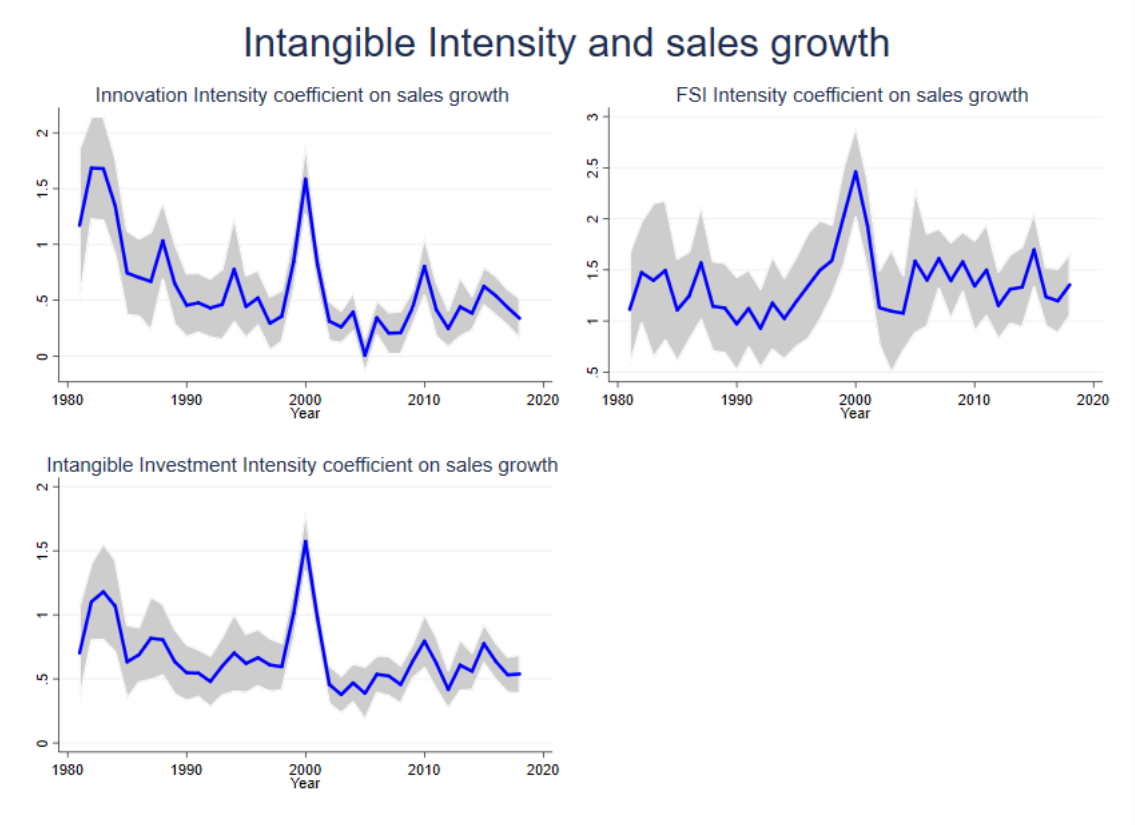



Figure C.6: Intangible intensity and sales growth, year on year regressions.
Regressions include industry effects a the 3 digit NAICS level

