**The London School of Economics
and Political Science**

Essays on Financial Frictions and Productivity

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it). The thesis has been cross-checked through iThenticate®.

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I declare that my thesis consists of 53,421 words, excluding the content of tables and figures (as calculated with TeXcount web service (version 3.0.0.24)).

London, 30 September 2016

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Statement of conjoint work

Chapter 1, ***"Credit Market Frictions and the Productivity Slowdown"***, was jointly co-authored with Professor Tim Besley (London School of Economics) and Professor John Van Reenen (Massachusetts Institute of Technology and London School of Economics). This statement is to confirm that I contributed a minimum of a third of this work.

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Chapter 3, ***"When Does Leverage Hurt Productivity Growth? A Firm-Level Analysis"***, was jointly co-authored with Professor Fabrizio Coricelli (Paris School of Economics), Professor Nigel Driffield (Warwick Business School), and Professor Sarmistha Pal (University of Surrey). This statement is to confirm that I contributed a minimum of a fourth of this work. The paper has been published as:

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Disclaimers

The first chapter, ***"Credit Market Frictions and the Productivity Slowdown"***, joint with John Van Reenen and Timothy Besley, received financial support from the Lamfalussy Fellowship Programme of the European Central Bank. The paper should not be reported as representing the views of the European Central Bank (ECB). The views expressed are those of the authors and do not necessarily reflect those of the ECB.

The first chapter, ***"Credit Market Frictions and the Productivity Slowdown"***, and the second chapter, ***"Management practices, precautionary savings, and company investment dynamics "***, make use of confidential data collected by the UK Office for National Statistics and securely provided by the UK Data Service. The use of these data does not imply the endorsement of the data owner or the UK Data Service at the UK Data Archive in relation to the interpretation or analysis of the data. This work uses research data sets which may not exactly reproduce National Statistics aggregates.

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Abstract

Productivity - the efficiency with which firms transform inputs into outputs - is the root of economic growth and the improvement of living standards. This thesis explores different financial frictions that affect productivity at the corporate level and their aggregate consequences.

The first chapter, ***"Credit Market Frictions and the Productivity Slowdown"***, is joint work with John Van Reenen and Timothy Besley. UK labour productivity growth has been particularly weak since the financial crisis. We develop a theoretical framework to quantitatively assess the magnitude of financial frictions and their impact on aggregate productivity. We apply this framework to administrative panel data on UK firms. The approach highlights a firm's default probability as a sufficient statistic for credit frictions. We use Standard and Poor's "PD Model" algorithm to measure market participants' perceptions of firm-specific default risk. The theoretical framework suggests an aggregate measure of credit market inefficiency which we show can be applied to UK administrative panel data to explain how far the dramatic productivity slowdown in the wake of the crisis is due to credit market frictions. We find that credit frictions cause a loss of 7% to 9% of GDP on average per year in 2004-12. These frictions increased during the crisis and lingered thereafter accounting for between one-quarter and one-third of the productivity fall in 2008-2009 and of the gap between actual and trend productivity by the end of 2012.

The second chapter, ***"Management practices, precautionary savings, and company investment dynamics"***, investigates a potential channel behind the well-documented positive correlation between the quality of management practices and firm performance. The main hypothesis of the paper is that financially constrained firms accumulate larger cash reserves when they are better managed. This allows them to avoid the costs of underinvestment when future profitable investment opportunities arise. The theoretical analysis predicts that well managed firms which face financial constraints save relatively more out of their cash flows and accumulate more cash

when their cash flows are more volatile. This enhanced precautionary behaviour arises because management quality alleviates agency problems between equity holders and managers. The empirical analysis provides evidence to support these predictions using data from the World Management Survey and administrative and accounting data on UK firms. A direct consequence of this enhanced precautionary behaviour is that well managed firms invest more efficiently. Specifically, they adjust more quickly towards their long-run equilibrium capital stock when their current capital stock falls short of the latter. The paper provides evidence of this using a dynamic model of investment.

The third chapter, ***"When Does Leverage Hurt Productivity Growth? A Firm-Level Analysis"***, is joint work with Fabrizio Coricelli, Nigel Driffield, and Sarmistha Pal. Following the global financial crisis, several macroeconomic contributions have highlighted the risks of excessive credit expansion. In particular, too much finance can have a negative impact on growth. We examine the microeconomic foundations of this argument, positing a non-monotonic relationship between leverage and firm-level total factor productivity (TFP) growth. A threshold regression model estimated on a sample of Central and Eastern European countries confirms that TFP growth increases with leverage until the latter reaches a critical threshold beyond which leverage lowers TFP growth. We find similar non-monotonic relationships between leverage and proxies for firm value.

The fourth chapter, ***"The sullying effect of credit sclerosis on productivity"***, explores the impact of depressed credit flows on productivity in a partial equilibrium search and matching model of the banking market. Reputational costs associated with the termination of lending relationships drive a wedge between rates on new and existing loans. This induces misallocation of capital across borrowers. The phenomenon is one of "credit sclerosis": Low-productivity firms are kept alive through subsidised loan rates, while high-productivity entrants face an inefficiently high cost of borrowing and limited supply of new loan facilities. As a consequence, too much credit is allocated to old firms. Aggregate labour productivity and TFP are reduced. The model also sheds some light on why a policy tool like the UK's Funding for Lending Scheme might fail to revive productivity in the presence of costly loan termination.

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Chapter 1

Credit Market Frictions and the Productivity Slowdown[1]

Abstract

The fallout from the global financial crisis has heightened awareness of the importance of credit market frictions. This paper develops and then applies a theoretical framework to quantitatively assess the magnitude of financial frictions and their impact on aggregate productivity. The approach highlights a firm's default probability as a sufficient statistic for credit frictions. We use Standard and Poor's "PD Model" algorithm to measure market participants' perceptions of firm-specific default risk. The theoretical framework also suggests an aggregate measure of credit market inefficiency which we show can be applied to UK administrative panel data to explain how far the dramatic productivity slowdown in the wake of the crisis is due to credit market frictions. The paper finds that credit frictions cause a loss of 7% to 9% of GDP on average per year in 2004-12. These frictions increased during the crisis and lingered thereafter accounting for between one-quarter and one-third of the productivity fall in 2008-2009 and of the gap between actual and trend productivity by the end of 2012.

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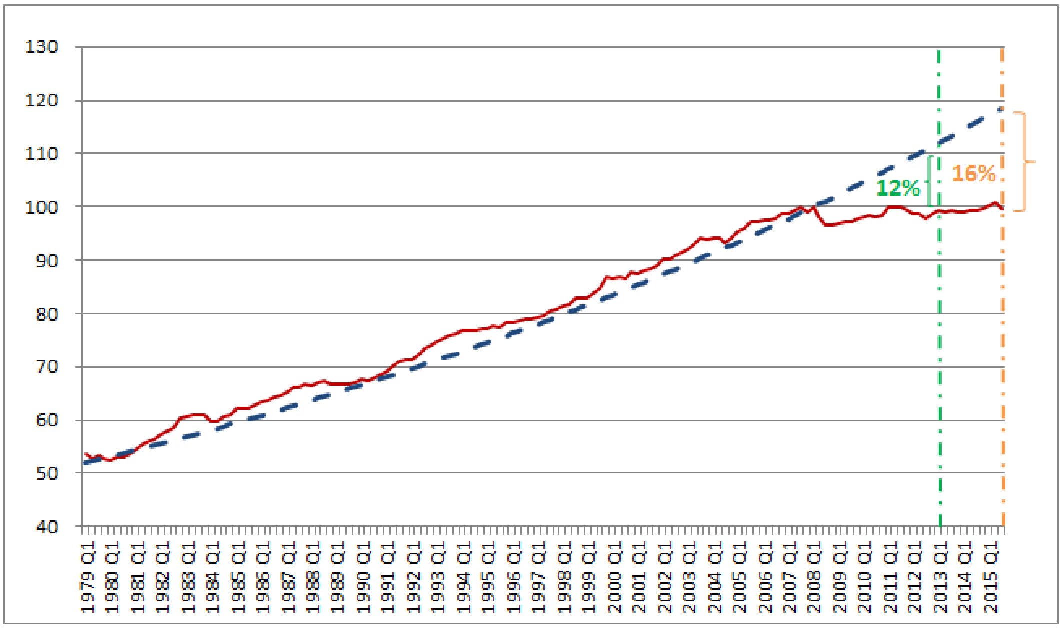
1.1 Introduction

The period following the financial crisis heightened awareness of the role of credit frictions in affecting economic efficiency. For finance to play a role in supporting living standards, it must facilitate the allocation of capital to the highest return projects. The fear is that when the financial system is impaired, investment is diminished and capital is less efficiently allocated. This issue is brought into sharp relief by the fall in productivity growth that has affected most major countries since the Great Recession. Falls or slowdowns in GDP per worker are a common feature of recessions, but the persistence of low productivity growth in the recovery period on this occasion has been an ongoing source of concern (e.g. Gordon, 2016; Summers, 2016). Although there is ample room for mismeasurement of productivity, it is difficult to believe that such problems have become so much worse in recent years that they can account for the drastic changes (see Byrne, Fernald and Reinsdorf, 2016 or Syverson, 2016). Countries with relatively large financial sectors appear to have been particularly affected by the slowdown. Figure 1.1.1 shows that in the UK GDP per hour was around 16% below its pre-crisis trend by the end of 2015.

Figure 1.1.1: **Whole Economy GDP per hour, 1979Q1 - 2015Q4 (2008Q2 = 100)**



Note: Whole Economy GDP per hour, seasonally adjusted (Q2 2008 =100). ONS Statistical Bulletin, Labour Productivity, Q4 2015. Predicted value after 2008Q2 is the dashed line, assuming a historical average growth of 2.3% per annum (the average over the period Q1-1979 to Q2-2008).