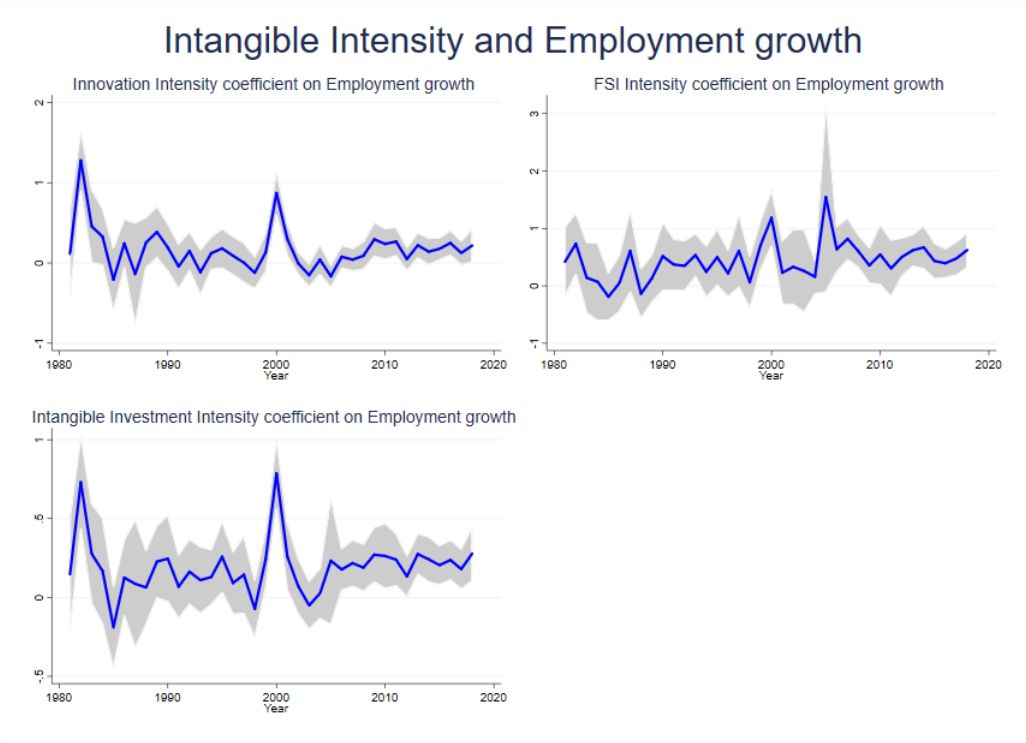



Figure C.7: Intangible intensity and employment growth, year on year regressions. Note that sales growth coefficients display a slight downward trend, whilst for employment growth this is not the case. If we consider employment as a reliable indicator of quantity produced, we could interpret this result as capturing the effect of intangible intensity on prices, even though we are controlling for mark-ups. COMPUSTAT does not allow us to disentangle prices and quantity, so we are unable to thoroughly investigate this issue. However, we consider the effort to understand the role on intangible intensity on prices, through increased efficiency and/or rising market power a very promising avenue of future research.

## C.5 GDP and Export shock

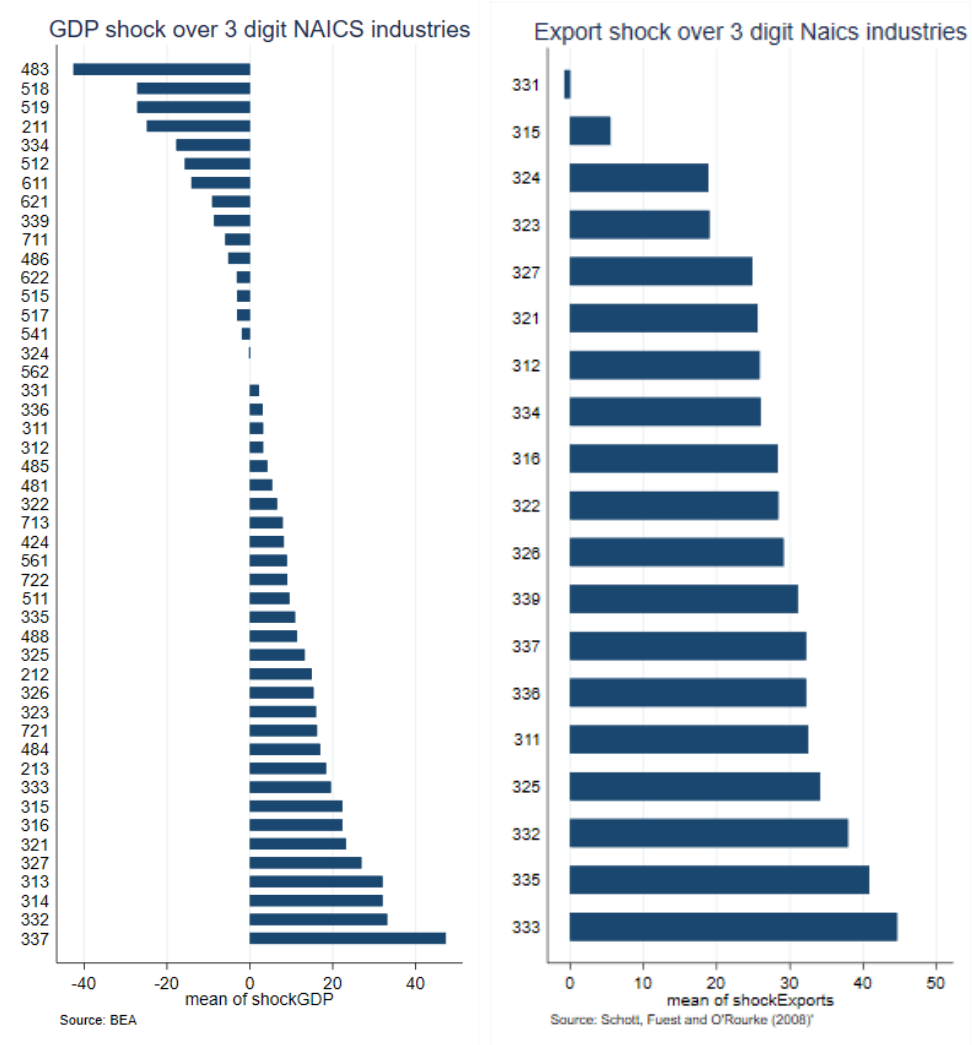



Figure C.8: Great Recession GDP and export shock over NAICS industries.

| | (1) $\frac{R\&D}{sales}$ b/se | (2) $\frac{R\&D}{sales}(Low)$ b/se | (3) $\frac{R\&D}{sales}(Medium)$ b/se | (4) $\frac{R\&D}{sales}(High)$ b/se |
|---|---|---|---|---|
| year=2011 | 0.106 | 0.034 | 0.063 | -0.030 |
| | (0.117) | (0.063) | (0.090) | (0.501) |
| year=2012 | 0.388** | 0.006 | 0.139 | 0.919 |
| | (0.167) | (0.080) | (0.113) | (0.652) |
| year=2013 | 0.458** | -0.028 | 0.153 | 0.923 |
| | (0.190) | (0.095) | (0.130) | (0.703) |
| year=2014 | 0.371** | -0.061 | 0.219 | 0.464 |
| | (0.177) | (0.100) | (0.137) | (0.634) |
| year=2015 | 0.483** | -0.074 | 0.121 | 1.291 |
| | (0.214) | (0.101) | (0.154) | (0.789) |
| year=2016 | 0.620*** | -0.104 | 0.069 | 1.470** |
| | (0.214) | (0.094) | (0.156) | (0.708) |
| year=2017 | 0.417* | -0.070 | 0.070 | 1.044 |
| | (0.229) | (0.099) | (0.156) | (0.829) |
| year=2018 | 0.471* | -0.216** | 0.009 | 1.723** |
| | (0.245) | (0.105) | (0.162) | (0.841) |
| year=2010*shockGDP | -0.027*** | -0.003 | -0.067*** | -0.106*** |
| | (0.009) | (0.005) | (0.009) | (0.029) |
| year=2011*shockGDP | -0.033*** | -0.008 | -0.072*** | -0.107*** |
| | (0.010) | (0.006) | (0.009) | (0.029) |
| year=2012*shockGDP | -0.047*** | -0.014** | -0.077*** | -0.113*** |
| | (0.011) | (0.006) | (0.010) | (0.035) |
| year=2013*shockGDP | -0.046*** | -0.016** | -0.071*** | -0.120*** |
| | (0.012) | (0.007) | (0.010) | (0.039) |
| year=2014*shockGDP | -0.045*** | -0.013* | -0.080*** | -0.144*** |
| | (0.011) | (0.008) | (0.010) | (0.036) |
| year=2015*shockGDP | -0.043*** | -0.014* | -0.075*** | -0.166*** |
| | (0.012) | (0.008) | (0.011) | (0.041) |
| year=2016*shockGDP | -0.037*** | -0.010 | -0.078*** | -0.113*** |
| | (0.012) | (0.007) | (0.010) | (0.034) |
| year=2017*shockGDP | -0.037*** | -0.008 | -0.074*** | -0.141*** |
| | (0.013) | (0.007) | (0.010) | (0.042) |
| year=2018*shockGDP | -0.033** | -0.010 | -0.071*** | -0.131*** |
| | (0.014) | (0.007) | (0.010) | (0.045) |
| Constant | 0.676** | 0.259** | 2.214*** | 5.318*** |
| | (0.290) | (0.125) | (0.308) | (1.112) |
| Number of obs. | 9,053 | 2,460 | 4,701 | 1,892 |
| $R^2$ | 0.194 | 0.724 | 0.613 | 0.298 |
| Firm level controls | YES | YES | YES | YES |
| Clustered s.e. at firm level | YES | YES | YES | YES |