This paper develops a framework for studying financial frictions which can be applied to firm-level data. The UK is an excellent case study for this approach for three main reasons. First, although it has a relatively large financial services sector, there is a long-standing concern about how well that sector serves the real economy. Second, the UK's productivity performance has been consistently disappointing since the financial crisis. Third, we have access to firm-level data on firms' output, employment and investment decisions which can be matched to data on their perceived default probabilities, to create a unique data set where the ideas of the theory can be applied both to individual firms and the economy as a whole.

We begin by using the framework from Besley et al (2012) to motivate a specific measure of credit frictions where a sufficient statistic for credit market access and the allocation of capital is the probability that a firm is able to pay its credit obligations. This can be quantified using a firm-level credit-scoring model. The model also gives a simple micro-foundation of the financial frictions driving the firm-specific "tax rates" on the rental price of capital in, for example, Hsieh and Klenow (2009). The approach can be embedded in a standard model of firm heterogeneity to study how competition between lenders, lenders' funding costs, productivity, demand or asset value shocks affect aggregate output and productivity. The impact of these shocks is heterogeneous across firms and is summarised in each firm's equilibrium repayment probability.

To apply this model, we use a large administrative establishment-level panel data set, the Annual Business Inquiry and Annual Business Survey (ABI/ABS), which provides measures of value added, employment, and capital expenditures. The main innovation in the empirical approach, which provides a direct link to theory, is the use of an estimate of each firm's probability of default (PD) as an empirical measure of its access to credit. Specifically, we use the "PD Model" of Standard and Poor's, a tool that is widely used for firm-level credit scoring in financial markets and hence is likely to affect access to credit by firms. PD Model uses a combination of financial accounts data, industry, and macroeconomic factors to assess the credit risk of a company. Together with population data on private and publicly listed incorporated company accounts, this allows us to construct a firm-specific time-varying financial friction measure. We use it to study firm-level behaviour and to estimate measures of aggregate output loss following the underlying theory as a guide.

Our micro-level analysis validates the role of a firm's probability of default as an important determinant of its performance (e.g. capital investment, employment, value added, and the probability of survival). Our macro-level analysis suggests that credit frictions caused on average a 6.6% to 8.6% annual loss of UK GDP between 2004 and 2012 when compared to the frictionless benchmark. Credit frictions depressed output pre-crisis but were particularly acute at the height of the financial crisis in 2008 and 2009. They help account for between a quarter and a third of the aggregate productivity fall. Furthermore, these factors also dragged on throughout the post-crisis period, which helps account for the near stagnation of productivity in the recovery. The model can also account for between a quarter and a third of the difference between current UK productivity and its pre-crisis trend.

We also highlight three further findings that speak to on-going debates about the role of credit in the macro-economy. First, our results are driven by worsening credit conditions across firms as a whole rather than increasing misallocation of credit to less productive firms as in Hsieh and Klenow (2009) or Gopinath et al (2015). Second, credit frictions play a larger role in depressing output and labour productivity among Small and Medium Sized enterprises (SMEs). This appears consistent with the fact that SMEs are more dependent on bank financing and face tighter credit constraints than larger firms. Interestingly, the aggregate deterioration is driven almost entirely by increasing credit frictions for SMEs. Third, there is heterogeneity across sectors with construction, and hotels and restaurants being the worst affected by credit frictions on average - two sectors in which the productivity slowdown was particularly strong. All three of these findings make use of the fact that we use firm-level data to look at the macro-economic picture.

The remainder of the paper is organized as follows. In section 1.2, we review some relevant background literature. Section 1.3 develops the conceptual framework. It presents a model of the credit market where a firm's repayment probability is determined by optimal credit contracts in market equilibrium. We show how the repayment probability is a sufficient statistic for capital allocation across firms. Section 1.4 derives empirical implications in a model with heterogeneous firms. It identifies a way of quantifying the impact of credit frictions, measured in terms of equilibrium repayment probabilities, on aggregate output and labour productivity. Section 1.5 describes the data set and discusses how the key variables from the theory can be measured. Results are discussed in Section 1.6 and Section 1.7 concludes.

1.2 Related Literature

Our approach follows the spirit of the literature on the aggregate consequences of firm-level distortions[2]. This literature shows how firm-specific distortions to output or input prices can lead to sizeable decreases in aggregate output and measured total factor productivity (TFP) by distorting the allocation of inputs (and hence the size of firms) and the selection of firms producing in the market. The approach relies on model-based measures of firm-level distortions which can be estimated empirically. The model also guides the empirical evaluation of the impact of those distortions on aggregate productivity. The measured distortions can result from a large number of policy-induced frictions, for example labour market regulation or preferential interest rates to state-owned firms. Our aim is to isolate the distortions that result from financial frictions. An example of a parallel approach is Gilchrist, Sim, and Zakrajsek (2012). Distortions are embodied in firm-specific borrowing costs, measured for a subset of U.S. manufacturing firms using the interest rate spreads on their outstanding publicly-traded debt. While borrowing costs are also firm-specific in our analysis, we show that it is the firm's probability of default which is key as capital allocation adjusts to equate the marginal product of capital to a risk-adjusted cost of lending to a particular firm.

During recessions the economy is expected to shed its less productive firms (Caballero and Hammour, 1994), but these cleansing effects can be weakened during crises of a financial nature. There is a large empirical and theoretical literature which examines why banking crises may slow down aggregate productivity growth by reducing the efficiency of resource allocation across firms. When capital markets are imperfect, the availability of finance (internal or external) becomes an important determinant of a firm's investment[3]. In a banking crisis bank-dependent firms (typically smaller and younger) face a credit crunch, potentially forcing them to forgo profitable investment opportunities. This may impede the entry or growth of high productivity firms that are bank-dependent, or cause them to exit. Reduced competitive pressure from bank-dependent firms may also delay the exit of low productivity firms that do not depend on bank finance, or allow them to maintain market share. These ideas have been explored in papers such as Caballero and Hammour (2005), Barlevy (2003), Khan and Thomas (2013), and Midrigan and Xu (2014). Cerra and Saxena (2008) show that recessions associated with a financial crisis

[2] See among others Foster, Haltiwanger and Krizan (2002), Restuccia and Rogerson (2008) and Bartelsman, Haltiwanger and Scarpetta (2013). See Disney et al (2003) on UK manufacturing.

[3] See Bond and Van Reenen (2007) for a survey.

tend to be deeper and longer lasting in terms of output losses. Oulton and Sebastiá-Barriel (2013) suggest that financial crises permanently reduce the long-run level of productivity. Foster et al (2014) find that the intensity of reallocation fell rather than rose in the US during the Great Recession. In addition, the reallocation that occurred was less productivity enhancing than in previous recessions.

Forbearance is another channel by which a financial crisis might distort resource allocation. Forbearance is the practice of providing measures of support to a borrower struggling to meet its debt obligations. It may be applied by troubled banks as they seek to avoid crystallizing losses on their balance sheets. There is evidence that Japanese banks widely practiced forbearance in the early 1990s[4] - prolonging the Japanese "Lost Decade". There is some evidence of this phenomenon happening in the UK.

In the case of the UK productivity slowdown, a range of explanations have been put forward but work on the role of credit supply remains sparse[5]. Franklin et al (2015) use financial statement data for a set of UK firms and information on the identity of firms' lenders in the pre-crisis period to identify the negative impact of the contraction in credit supply on labour productivity, wages and the capital intensity of production at the firm level. Using decomposition techniques to separate contributions to aggregate productivity of business restructuring and of productivity growth within firms, Barnett et al (2014) and Riley et al (2015) find that the within-firm component accounts for the vast majority of the fall in UK productivity. These papers also provide some evidence of reallocation being subdued during the crisis. Barnett et al (2014) find that the contribution from reallocation declined in 2008-2009 and became negligible between 2010 and 2012, instead of increasing significantly as one would expect in a recession. They estimate that less efficient reallocation and slower creative destruction account for around one third of the decline in average annual productivity growth between 2002-2007 and 2008-2011. Similarly, Riley et al (2015) find that the growth contribution of both between-firm effects (changes in market share among continuing firms) and net entry were more subdued between 2007 and 2013 than between 1998 and 2007. Those two papers also provide some evidence of a weakening correlation between firms' health and their investment and employment behaviour.

[4]See Peek and Rosengren (2005) and Caballero, Hoshi and Kashyap (2008).

[5]For example, Bryson and Forth (2015) and Bank of England Quarterly Bulletin (2013).

1.3 Conceptual Framework

The lending model is based on Besley et al (2012). The aim is to provide a tractable framework where the main financial friction is the probability of default which affects access to capital. In the model, borrowers (firms) and lenders (banks) interact in a credit market. Firms have collateralizable assets on their balance sheets. We derive the properties of optimal credit contracts and show how competition between lenders affects the division of surplus between the firm and the bank, and the equilibrium probability of default of the borrower. Our measure of imperfect competition is captured by the cost of switching lenders.

1.3.1 Basics

Firms Firms are heterogeneous and have inherent productivities/market opportunities which are summarised in a productivity parameter, θ, and own different levels of assets, A. They require capital to operate, which they must secure from the credit market or from their own resources. Let

$$\Pi(\theta, w, K)$$

be the conditional profit function where w is the wage, common to all firms, and K is productive capital. We assume that $\Pi(\theta, w, K)$ is increasing in θ, increasing and concave in K and $\Pi_{\theta K} > 0$, i.e. more productive firms have a higher marginal product of capital. The price of output is normalized to one. The framework allows for conventional productivity shocks which affect θ. However, demand shocks will also affect θ. Total capital of the firm, K, is equal to borrowed capital B plus assets A.