Table C.22: Innovation intensity response to GDP shock.

| | (1) $\frac{FSIInvest}{sales}$ b/se | (2) $\frac{FSIInvest}{sales}(Innovative)$ b/se | (3) $\frac{FSIInvest}{sales}(NonInnovative)$ b/se |
|---|---|---|---|
| year=2011 | -0.214*** | -0.227*** | -0.156 |
| | (0.078) | (0.085) | (0.143) |
| year=2012 | -0.188* | -0.210** | -0.055 |
| | (0.097) | (0.105) | (0.211) |
| year=2013 | -0.130 | -0.137 | -0.225 |
| | (0.109) | (0.116) | (0.320) |
| year=2014 | -0.045 | -0.055 | -0.062 |
| | (0.122) | (0.129) | (0.358) |
| year=2015 | -0.028 | -0.117 | 0.586 |
| | (0.147) | (0.130) | (0.840) |
| year=2016 | 0.056 | 0.057 | -0.018 |
| | (0.136) | (0.144) | (0.428) |
| year=2017 | -0.062 | -0.068 | -0.020 |
| | (0.138) | (0.146) | (0.470) |
| year=2018 | -0.057 | -0.059 | -0.606 |
| | (0.156) | (0.164) | (0.366) |
| year=2010*shockGDP | 0.004 | 0.002 | 0.049** |
| | (0.006) | (0.006) | (0.019) |
| year=2011*shockGDP | 0.000 | -0.001 | 0.048** |
| | (0.006) | (0.006) | (0.020) |
| year=2012*shockGDP | -0.005 | -0.006 | 0.041* |
| | (0.005) | (0.005) | (0.022) |
| year=2013*shockGDP | -0.006 | -0.007 | 0.048 |
| | (0.007) | (0.007) | (0.031) |
| year=2014*shockGDP | -0.004 | -0.006 | 0.066** |
| | (0.008) | (0.008) | (0.033) |
| year=2015*shockGDP | 0.001 | -0.004 | 0.096** |
| | (0.007) | (0.006) | (0.037) |
| year=2016*shockGDP | -0.000 | -0.002 | 0.087** |
| | (0.007) | (0.007) | (0.038) |
| year=2017*shockGDP | -0.005 | -0.007 | 0.084** |
| | (0.007) | (0.007) | (0.041) |
| year=2018*shockGDP | -0.012 | -0.014 | 0.124*** |
| | (0.008) | (0.009) | (0.033) |
| Number of obs. | 8,833 | 8,118 | 715 |
| $R^2$ | 0.338 | 0.359 | 0.232 |
| Firm level controls | YES | YES | YES |
| Clustered s.e. at firm level | YES | YES | YES |

Table C.23: $FSI$ intensity response to GDP shock.

| | (1) $\frac{IntanInvest}{sales}$ b/se | (2) $\frac{R\&D}{SG\&A}$ b/se | (3) $\frac{R\&D}{TotalInvestment}$ b/se | (4) $\frac{IntanInvest}{TotalInvestment}$ b/se |
|---|---|---|---|---|
| year=2011 | -0.129 | 0.418*** | 0.382* | -1.332*** |
| | (0.165) | (0.115) | (0.227) | (0.355) |
| year=2012 | 0.180 | 0.658*** | 0.848*** | -0.384 |
| | (0.229) | (0.165) | (0.242) | (0.349) |
| year=2013 | 0.295 | 0.826*** | 0.876*** | 0.068 |
| | (0.257) | (0.201) | (0.230) | (0.313) |
| year=2014 | 0.298 | 0.747*** | 0.700*** | 0.397 |
| | (0.256) | (0.230) | (0.222) | (0.305) |
| year=2015 | 0.439 | 0.913*** | 0.877*** | 0.171 |
| | (0.300) | (0.267) | (0.235) | (0.328) |
| year=2016 | 0.661** | 1.113*** | 1.005*** | 0.783** |
| | (0.300) | (0.293) | (0.230) | (0.310) |
| year=2017 | 0.315 | 0.979*** | 0.023 | 0.327 |
| | (0.311) | (0.310) | (0.228) | (0.343) |
| year=2018 | 0.409 | 1.116*** | 0.628** | -0.113 |
| | (0.346) | (0.338) | (0.250) | (0.340) |
| year=2010*shockGDP | -0.023* | -0.064*** | 0.000 | 0.058*** |
| | (0.012) | (0.014) | (0.010) | (0.015) |
| year=2011*shockGDP | -0.032** | -0.065*** | -0.029*** | -0.022* |
| | (0.013) | (0.015) | (0.009) | (0.013) |
| year=2012*shockGDP | -0.050*** | -0.071*** | -0.023** | 0.010 |
| | (0.013) | (0.016) | (0.011) | (0.015) |
| year=2013*shockGDP | -0.049*** | -0.074*** | -0.028*** | -0.001 |
| | (0.016) | (0.017) | (0.009) | (0.013) |
| year=2014*shockGDP | -0.049*** | -0.073*** | -0.020** | 0.023* |
| | (0.016) | (0.017) | (0.010) | (0.013) |
| year=2015*shockGDP | -0.042** | -0.072*** | -0.024** | 0.015 |
| | (0.016) | (0.018) | (0.010) | (0.014) |
| year=2016*shockGDP | -0.036** | -0.066*** | -0.019** | 0.050*** |
| | (0.016) | (0.019) | (0.009) | (0.014) |
| year=2017*shockGDP | -0.041** | -0.056*** | -0.010 | -0.000 |
| | (0.017) | (0.019) | (0.010) | (0.014) |
| year=2018*shockGDP | -0.045** | -0.051** | -0.004 | 0.044*** |
| Number of obs. | 8,833 | 8,651 | 9,093 | 9,093 |
| $R^2$ | 0.282 | 0.094 | 0.023 | 0.051 |
| Firm level controls | YES | YES | YES | YES |
| Clustered s.e. at firm level | YES | YES | YES | YES |

Table C.24: Intangible intensity response to GDP shock.

| | (1) $\frac{R\&D}{sales}$ b/se | (2) $\frac{FSIInvest}{sales}$ b/se | (3) $\frac{IntanInvest}{sales}$ b/se | (4) $\frac{R\&D}{SG\&A}$ b/se |
|---|---|---|---|---|
| year=2011 | 0.695 | 0.539 | 1.221 | 0.633 |
| | (0.524) | (0.502) | (0.831) | (0.508) |
| year=2012 | 1.257* | 1.052* | 2.309** | 0.734 |
| | (0.751) | (0.603) | (1.126) | (0.760) |
| year=2013 | 0.747 | 0.895 | 1.628 | 0.473 |
| | (0.823) | (0.611) | (1.174) | (0.883) |
| year=2014 | 0.371 | 0.375 | 0.732 | -0.100 |
| | (0.762) | (0.626) | (1.155) | (0.974) |
| year=2015 | -0.290 | 0.495 | 0.175 | -0.628 |
| | (0.885) | (0.652) | (1.244) | (1.075) |
| year=2016 | -0.350 | 0.315 | -0.069 | -0.256 |
| | (0.920) | (0.736) | (1.376) | (1.167) |
| year=2017 | 0.327 | 0.525 | 0.827 | 0.159 |
| | (0.987) | (0.778) | (1.436) | (1.237) |
| year=2018 | -0.064 | 1.123 | 1.021 | -1.059 |
| | (0.998) | (0.834) | (1.483) | (1.410) |
| year=2010*ExportShock | -0.056*** | 0.023 | -0.035 | -0.066*** |
| | (0.018) | (0.020) | (0.029) | (0.023) |
| year=2011*ExportShock | -0.074*** | -0.001 | -0.078*** | -0.070*** |
| | (0.021) | (0.014) | (0.029) | (0.025) |
| year=2012*ExportShock | -0.084*** | -0.016 | -0.103*** | -0.066** |
| | (0.025) | (0.013) | (0.031) | (0.030) |
| year=2013*ExportShock | -0.066** | -0.008 | -0.076** | -0.053* |
| | (0.026) | (0.015) | (0.035) | (0.030) |
| year=2014*ExportShock | -0.062** | 0.007 | -0.057 | -0.043 |
| | (0.025) | (0.019) | (0.036) | (0.031) |
| year=2015*ExportShock | -0.043 | 0.001 | -0.043 | -0.027 |
| | (0.027) | (0.014) | (0.034) | (0.032) |
| year=2016*ExportShock | -0.038 | 0.013 | -0.026 | -0.031 |
| | (0.027) | (0.017) | (0.037) | (0.036) |
| year=2017*ExportShock | -0.064** | 0.003 | -0.063* | -0.043 |
| | (0.027) | (0.019) | (0.036) | (0.039) |
| year=2018*ExportShock | -0.045* | -0.014 | -0.061 | 0.005 |
| | (0.026) | (0.020) | (0.037) | (0.044) |
| Constant | 2.680*** | 2.000*** | 4.586*** | 3.049*** |
| | (0.786) | (0.709) | (1.222) | (0.959) |
| Number of obs. | 6,720 | 6,720 | 6,720 | 6,720 |
| $R^2$ | 0.211 | 0.343 | 0.302 | 0.079 |
| Firm level controls | YES | YES | YES | YES |
| Clustered s.e. at firm level | YES | YES | YES | YES |