To model the possibility of default, we suppose that prior to production taking place, firms make a strategic managerial decision, denoted by $E \in [0, 1]$, which determines the probability that they can produce successfully. With probability E, output is successful and with probability $(1 - E)$, it is zero. So E corresponds directly to a firm's default probability. The cost of managerial effort, in utility terms is $c(E)$ and we assume that this function is increasing and convex with $c'''(E) > 0$. Managers who take this decision are assumed to be residual claimants on the firm's profits.

Banks Banks may offer loans to a firm based on its productivity and assets. A credit contract is a pair $\{B, R\}$ which comprises the amount borrowed, B, and the amount to repay, R. Hence

$(R-B)/B$ is the conventional interest rate. Banks care about whether firms repay their loans, which depends on E. We assume that lenders can access funds at opportunity cost $\rho > 1$. This could be from deposits or through interbank lending. A lender's expected profit when lending to a firm with assets A is:

$$ER + (1-E)A - \rho B.$$

With probability E, the bank is repaid and with probability $(1-E)$, it seizes the firm's collateral[6].

1.3.2 Optimal Lending Contracts

We determine an optimal credit contract for a firm of type $\{\theta, A\}$. We first consider incentive compatible effort, E. Then we look at the bank's choice of loan and interest rate. Finally, we model competition between banks.

Incentive Compatibility and Optimal Effort The expected profits of a firm under contract $\{B, R\}$ are:

$$E\left[\Pi(\theta, w, K) - R + A\right] - A - c(E) \tag{1.3.1}$$

where the total capital available is $K = A + B$. The first order condition for managerial effort (the incentive compatibility constraint) is:

$$\left[\Pi(\theta, w, K) - R + A\right] = c'(E). \tag{1.3.2}$$

It is easy to see from 1.3.2 that such effort is increasing in A and K and decreasing in R, all else equal. In other words, a firm with more collateral will face a higher cost of default and higher repayments to the bank reduce the incentive to repay.

Suppose that the outside option to a firm is u and is binding[7]. Then:

$$E\left[\Pi(\theta, w, K) - R + A\right] - A - c(E) = u. \tag{1.3.3}$$

Combining this with 1.3.2 implies that the level of effort exerted by managers in a firm with assets A and outside option u is:

$$E = \phi(u + A) \tag{1.3.4}$$

[6]It would be straightforward, at the cost of greater notational complexity, to allow for only some assets in a firm's balance sheet to be used as collateral.

[7] We show below that this need not be the case in which case the firm earns an efficiency payoff which gives it an incentive to repay the bank.

where $\phi(x)$ is defined from $\phi(x)c'(\phi(x)) - c(\phi(x)) = x$.[8] It is easy to check that $\phi(\cdot)$ is an increasing function of $(u + A)$.

Optimal Contracts Solving 1.3.3 for R and using 1.3.4 yields the following expression for the amount that will be repaid, given a level of capital, K, collateral, A and outside option u:

$$R(K, A, u) = \Pi(\theta, w, K) + A - \frac{u + A + c(\phi(u + A))}{\phi(u + A)} \tag{1.3.5}$$

Substituting this into the profit function yields the following expression for the bank's expected profit:

$$V(A + B, A, u) = \phi(u + A)\Pi(\theta, w, A + B) - u - c(\phi(u + A)) - \rho B. \tag{1.3.6}$$

The only endogenous variable in 1.3.6 is B. The first order condition for profit maximization yields:

$$\Pi_K\left(\theta, w, \hat{K}(\theta, \rho, u + A)\right) = \frac{\rho}{\phi(u + A)} \tag{1.3.7}$$

assuming an interior solution[9]. A necessary condition for any lending to take place is therefore that $\hat{K}(\theta, \rho, u + A) > A$.

Equation 1.3.7 is the core equation for capital allocation. To interpret it, recall that $\phi(u + A)$ is the loan repayment rate which depends on the share of the surplus that the firm receives, u, and the collateral that it can offer, A. In the absence of default, where $\phi(u + A) = 1$, the marginal product of capital is set equal to the funding rate ρ. Otherwise, there is less capital offered to the firm which depends on its perceived default rate. Firms get less capital, all else equal, when the probability of default is higher[10]. Although one can solve for an expression for the lending interesting rate $(R - B)/R$, the latter is not sufficient to capture access to credit since both lending and borrowing are being adjusted optimally in the contracts that are struck between lenders and borrowers.

Equilibrium Contracts The capital allocation and credit contract derived in the last section is a function of the firm's outside option. This is determined by the borrowing opportunities that the firm can receive elsewhere, which determines the division of surplus in the lending arrangement. We now explore how this division takes place.

[8] The assumption that $c'''(e) > 0$ ensures that $\phi(x)$ is a concave function.

[9] This requires that A be small enough. If A is large enough, the firm will choose not to borrow.

[10] As emphasised in Besley et al (2012), Equation 1.3.7 does not give any direct prediction about the interest rate at which firms are able to borrow since both B and R are endogenous.

Define $v = (u + A)$ as a sufficient statistic for the efficiency of the lending relationship. Now observe that the total surplus from undertaking the project with borrowing is given by:

$$S(v, \theta, A, \rho) = \phi(v) \Pi\left(\theta, w, \hat{K}(A, \rho, v)\right) - c(\phi(v)) - \rho\left[\hat{K}(\theta, \rho, v) - A\right]$$

for $\hat{K}(\theta, \rho, v) \geqslant A$. Using the arguments in Lemma 1 of Besley et al (2012), it is straightforward to show that $S(v, \theta, A, \rho)$ is increasing and concave in v for $v \in [\underline{v}(\theta, \rho), \bar{v}(\theta, \rho)]$ where $S_v(\underline{v}(\theta, \rho), \theta, A, \rho) = 0$ and $S_v(\bar{v}(\theta, \rho), \theta, A, \rho) = 0$. This says that there is an efficiency payoff $\underline{v}(\theta, \rho)$ (akin to an efficiency wage) below which it is counterproductive for a bank to push a firm since it reduces the managers' effort too much. There is also an upper bound on the payoff, $\bar{v}(\theta, \rho)$, which is reached at the point where the firm generates the first-best level of effort at which surplus is maximized. Using 1.3.4, it is clear that managerial effort is increasing on $[\underline{v}(\theta, \rho), \bar{v}(\theta, \rho)]$ as the firm is getting a larger share of the surplus.

Let

$$u^a(\theta, A, \rho) = \max_{(E,K)} \{E\Pi(\theta, w, K) - \rho[K - A] - c(E) : K \leqslant A\}$$

be a firm's outside option if it finances its investment out of retained earnings (autarky). A firm has sufficient internal funds to achieve its first-best capital allocation if and only if $A \geqslant \hat{K}(\theta, \rho, \bar{v}(\theta, \rho))$.

Competition divides the surplus between banks and firms. However, this also affects efficiency since a firm that can capture a large share of the surplus will have a lower default probability and hence more capital in line with 1.3.7. To model competition in a simple way, we suppose that each firm is initially allocated to a bank and can consider the possibility of switching at cost σ[11]. We do not need to be specific about how many active banks there are as long as there are at least two willing to serve any given firm[12]. Let M be the number of banks and let m denote a typical bank. We consider the following timing:

1. Firms are initially randomly allocated to a bank.

2. Banks post a menu of contracts available to *any* type of firm denoted $\{B^m(\theta, A), R^m(\theta, A)\}$ for $m = 1, .., M$.

[11]See Klemperer (1987) for a discussion on the importance of switching costs. Kim et al (2013) estimate such costs for banking. Since only existing firms pay switching costs, this would give new entrants a competitive advantage. We abstract from this here as we consider firms that are already active in the market.

[12] This is analogous to a model of Bertrand competition in the absence of capacity constraints.

3. Firms choose which contract to take. Those who switch to an alternative bank pay the switching cost σ.

4. Loans are made and effort decisions are chosen.

5. Firms produce if they are successful and repay their loans. Otherwise a firm defaults and its collateral is seized by the bank.

We look for a Nash equilibrium where banks do not wish to deviate from the contracts that they offer and firms choose the contract that is best for them from among those available. The following result is proven in Appendix 1.A:

Proposition 1. In a market equilibrium, the payoff of a firm of type $\{\theta, A\}$ is given by

$$U(\theta, A, \sigma, \rho) = \max\left\{u^a(\theta, A, \rho), u^b(\theta, A, \sigma, \rho)\right\}$$

where

$$u^b(\theta, A, \sigma, \rho) = \begin{cases} S(\bar{v}(\theta,\rho), \theta, A, \rho) - \sigma & \text{for } \hat{u}(\theta, A, \rho) > \bar{v}(\theta, \rho) - A \\ \hat{u}(\theta, A, \rho) - \sigma & \text{for } \hat{u}(\theta, A, \rho) \in [\underline{v}(\theta, \rho) - A, \bar{v}(\theta, \rho) - A] \\ \underline{v}(\theta, \rho) - A & \text{for } \hat{u}(\theta, A, \rho) < \underline{v}(\theta, \rho) - A + \sigma. \end{cases}$$

and $\hat{u}(\theta, A, \rho) = S(\hat{u}(\theta, A, \rho) + A, \theta, A, \rho)$.

The first observation is that a firm cannot do worse than under autarky. When it borrows from a bank, the terms that it receives depend on its productivity, θ, and assets, A, which affect its ability to offer collateral. The outside option will be set by the maximum amount that another bank will offer to the firm, i.e. the value of u which results in zero profits for the bank. A firm with sufficient assets A will be able to achieve the first-best effort this way. However, the switching cost will mean that they will not be offered such an arrangement with their existing lender. Hence the switching cost reduces efficiency. The same is true in the middle case where the outside bank will not offer a first-best contract. Finally, when the outside option is to offer the efficiency outcome, then it is not optimal for the current bank to offer less than this, so in this case σ does not matter to the firm's payoff. The firm's participation constraint is not binding in this case. However, a higher σ increases the range over which this minimum payoff is made, i.e. it could arise even when the lender offers more than the minimum payoff. Thus, a switching cost shifts the whole equilibrium contracting possibility set downwards. Note that factors which lower the equilibrium payoff of the firm also make it more likely that a firm will prefer to use its own resources rather than borrowing at all.