Table C.25: Intangible intensity measures and export shock.

| | (1)<br>OutcomeSales<br>b/se |
|---|---|
| year=2010*ShockGDP | -0.646*** |
| | (0.109) |
| year=2011*ShockGDP | -0.678*** |
| | (0.125) |
| year=2012*ShockGDP | -0.672*** |
| | (0.132) |
| year=2013*ShockGDP | -0.626*** |
| | (0.152) |
| year=2014*ShockGDP | -0.704*** |
| | (0.164) |
| year=2015*ShockGDP | -0.964*** |
| | (0.173) |
| year=2016*ShockGDP | -1.250*** |
| | (0.194) |
| year=2017*ShockGDP | -1.224*** |
| | (0.211) |
| year=2018*ShockGDP | -1.257*** |
| | (0.214) |
| year=2010*ShockGDP*$\frac{R\&D_{07}}{sales_{07}}$ | 0.639 |
| | (1.049) |
| year=2011*ShockGDP*$\frac{R\&D_{07}}{sales_{07}}$ | 1.319 |
| | (1.230) |
| year=2012*ShockGDP*$\frac{R\&D_{07}}{sales_{07}}$ | 1.075 |
| | (1.272) |
| year=2013*ShockGDP*$\frac{R\&D_{07}}{sales_{07}}$ | -0.156 |
| | (1.499) |
| year=2014*ShockGDP*$\frac{R\&D_{07}}{sales_{07}}$ | -1.167 |
| | (1.609) |
| year=2015*ShockGDP*$\frac{R\&D_{07}}{sales_{07}}$ | -1.695 |
| | (1.714) |
| year=2016*ShockGDP*$\frac{R\&D_{07}}{sales_{07}}$ | -1.601 |
| | (1.893) |
| year=2017*ShockGDP*$\frac{R\&D_{07}}{sales_{07}}$ | -1.803 |
| | (2.216) |
| year=2018*ShockGDP*$\frac{R\&D_{07}}{sales_{07}}$ | -0.826 |
| Number of obs. | 9,039 |
| $R^2$ | 0.151 |
| Time fixed effects | YES |
| Firm level controls | YES |
| S.e. clustered at firm level | YES |

Table C.26: *Ex ante* innovation intensity and sales growth after the Great Recession. Controls include employment, innovation intensity, leverage, equity, mark-up and GDP growth at the 3 digit industry level, all measured in 2007.