This result has implications for the default probability of firms in market equilibrium:

Corollary: A firm is less likely to default *ceteris paribus*, if:

1. It is more productive (higher θ),
2. It has more collateral (higher A),
3. There is greater competition among banks (lower σ),
4. Bank funding costs are lower (lower ρ).

The first two of these predictions are about idiosyncratic variation across firms, while the latter two are macro effects affecting all firms. The default probability is a sufficient statistic for capital allocation using Equation 1.3.7. Indeed, our model gives a market equilibrium micro-foundation for capital misallocation in a model such as that put forward by Hsieh and Klenow (2009). In our setting the "tax rate" on capital to a firm is

$$\tau\left(U\left(\theta, A, \sigma, \rho\right) + A\right) = \frac{1 - \phi\left(U\left(\theta, A, \sigma, \rho\right) + A\right)}{\phi\left(U\left(\theta, A, \sigma, \rho\right) + A\right)}$$

where, as above, $\phi\left(U\left(\theta, A, \sigma\right) + A\right)$ is the repayment rate. This wedge is endogenous in the model since it depends on $U\left(\theta, A, \sigma, \rho\right) + A$ as determined in Proposition 1.

It is arguable that all four of the effects mentioned in the corollary were at work during the credit crunch in the UK. First, banks' funding conditions deteriorated due to stress in financial markets in general. An indicator of bank funding conditions is the cost of insuring bank senior unsecured debt against the risk of default. This is given by a bank's Credit Default Swap (CDS) premium. The average annual CDS premium for the 6 major UK banks stood at 21.34 basis points in 2007. It peaked at 211.28 basis points in 2012[13]. The true cost of granting new loans is likely to be even higher because it is affected by the need to repair balance sheets and adhering to stricter capital requirements.

Second, the valuation of commercial real estate (CRE) registered a sharp decline during the crisis, thereby reducing firms' debt capacity. According to Benford and Burrows (2013), by the end of 2007 CRE loans represented more than a third of the stock of lending to UK private non-financial companies by UK-resident banks. Since the availability of pledgeable assets has

[13] Bank of England, Trends in Lending January 2014.

been shown to influence debt capacity, the fall in valuation may have played an important role in the decline in corporate investment[14].

Finally, competition in the UK banking sector was negatively affected during the crisis. There have been long-standing concerns about the effectiveness of competition in the retail lending market[15] and the financial crisis has led to an increase in concentration in retail banking through mergers and exits from the market[16]. In 2010, concentration was higher than before the crisis in many retail banking sub-markets, in particular SME banking (Independent Commission on Banking, 2011). In addition, the UK SME banking sector has long been characterized by very low switching rates (OFT, 2006, 2010). In our framework, σ can be interpreted as a switching cost or as increasing local monopoly power so that a borrower cannot access another bank conveniently in a neighborhood when concentration increases. These imperfections will also interact with θ, the firm's underlying productivity. Falls in θ may also reflect reductions in demand which affect the relative price of the firm's goods. In short, the model gives an insight into the various factors that increased probabilities of default and worsened the allocation of capital after 2008. The impact of these shocks is summarised in each firm's equilibrium probability of repayment.

1.4 Empirical Implications

We now derive the empirical implications of the model. Let N_t be the number of firms active at date t with characteristics $\{\theta_{nt}, A_{nt}\}_{n=1}^{N_t}$. We allow (σ_t, ρ_t) to be time dependent to reflect shocks to competition and funding costs.

1.4.1 Firm-Level Implications

To generate implications for output, investment and employment, we will use a Lucas span of control model with production function:

$$Y_{nt} = \theta_{nt} \left(L_{nt}^{1-\alpha} K_{nt}^{\alpha} \right)^{\eta}$$

[14] See for example Gan, 2007, and Chaney, Sraer and Thesmar, 2012.

[15] There have been several studies on this topic since 2000: the Cruickshank report into competition in UK banking (2000), the Competition Commission's inquiry into SME Banking (2002), the Office of Fair Trading's (OFT) Survey of SME Banking (2006), the OFT's Review of Barriers to Entry, Expansion and Exit in Retail Banking (2010) and the Final Report of the Independent Commission on Banking (2011).

[16] In particular the mergers of Lloyds TSB with HBOS and Santander with Alliance & Leicester have removed the most compelling challengers identified by the OFT before the crisis.

with $\eta < 1$. In this world, profits are a return to the ownership of technology represented by θ_{nt}[17]. Labour is fully flexible while capital is determined by a firm's interaction with banks as described above. To describe the factor allocation for a firm with characteristics $\{\theta_{nt}, A_{nt}\}$, note that it is as if the firm faces factor prices $\{w_t, \hat{\rho}(\theta_{nt}, A_{nt}, \sigma_t, \rho_t)\}$ where

$$\hat{\rho}(\theta_{nt}, A_{nt}, \sigma_t, \rho_t) = \frac{\rho_t}{\phi(U(\theta_{nt}, A_{nt}, \sigma_t, \rho_t) + A_{nt})}.$$

$U(\theta_{nt}, A_{nt}, \sigma_t, \rho_t)$ is determined in Proposition 1 along with Equation 1.3.7. Factor demands maximise the objective function

$$\theta_{nt}\left(L_{nt}^{1-\alpha}K_{nt}^{\alpha}\right)^{\eta} - w_t L_{nt} - \hat{\rho}(\theta_{nt}, A_{nt}, \sigma_t, \rho_t) K_{nt}$$

Note that A affects firm decisions only through its impact on the price of capital. This yields the first-order conditions for labour and capital:

$$\eta(1-\alpha)\frac{Y_{nt}}{L_{nt}} = w_t \text{ and } \eta\alpha\frac{Y_{nt}}{K_{nt}} = \hat{\rho}(\theta_{nt}, A_{nt}, \sigma_t, \rho_t).$$

Hence

$$Y_{nt} = \theta_{nt}\left(\left[\frac{\eta(1-\alpha)Y_{nt}}{w_t}\right]^{(1-\alpha)}\left[\frac{\eta\alpha Y_{nt}}{\hat{\rho}(\theta_{nt}, A_{nt}, \sigma_t, \rho_t)}\right]^{\alpha}\right)^{\eta}$$

Solving for Y_{nt} yields the output of firm n at date t:

$$Y_{nt} = Y(\theta_{nt}, A_{nt} : \rho_t, \sigma_t) = \theta_{nt}^{\frac{1}{1-\eta}}\psi(w_t, \rho_t)\,\phi(U(\theta_{nt}, A_{nt}, \sigma_t, \rho_t) + A_{nt})^{\frac{\eta\alpha}{1-\eta}}$$

where $\psi(w,z) = \left(\frac{w}{\eta(1-\alpha)}\right)^{-\frac{\eta(1-\alpha)}{1-\eta}}\left(\frac{z}{\eta\alpha}\right)^{-\frac{\eta\alpha}{1-\eta}}$. Suppose also that we have data on the repayment probability of each firm, then

$$\phi_{nt} = \phi(U(\theta_{nt}, A_{nt}, \sigma_t, \rho_t) + A_{nt})$$

[17] The model could also be interpreted as a model with monopolistic competition where

$$\eta = 1 - \frac{1}{\varepsilon}$$

and ε is the elasticity of demand.

Taking logs yields

$$\log(Y_{nt}) = \log(\psi(w_t, \rho_t)) + \frac{1}{1-\eta}\log(\theta_{nt}) + \frac{\eta\alpha}{1-\eta}\log(\phi_{nt}). \tag{1.4.1}$$

Output is an increasing function of the repayment probability, all else equal. Firm-level productivity θ_{nt} should also matter along with factors which affect factor prices. The optimal capital stock, K_{nt}, is given by

$$\begin{aligned} \log(K_{nt}) &= \log\left(\frac{\eta\alpha\phi_{nt}}{\rho_t}\right) + \log(Y_{nt}) \\ &= \log(\eta\alpha) + \log\left(\frac{\psi(w_t, \rho_t)}{\rho_t}\right) + \frac{1}{1-\eta}\log(\theta_{nt}) \\ &\quad + \left[\frac{1-\eta(1-\alpha)}{1-\eta}\right]\log(\phi_{nt}). \end{aligned}$$

Capital is also increasing in the repayment probability. Hence we would expect factors which make repayment more likely to increase the use of capital. As in the case of total output, firm level productivity should also matter alongside macro effects which affect factor prices.

1.4.2 Aggregate Implications

To generate aggregate implications, we sum expected output across firms. Expected output of firm n at date t is:

$$Y_{nt}^e = \phi(U(\theta_{nt}, A_{nt}, \sigma_t, \rho_t) + A_{nt})\, Y(\theta_{nt}, A_{nt} : \rho_t, \sigma_t)$$

Hence, aggregate expected output in the economy is:

$$\begin{aligned} Y_t^e &= \sum_{n=1}^{N} \phi(U(\theta_{nt}, A_{nt}, \sigma_t, \rho_t) + A_{nt})\, Y(\theta_{nt}, A_{nt} : \rho_t, \sigma_t) \\ &= \sum_{n=1}^{N} \theta_{nt}^{\frac{1}{1-\eta}} \psi(w_t, \rho_t)\, \phi(U(\theta_{nt}, A_{nt}, \sigma_t, \rho_t) + A_{nt})^{1+\frac{\eta\alpha}{1-\eta}} \\ &= \hat{\theta}_t^{\frac{1}{1-\eta}} \psi(w_t, \rho_t) \sum_{n=1}^{N} \left(\frac{\theta_{nt}}{\hat{\theta}_t}\right)^{\frac{1}{1-\eta}} \phi(U(\theta_{nt}, A_{nt}, \sigma_t, \rho_t) + A_{nt})^{1+\frac{\eta\alpha}{1-\eta}} \end{aligned}$$

Let

$$\omega(\theta_{nt}) = \left(\frac{\theta_{nt}}{\hat{\theta}_t}\right)^{\frac{1}{1-\eta}} \tag{1.4.2}$$

be productivity weights such that $\sum_{n=1}^{N} \omega(\theta_{nt}) = 1$ at each t. Then for

$$\sum_{n=1}^{N} \left(\frac{\theta_{nt}}{\hat{\theta}_t}\right)^{\frac{1}{1-\eta}} = 1$$

we require that $\hat{\theta}_t = \left(\sum_{n=1}^{N_t} (\theta_{nt})^{\frac{1}{1-\eta}}\right)^{1-\eta}$. Now

$$Y_t^e = \psi(w_t, \rho_t)\, \hat{\theta}_t^{\frac{1}{1-\eta}} \sum_{n=1}^{N} \omega(\theta_{nt})\, \phi\left(U(\theta_{nt}, A_{nt}, \sigma_t, \rho_t) + A_{nt}\right)^{1+\frac{\eta\alpha}{1-\eta}}$$

The key magnitude for the efficiency loss due to imperfect credit markets is

$$\Theta(\sigma_t, \rho_t) = \sum_{n=1}^{N} \omega(\theta_{nt})\, \phi\left(U(\theta_{nt}, A_{nt}, \sigma_t, \rho_t) + A_{nt}\right)^{1+\frac{\eta\alpha}{1-\eta}}. \tag{1.4.3}$$

$\Theta(\sigma_t, \rho_t)$ is a weighted average of repayment probabilities with productivity weights. If there is no default, i.e. $\phi(U(\theta_{nt}, A_{nt}, \sigma_t, \rho_t) + A_{nt}) = 1$ for all n, then $\Theta(\sigma_t, \rho_t) = 1$ and output is at its first-best level. Equation 1.4.3 provides the link between factors affecting access to capital and the credit crunch. Reduced competition (higher σ_t) and a higher funding cost (ρ_t) reduce output. A reduction in asset values, e.g. a first order stochastic dominating shift in the marginal distribution of A_n will also lower output. Below, we provide estimates of $\Theta(\sigma_t, \rho_t)$ and how it has changed over time using firm-level data from the UK.

Suppose that ρ_t is determined in global capital markets. Using the first-order condition for labour and Equation (1.4.3), the equilibrium real wage solves

$$w_t = \left[(1-\alpha)\,\eta \left(\psi(w_t, \rho_t)\, \hat{\theta}_t^{\frac{1}{1-\eta}}\right) \Theta(\sigma_t, \rho_t)\right] / L \tag{1.4.4}$$

assuming an exogenously fixed aggregate labour supply of L. The output loss due to credit market imperfections, i.e. the difference between actual expected output and expected output in a situation where there is no default, denoted by Y_t^*, is given by[18]:

$$\frac{Y_t^* - Y_t^e}{Y_t^*} = 1 - \Theta(\sigma_t, \rho_t)^{\frac{1-\eta}{1-\alpha\eta}}. \tag{1.4.5}$$

$\Theta(\sigma_t, \rho_t)$ is a sufficient statistic for gauging the aggregate output loss in the economy due to capital market imperfections. The model also gives a prediction for how aggregate labour

[18]See Proof in Appendix 1.B.

productivity depends on credit market frictions:

$$\log\left(w_t\right) = \text{constant} - \frac{\eta\alpha}{1-\alpha\eta}\log\left(\rho_t\right) + \frac{1-\eta}{1-\alpha\eta}\left[\log\left(\Theta\left(\sigma_t,\rho_t\right)\right) + \frac{1}{1-\eta}\log\left(\hat{\theta}_t\right)\right]. \quad (1.4.6)$$

Hence the change in aggregate labour productivity between two dates can be decomposed into three factors:

$$\Delta\log\left(w_t\right) = \frac{1-\eta}{1-\alpha\eta}\left[\Delta\log\left(\Theta\left(\sigma_t,\rho_t\right)\right) + \frac{1}{1-\eta}\Delta\log\left(\hat{\theta}_t\right)\right] - \frac{\eta\alpha}{1-\alpha\eta}\Delta\log\left(\rho_t\right) \quad (1.4.7)$$

This gives three natural components of aggregate productivity shocks. The term $\Delta\log\left(\Theta\left(\sigma_t,\rho_t\right)\right)$ reflects changes in repayment probabilities and will capture changes in credit allocation coming via changes to repayment probabilities and how these are distributed across firms. The term $\Delta\log\left(\hat{\theta}_t\right)$ picks up aggregate productivity shocks and could be thought of as also reflecting demand shocks. Finally $\Delta\log\left(\rho_t\right)$ reflects the price of funds available for credit allocation.

1.5 Data and Measurement

In this section, we describe our data sources and show how the key theoretical concepts can be measured empirically. Technical details are relegated to the Appendix. The main concept of interest is $\Theta\left(\sigma_t,\rho_t\right)$.

1.5.1 Firm Productivity and Size

Our main sources of firm-level data are the Annual Business Inquiry and the Annual Business Survey (ABI/ABS). These are establishment-level business surveys conducted by the UK Office for National Statistics (ONS). They are primarily used in the construction of various national account aggregates for the UK [19]. The sampling frame is the Inter-Departmental Business Register (IDBR). The surveys are a census of larger businesses and a stratified random sample (by industry, region and employment size) of businesses with fewer than 250 employees (SMEs). The surveys cover the entire private sector from 2002 onwards and some sectors, such as manufacturing, back to 1979. We drop agriculture, mining and quarrying and utilities as well as sectors where output is particularly hard to measure - education, health care, financial

[19] See e.g. Barnett et al (2014) and Riley et al (2015) for useful discussions of these data sets and recent work on productivity using them. Details of the ABI and ABS data can also be found in Griffith (1999) and Bovill (2012) respectively.

services, real estate and non-profit organizations. We refer to the sectors we keep as the "market sector". Sampling weights are applied to ensure that our results are representative of aggregate productivity developments (see Appendix 1.C.1 for more details on the sampling frame and weights). Table 1.5.1 shows the number of employees for the market sector. We cover on average 15.6 million employees per year, roughly split in half between SMEs and larger firms. Tables 1.D.1 and 1.D.2 in the Appendix give more details about this population of firms.

Table 1.5.1: **Employment in the market sector - by size**

	Total	**SMEs**	**% of total**	**Large firms**	**% of total**
2004	15,340,910	7,817,579	50.96	7,523,331	49.04
2005	15,527,559	7,960,666	51.27	7,566,893	48.73
2006	15,603,305	8,025,709	51.44	7,577,596	48.56
2007	15,427,650	7,993,888	51.82	7,433,762	48.18
2008	16,196,539	8,387,324	51.78	7,809,215	48.22
2009	15,923,921	8,150,652	51.18	7,773,269	48.82
2010	15,292,144	7,948,642	51.98	7,343,502	48.02
2011	15,450,091	8,052,564	52.12	7,397,527	47.88
2012	15,710,015	8,218,774	52.32	7,491,241	47.68
Average	*15,608,015*	*8,061,755*	*51.65*	*7,546,260*	*48.35*

Note: Number of employees in the "market sector" (entire population). "Market sector" stands for all sectors covered in the ABI/ABS, except those for which output is hard to measure: financial services, non-market service sectors (e.g. education, health, social work and the public sector), agriculture, mining and quarrying, utilities, real estate, and non-profit organizations. Sampling weights are applied to ensure that our estimation results are representative of aggregate productivity developments in this population (see Appendix 1.C.1 for more details on the sampling frame and weights). SMEs are firms with under 250 employees.

We measure labour productivity as real gross value added (GVA) per employee using industry producer price deflators. We truncate the top and bottom 1% of the labour productivity distribution in the ABI/ABS market sector sample to ensure that our results are not driven by extreme values. We construct capital stocks using the Perpetual Inventory Method based on industry-level capital stocks, investment (gross fixed capital formation), as well as investment deflators split by asset and industry obtained from the ONS Volume of Capital Services data set (see Appendix 1.C.2 for details).

The productivity fall observed in aggregate statistics in Figure 1.1.1 is also apparent in the ABI/ABS surveys. Table 1.5.2 reports estimates of the evolution of aggregate labour productivity (2007 = 100) for the period 2005-2012 based on three different sources (i) the entire ABI/ABS market sector data set, (ii) the smaller core sample of firms from the ABI/ABS which we use for our estimates and whose construction is described below and (iii) the numbers from official publications[20].

Table 1.5.2: **Aggregate labour productivity, Index 2007 = 100**

	ABI/ABS market sector	Calibration sample	ONS sector publications
2005	88.88	90.16	93.53
2006	92.85	93.52	96.99
2007	100	100	100
2008	98.21	99.4	100.9
2009	89.77	91.3	94.34
2010	97.3	98.37	97.27
2011	99.55	100.29	98.53
2012	100.32	101.24	98.83

Note: Index 2007=100. Labour productivity is defined as real gross value added (GVA) per employee. "ABI/ABS market sector" refers to the entire ABI/ABS market sector (i.e. we drop agriculture, education, health, social work, mining and quarrying, utilities, real estate and finance). "Calibration Sample" refers to the sub-sample of the ABI/ABS market sector for which we have data on probabilities of default and positive capital stock estimates. "Sector publications" refer to estimates of aggregate labour productivity based on the sectoral figures (4-digit SIC) released publicly by the ONS for the sectors included in the sample (See ONS UK non-financial business economy Statistical bulletins, for example: http://www.ons.gov.uk/businessindustryandtrade/business/businessservices /data sets/uknonfinancialbusinesseconomyannualbusinesssurveysectionsas).