| | (1)<br>OutcomeSales<br>b/se |
|---|---|
| year=2010*ShockGDP | -0.598*** |
| | (0.180) |
| year=2011*ShockGDP | -0.532** |
| | (0.210) |
| year=2012*ShockGDP | -0.465** |
| | (0.194) |
| year=2013*ShockGDP | -0.445** |
| | (0.221) |
| year=2014*ShockGDP | -0.573** |
| | (0.242) |
| year=2015*ShockGDP | -1.109*** |
| | (0.262) |
| year=2016*ShockGDP | -1.660*** |
| | (0.294) |
| year=2017*ShockGDP | -1.707*** |
| | (0.328) |
| year=2018*ShockGDP | -1.738*** |
| | (0.342) |
| year=2010*ShockGDP*$\frac{FSI_{07}}{sales_{07}}$ | -0.874 |
| | (2.068) |
| year=2011*ShockGDP*$\frac{FSI_{07}}{sales_{07}}$ | -1.372 |
| | (2.485) |
| year=2012*ShockGDP*$\frac{FSI_{07}}{sales_{07}}$ | -2.394 |
| | (2.149) |
| year=2013*ShockGDP*$\frac{FSI_{07}}{sales_{07}}$ | -3.100 |
| | (2.437) |
| year=2014*ShockGDP*$\frac{FSI_{07}}{sales_{07}}$ | -3.201 |
| | (2.700) |
| year=2015*ShockGDP*$\frac{FSI_{07}}{sales_{07}}$ | -0.075 |
| | (3.003) |
| year=2016*ShockGDP*$\frac{FSI_{07}}{sales_{07}}$ | 3.414 |
| | (3.394) |
| year=2017*ShockGDP*$\frac{FSI_{07}}{sales_{07}}$ | 4.094 |
| | (3.884) |
| year=2018*ShockGDP*$\frac{FSI_{07}}{sales_{07}}$ | 5.025 |
| | (4.102) |
| Number of obs. | 9,039 |
| $R^2$ | 0.157 |
| Time fixed effects | YES |
| Firm level controls | YES |
| S.e. clustered at firm level | YES |

Table C.27: *Ex ante* $FSI$ intensity and sales growth after the Great Recession.
Controls include employment, $FSI$ intensity, leverage, equity, mark-up and GDP growth at the 3 digit industry level, all measured in 2007.

| | (1)<br>OutcomeSales<br>b/se |
|---|---|
| year=2010*ShockGDP | -0.555*** |
| | (0.148) |
| year=2011*ShockGDP | -0.577*** |
| | (0.168) |
| year=2012*ShockGDP | -0.551*** |
| | (0.174) |
| year=2013*ShockGDP | -0.463** |
| | (0.197) |
| year=2014*ShockGDP | -0.525** |
| | (0.212) |
| year=2015*ShockGDP | -0.897*** |
| | (0.222) |
| year=2016*ShockGDP | -1.316*** |
| | (0.249) |
| year=2017*ShockGDP | -1.316*** |
| | (0.277) |
| year=2018*ShockGDP | -1.393*** |
| | (0.287) |
| year=2010*ShockGDP*$\frac{IntanInvest_{07}}{sales_{07}}$ | -0.099 |
| | (0.834) |
| year=2011*ShockGDP*$\frac{IntanInvest_{07}}{sales_{07}}$ | 0.173 |
| | (0.990) |
| year=2012*ShockGDP*$\frac{IntanInvest_{07}}{sales_{07}}$ | -0.079 |
| | (0.996) |
| year=2013*ShockGDP*$\frac{IntanInvest_{07}}{sales_{07}}$ | -0.934 |
| | (1.124) |
| year=2014*ShockGDP*$\frac{IntanInvest_{07}}{sales_{07}}$ | -1.481 |
| | (1.213) |
| year=2015*ShockGDP*$\frac{IntanInvest_{07}}{sales_{07}}$ | -0.948 |
| | (1.293) |
| year=2016*ShockGDP*$\frac{IntanInvest_{07}}{sales_{07}}$ | 0.015 |
| | (1.443) |
| year=2017*ShockGDP*$\frac{IntanInvest_{07}}{sales_{07}}$ | 0.092 |
| | (1.705) |
| year=2018*ShockGDP*$\frac{IntanInvest_{07}}{sales_{07}}$ | 0.863 |
| | (1.802) |
| Number of obs. | 9,039 |
| $R^2$ | 0.162 |
| Time fixed effects | YES |
| Firm level controls | YES |
| S.e. clustered at firm level | YES |

Table C.28: *Ex ante* intangible intensity and sales growth after the Great Recession. Controls include employment, intangible intensity, leverage, equity, mark-up and GDP growth at the 3 digit industry level, all measured in 2007.