Across all series we observe that productivity fell sharply in 2009 and recovered very slowly thereafter. Note that the core sample that we use for our estimates (Column (2)) appears representative of the economy as a whole. At Q4 2012 (the end of our sample period), labour productivity was 11% lower than it would have been had it continued on its post-1970 trend (see Figure 1.D.1)[21]. There is some evidence of sector level heterogeneity, but again the broad pattern is similar (Table 1.5.3). The sectors worst hit in terms of labour productivity in 2009 were construction, hotels/restaurants and business services - all these are quite reliant on commercial property. The productivity decline was accompanied by a fall in business investment that was significantly larger than in previous recessions (Benito et al, 2010). It took until the third quarter of 2013 for business investment to reach its level in the second quarter of 2008 (Figure 1.5.1). There are many factors that could explain the decline in investment such as weak demand, pessimism over future productivity growth and uncertainty.

[20] Sector publications refer to estimates of aggregate labour productivity based on the sectoral figures (4-digit SIC) released publicly by the ONS for the sectors included in the sample (See ONS UK non-financial business economy Statistical bulletins).

[21] The trend assumes a historical average growth of 2.3% per annum (the average over the period Q1-1979 to Q2-2008). The productivity gap is close to that estimated using national accounts data.

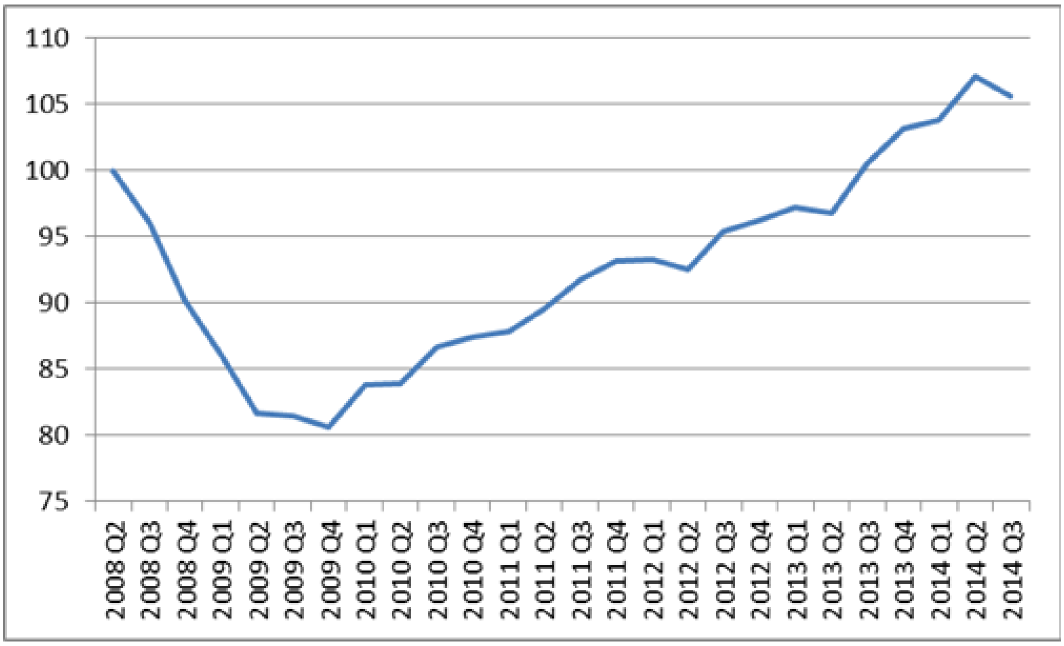
Table 1.5.3: **Annual labour productivity growth (in %) by firm size and sector**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All firms	**SMEs**	**Large firms**	**Manufacturing**	**Construction**	**Wholesale and retail trade**	**Hotels and restaurants**	**Transport, storage and communication**	**Business services**
2005	4.8	7.1	2.6	4.1	5.1	1.0	-0.7	5.0	12.0
2006	3.7	5.6	1.8	1.4	1.4	7.7	8.0	2.1	3.9
2007	6.9	5.6	8.0	15.3	4.6	1.1	4.8	5.7	9.0
2008	-0.6	-0.4	-0.9	2.4	-5.0	-10.4	-1.2	-4.0	5.4
2009	-8.2	-8.6	-7.8	-5.2	-17.3	-4.6	-9.4	-5.9	-9.5
2010	7.7	8.5	7.2	8.0	12.1	3.4	6.6	6.7	11.0
2011	2.0	1.0	3.0	7.0	-1.1	3.2	3.4	3.8	-1.2
2012	0.9	1.8	0.0	-3.1	-4.6	1.9	0.6	-5.4	6.4
Employees (2012)	15,710,015	8,218,774	7,491,241	2,471,350	1,182,144	4,463,108	1,779,978	1,358,337	4,455,098

Note: Labour productivity is defined as real gross value added per employee. Sectors are defined at the SIC 1992 section level. "Business services" is sector K excluding real estate. SMEs are firms with strictly fewer than 250 employees. Large firms are firms with 250 employees or more.

But the financial crisis also led to a sharp decline in bank lending to non-financial firms. The contraction in bank lending to the corporate sector in the UK continued long after the height of the financial crisis. While large firms can have recourse to other sources of finance, for instance by issuing bonds or equities, SMEs are more likely to be constrained. They are also more dependent on banks for their external finance[22].

Figure 1.5.1: **Gross Fixed Capital Formation by UK businesses, 2008 Q2=100**



Source: ONS Statistical Bulletin, Business Investment, Q3 2014 Revised Results, 23 December 2014. Series Business Investment, Chained Volume Measure, seasonally adjusted.

1.5.2 Financial Statements and Default Probabilities

A unique feature of our study is that we have estimates of firms' repayment probabilities ϕ_{nt} (we generally work with the default probability, $\delta_{nt} = (1 - \phi_{nt})$. In order to estimate δ_{nt}, we use financial statement data from Orbis in combination with S&P's "PD Model". The PD Model is a web-based credit scoring facility which uses a combination of financial accounts data, industry, and country-specific macroeconomic factors to assess the credit risk of a company. The scoring algorithm can be applied both to private and public firms. Financial inputs include for example total assets, cash on the balance sheet, pre-tax profits (EBIT), and total liabilities. Our source of information for company accounts is Bureau Van Dijk's (BVD) Orbis database[23]. The model

[22] In 2010, only around 2% of SMEs used external equity as a source of finance (BIS, 2010). Armstrong et al (2013) show that SMEs have faced a very challenging environment for accessing credit after the financial crisis and during the subsequent recession.

[23] Since smaller firms typically have less stringent reporting requirements, they are subject to more missing values in the BvD Orbis database. However, PD Model can handle missing values for non-essential inputs. As a robustness

also incorporates a score which reflects the risk of doing business in a certain industry based on factors such as market concentration, market size, and the regulatory regime.

The PD Model's primary output is the probability that the firm will default within one year estimated using data on actual defaults provided by various regulators[24]. The model then maps the probabilities of default into risk scores (called implied credit worthiness) using forward-looking expectations. The scores are expressed using S&P's traditional rating symbols, ('triple A' = aaa, 'triple B' = bbb, etc.). These risk scores are the basis for our estimation of historical probabilities of default. We are interested in the *historical* perception of default probabilities, i.e. the probability of default as perceived at the time of the financial accounts data. We obtain data on observed default rates in the entire universe of firms rated by S&P from S&P CreditPro. The data incorporate observed default rates by risk category up to each year in our sample, i.e. up to 2005 for perceived probabilities of default in 2005, up to 2006 for perceived probabilities of default in 2006, etc. The historical one-year probability of default is the probability that the firm will default within one year as perceived at the time. The financial data and the default probabilities were linked to our ABI/ABS data set by the UK Data Service (See Appendix 1.C.3 and Table 1.D.3).

The increase in default probabilities in our sample reflects the deterioration of credit conditions faced by UK firms during and after the financial crisis. Figure 1.5.2 shows the evolution of the aggregate probability of default of UK firms, by size category[25]. This shows clearly that default probabilities are systematically higher for SMEs - consistent with the idea that lenders regard SMEs to be riskier[26]. Second, the time series pattern suggests that there is a tendency for default probabilities to increase among SMEs throughout the sample period but particularly after 2007 (with a slight recovery in 2012). This is consistent with evidence from Armstrong et al (2013) that SMEs faced severe credit constraints during the crisis. The time series pattern for large firms is generally much flatter; there is some deterioration during the financial crisis

check, we impute missing values ourselves using regressions where possible before feeding the financial data into the software.