## C.6 R&D Off-shoring

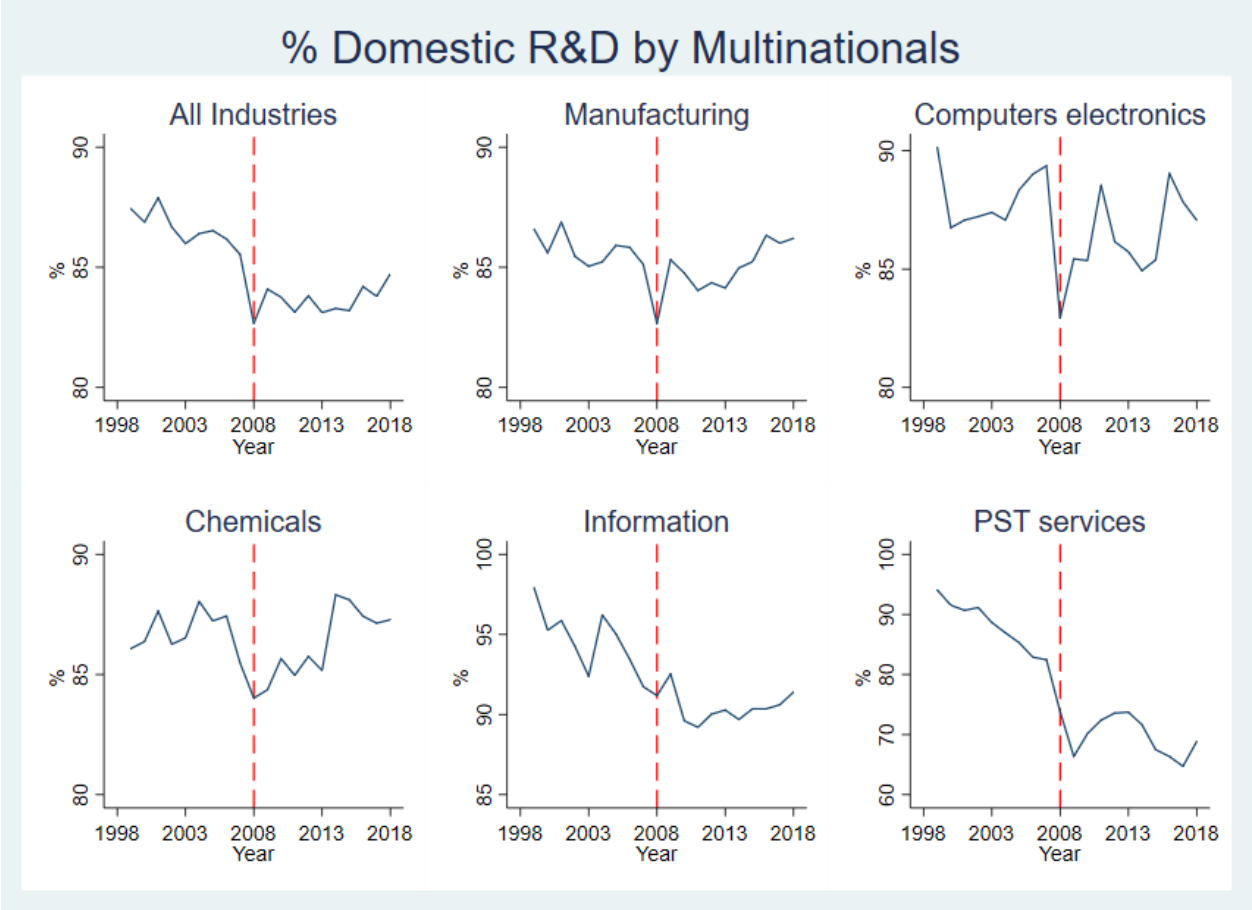



Figure C.9: % of Domestic *R&D* by Multinational Enterprises.
Percentage of *R&D* expenditure by U.S. Parent to total *R&D* for Multinational Enterprises, U.S. BEA data Note: PST stands for professional, scientific and technical.

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