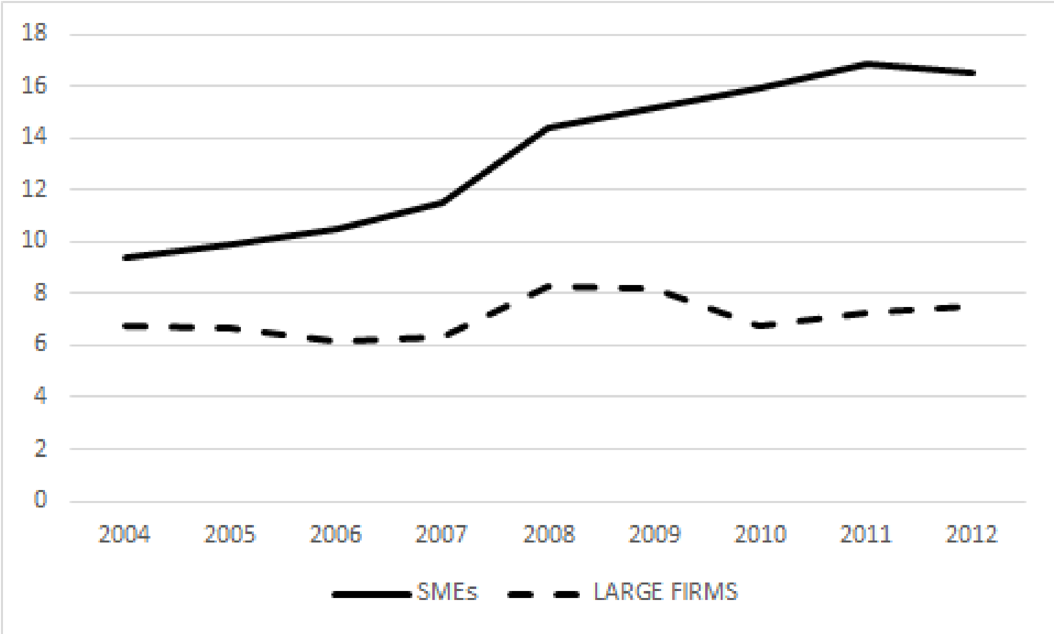
[24]PD Model takes into account a variety of default events, for example: The bank considers that the obligor is unlikely to pay its credit obligations to the banking group in full, without recourse by the bank to actions such as realizing security (if held); the obligor is past due more than 90 days on any material credit obligation to the banking group. Elements taken as indications of unlikeliness to pay include, among others: The bank consents to a distressed restructuring of the credit obligation; the bank sells the credit obligation at a material credit-related economic loss; the firm has been placed in bankruptcy. Note that bankruptcy (exit from the market) only represents a minority of default events.

[25]The aggregate probability of default is a weighted average of industry-level probabilities of default, where the weights are industry shares in total employment. Industry-level probabilities of default are themselves weighted averages of firm-level probabilities of default by industry, where the weights are sample weights.

[26]This is implied by our model as they have a lower value of θ_n.

followed by a recovery.

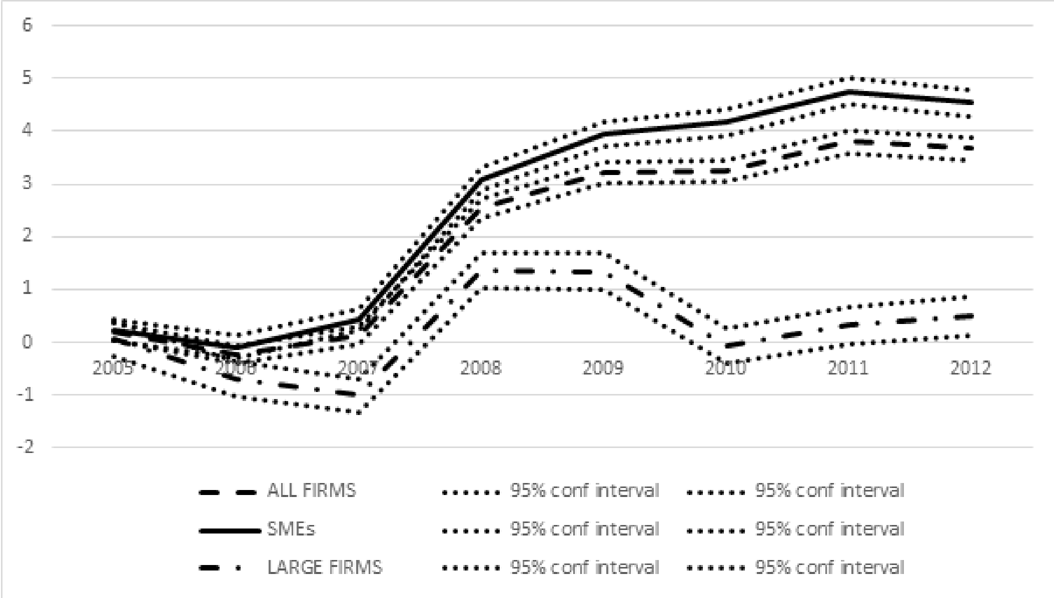
Figure 1.5.2: **Aggregate probability of default at the 1-year horizon (in %) - by firm size**



Note: A firm's probability of default is the probability that it will default on its payments at the one-year horizon estimated using S&P's PD Model and historical default rates from S&P's CreditPro. SMEs (solid line) are firms with fewer than 250 employees. Large firms (dashed line) are firms with 250 employees or more. Default probabilities are estimated at the firm level and aggregated using sampling weight corrections.

Figure 1.5.3 presents an alternative picture of the data. We regress probabilities of default on year dummies (with 2004 as our base year) controlling for two-digit industries. This shows that there is an increase in default probabilities coming from the PD model for all firms after 2007 and that it is statistically significant. It is also largely driven by SMEs, which motivates looking further at differences between large firms and SMEs in the analysis of the data below.

Figure 1.5.3: **Firm one-year ahead Default Probabilities (controlling for industry) - by firm size**



Note: Coefficients(*100) on year dummies from regression of firm-level 1-year PDs on year and industry dummies (reference year=2004). PD is the probability that a firm will default on its payments within 1 year. Industry fixed effects are at the two digit level. SMEs (solid line) are firms with fewer than 250 employees. Large firms (dash-dot line) are firms with 250 employees or more.

1.5.3 Sample

Our core sample is a sub-sample of the ABI/ABS market sector. The key data requirements are the availability of a positive capital stock estimate for each firm[27]. We have on average 24,000 establishments each year. Large establishments (250 employees or more) make up on average around 18% of the sample and 89% of employment. We correct for the over-representation of large establishments using sampling weights. While the core sample covers approximately 65% of firms in the entire ABI/ABS market sector, it covers approximately 97% of total employment.

1.5.4 Measuring the key theoretical concepts

Equation 1.4.3 suggests a particular quantification of aggregate credit market frictions, Θ_t, whose measurement can be approached in different ways depending on how the parameters are chosen and the productivity weights are constructed. In all of the empirical exercises below, η is set equal to $\frac{3}{4}$[28].

[27]The capital stock is needed for TFP estimation and the calculation of productivity weights. We also require a default probability. About 22% of valid ABI/ABS establishments are not directly matched, so these are imputed (see Data Appendix for details). The results are robust to not imputing any data.

[28]See for example Bloom (2009).

We use two main approaches. The first involves estimating the productivity weights ω_{nt} defined in Equation 1.4.2 using firm-level TFP estimates. To do so, we compute firm-level capital stocks by applying a Perpetual Inventory Method using the ABI/ABS capital expenditures (see Appendix 1.C.2)[29]. We then construct a Solow residual to measure TFP, $\hat{\theta}_{nt}$. In our baseline we set $\alpha = 1/3$ in all industries. As an alternative we use industry-specific factor shares calculated from the data (See Appendix 1.D.1 for details on the estimation of the capital share consistent with the model). The second approach relies exlcusively on employment data, without the need for TFP estimates. Since there are many measurement issues with firm-level data, particularly as regards calculating the capital stock (e.g. De Loecker, Jan and A. Collard-Wexler, 2016), we also estimate productivity differences across firms using data on employment shares by implementing Equation 1.5.3 below. This approach uses the theoretical structure of the model to obtain an estimate of underlying TFP without using information on capital or value added.

Employment in firm n at date t is

$$L_{nt} = \frac{(1-\alpha)\eta Y^e_{nt}}{w_t}. \tag{1.5.1}$$

Denote with γ_{nt} the average employment share of firm n at date t in total industry employment defined as

$$\gamma_{nt} = \frac{L_{nj}}{\sum_{n=1}^{N_{jt}} L_{nj}} \tag{1.5.2}$$

where L_{nj} is the average employment of firm n in industry j over the sample period and N_{jt} is the number of firms in industry j at date t. Combining Equations (1.5.1) and (1.5.2) and substituting for Y^e_{nt} and w_t, the model implies that

$$\gamma_{nt} = \frac{\omega_{nt}\phi_{nt}^{1+\frac{\eta\alpha}{1-\eta}}}{\Theta_t}$$

This suggests another way of estimating the productivity weights and Θ_t using the observable employment shares and data on ϕ_{nt}. We can back out productivity weights from the following equation:

$$\omega_{nt} = \frac{\gamma_{nt}\Theta_t}{\phi_{nt}^{1+\frac{\eta\alpha}{1-\eta}}} \tag{1.5.3}$$

where Θ_t is pinned down so that $\sum_{n=1}^{N} \omega_{nt} = 1$. The advantage of this method is that it circum-

[29]There are many approaches to estimating TFP using firm level data. At the micro-level, different methods tend to produce highly correlated TFP estimates (Syverson, 2011).

vents the estimation of firm-level TFP. The estimation of TFP relies on the correct measurement of capital expenditures (much harder to measure than employment), the assumptions made in the PIM, and the estimation method. Therefore, the use of directly measured employment shares provides a useful robustness check for the results obtained via TFP estimation. We implement this estimate using $\alpha = \frac{1}{3}$ in all industries and empirical factor shares as an alternative.

1.5.5 Sampling adjustments

Since our sample is a survey, we also need to use sampling weights. The ABI and ABS surveys contain grossing weights which reflect the survey design (See Appendix 1.C.1 for more details). Denote the sampling weight of firm n in year t with ξ_{nt} . A firm's sampling weight represents the inverse of its sampling probability. For empirical purposes, we measure firms' underlying productivities θ_{nt} by averaging the period-by-period measures over 1990-2012. Averaging should help mitigate measurement error in the measurement of productivity. Conceptually, it also makes sense to think of firms having fixed productivities over a relatively short window of time. Let θ_n denote our time-invariant estimate of firm-level productivity. Aggregate expected output in the economy is then given by:

$$Y_t^e = \psi\left(w_t, \rho_t\right) \hat{\theta}_t^{\frac{1}{1-\eta}} \sum_{n=1}^{N} \tilde{\omega}\left(\theta_n, \xi_{nt}\right) \phi\left(U\left(\theta_n, A_{nt}, \sigma_t, \rho_t\right) + A_{nt}\right)^{1+\frac{\eta\alpha}{1-\eta}} \tag{1.5.4}$$

where $\hat{\theta}_t = \left(\sum_{n=1}^{N_t} \left(\xi_{nt}\, \theta_n\right)^{\frac{1}{1-\eta}}\right)^{1-\eta}$ and $\tilde{\omega}\left(\theta_n, \xi_{nt}\right) = \left(\frac{\xi_{nt}\, \theta_n}{\hat{\theta}_t}\right)^{\frac{1}{1-\eta}}$ are sampling-adjusted productivity weights. By construction, these weights sum to one at each date, i.e. $\sum_{n=1}^{N} \tilde{\omega}\left(\theta_n, \xi_{nt}\right) = 1$ at each t.

1.5.6 From industry Θ to aggregate Θ

We construct an aggregate value of credit market frictions, Θ_t, by first constructing a measure for each 3-digit industry j, Θ_{jt}. This will permit us, should we choose, to allow for technology differences across industries and will also mean that we can look at credit frictions by industry. For each j, we have a sample N_{jt} of firms at date t and for each firm, we have a measure of the repayment probability, ϕ_{njt}, of firm n in industry j at date t, generated using the PD Model. We then obtain an economy-wide measure by weighting industries with their respective shares in total employment in year t, denoted by χ_{jt}. Putting this together, we have the following estimate of the aggregate effect of credit frictions:

$$\Theta_t = \sum_{j=1}^{J} \chi_{jt}\Theta_{jt} = \sum_{j=1}^{J} \chi_{jt} \left(\sum_{n=1}^{N_{jt}} \tilde{\omega}_{njt}\phi_{njt}^{1+\frac{\eta\alpha}{1-\eta}} \right)$$

where

$$\tilde{\omega}_{njt} = \tilde{\omega}\left(\theta_{nj}, \xi_{nt}\right) = \left(\frac{\xi_{nt}\theta_{nj}}{\left(\sum_{n=1}^{N_{jt}} \left(\xi_{nt}\theta_{nj}\right)^{\frac{1}{1-\eta}}\right)^{1-\eta}} \right)^{\frac{1}{1-\eta}}.$$

is the sampling-adjusted productivity weight of firm n at time t with respect to its industry j.

1.6 Evidence

We begin by looking at the firm-level implications outlined in Section 1.4.1 and then turn to quantifying the macroeconomic effects of credit frictions following the analysis in Section 1.4.2.

1.6.1 Firm-level Outcomes

We consider eight different firm-level outcomes: employment, value-added, total purchases (inputs), total assets, investment[30], capital stock, fixed assets, and TFP. We estimate the following empirical model for firm n in industry j at date t:[31]

$$ln(y_{njt}) = \beta\delta_{njt} + a_n + \tau_t + \varepsilon_{njt} \tag{1.6.1}$$

where y_{njt} is the performance outcome, δ_{njt} is the default probability[32], a_n are firm fixed effects, τ_t are year dummies and ε_{njt} is a serially correlated error term (we allow it to be clustered by firm). The data for these regressions are from the ABI/ABS surveys except for total assets and fixed assets, which are from Orbis. As an alternative to firm fixed effects, we also estimate Equation 1.6.1 using only industry dummies. In our baseline specifications, the variable δ_{njt} is the firm's predicted default probability at t using the PD model parameters and information on the firm available at $t-1$.

[30] Linking back to the theory, estimating an investment equation makes sense if there are adjustment costs which imply that

$$investment_{njt} = \zeta\left[K^*_{njt} - \left(1 - d_{jnt}\right)K_{njt}\right]$$

where K^*_{njt} is the optimal capital stock and d_{njt} is the depreciation rate.

[31] Strictly speaking, the data is for an establishment rather than a firm but we use the term firm throughout.

[32] This semi-log format uses the approximation $\ln\phi_{njt} = \ln\left(1-\delta_{njt}\right) \simeq -\delta_{njt}$.

For all of our outcome measures, we expect $\beta < 0$, i.e. higher predicted default is associated with worse firm-level performance. These regressions can be viewed primarily as validating the default probabilities estimated using financial statements from Orbis, rather than being indicative of a causal relationship between credit and firm-level behaviour. By putting them in the form of a sufficient statistic suggested by the theory, this will also include judgement made by financial modelers who create the PD model on behalf of their clients in the financial sector. We will now show that there is a robust reduced-form correlation between these performance measures and the estimated default probabilities.

The results are in Table 1.6.1 where Panel A controls for industry fixed effects and Panel B for firm fixed effects[33]. There is a robust negative and significant correlation between the firm-specific default probability and all performance variables in both panels. Across seven of the eight outcomes the coefficient on the default probability is larger in Panel A than in Panel B which is consistent with the fact that δ_{njt} is correlated with unobserved productivity differences (as confirmed by the last column for TFP).

[33] There are fewer observations in Panel B as it conditions on the sub-sample where there are least two or more observations per establishment in order to estimate the fixed effects.

Table 1.6.1: **Firm performance and lagged default probabilities**

PANEL A: Industry fixed effects								
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	Ln(N)	**Ln(GVA)**	**Ln(Purchases)**	**Ln(TA)**	**Ln(Net capex)**	**Ln(K)**	**Ln(FA)**	**Ln(TFP)**
Lagged Default	-3.340***	-4.192***	-3.998***	-5.115***	-4.796***	-4.207***	-5.760***	-0.383***
Probability	(0.070)	(0.075)	(0.086)	(0.093)	(0.099)	(0.090)	(0.108)	(0.028)
Observations	80,942	80,942	80,942	80,942	80,942	80,942	80,942	80,942
R^2	0.111	0.122	0.178	0.14	0.133	0.201	0.16	0.212
PANEL B: Firm fixed effects								
	Ln(N)	**Ln(GVA)**	**Ln(Purchases)**	**Ln(TA)**	**Ln(Net capex)**	**Ln(K)**	**Ln(FA)**	**Ln(TFP)**
Lagged Default	-0.104***	-0.620***	-0.222***	-0.387***	-0.932***	-0.082***	-0.382***	-0.463***
Probability	(0.026)	(0.045)	(0.041)	(0.037)	(0.097)	(0.021)	(0.057)	(0.036)
Observations	60,798	60,798	60,798	60,798	60,798	60,798	60,798	60,798
R^2	0.981	0.944	0.963	0.983	0.827	0.993	0.969	0.824

Notes: **N**=Employees; **TA**=Total assets; **K**=Capital stock estimate in real terms; **FA**=Fixed assets; **Purchases**=Total purchases of goods and materials; **TFP**=TFP estimate; **Net capex**=Real net capital expenditures; **GVA**=Real gross value added. OLS estimates with standard errors clustered by firm in parantheses; *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. Data runs from 2004-2012. Data on employment, value added, purchases, investment, capital and TFP are from the ABI/ABS. Data on total assets and fixed assets from BVD Orbis. "Lagged Default Probability" is the firm's estimated one year ahead probability of default from Standard and Poor's PD model. Full set of year dummies in all models. Both panels condition on a sub-sample with non-missing values on all left-hand side variables. Panel B also conditions on a sub-sample with at least two firm-level observations (in order to be able to include firm fixed effects).

The coefficients are non-trivial in an economic as well as a statistical sense. For example, a ten percentage point increase in the default probability (similar to the rise suffered by SMEs over the sample period) is associated with a 9% fall in investment (Column (5))[34] and a 6% fall in value added (Column (2)) in the fixed effects specifications of Panel B.

The findings in Table 1.6.1 are robust to a large number of alternative ways of looking at the data with an extensive range of possibilities in Appendix 1.D.4. First, Table 1.D.4 winsorizes the outcomes in the top and bottom percentiles to check that the results are not driven by outliers. Second, Table 1.D.5 relaxes the restriction of having a common sample across all firms and uses the maximum number of ABI/ABS observations to generate the regressions.[35] Third, Table 1.D.6 shows that higher default risk significantly decreases a firm's probability of survival. This is encouraging since our measure of default at face value is based on the idea that a firm cannot operate when it defaults. Of course, this is extreme and the default risk estimated with PD Model captures a swathe of default events, bankruptcy being only one of them which may explain the small coefficient. Hence, in a fully dynamic model, it is possible that firms can reschedule their debts rather than disappearing completely. Finally, Table 1.D.7 shows some results using ORBIS data before we match them into the ABI/ABS. This enables us to use an even bigger sample (e.g. approximately 8.3 million observations in Column (4) using net assets). The negative correlations with the default probability are also clear in this case.

Taken together, these results are consistent with the role of the default probability in affecting firm-level behaviour as suggested by the theory. Firms with high default probabilities will tend to have less access to capital with potential knock-on effects to employment and fixed assets, conditional on their underlying productivity. Perhaps most importantly, these results show that the default probability estimates from the PD model predict firm-level outcomes, even with firm fixed effects. These probabilities are drawn from an entirely different source compared to the data from which firm outcomes are drawn. Hence, they provide encouragement for using these default probabilities, together with our estimates of firm-level productivity, to look at aggregate credit frictions.

[34] %Δ Net capex = 100*$\beta * \Delta\delta$.

[35] The final column also shows that default risk can be a proxy for access to credit as the probability of default has a negative correlation with a firm's annual change in total debt.

1.6.2 Aggregate Outcomes

1.6.2.1 Main Results

We now turn to the analysis of the macroeconomic effects of credit frictions following Section 1.4.2 where we report estimates of the efficiency losses from credit market frictions as measured by Equation 1.4.5. There are two key dimensions to this. The first is to consider what estimates of Θ_t say about the magnitude of credit frictions in reducing output in the economy using the observation that $\Theta_t = 1$ is a world where all firms always repay their loans. The second is to ask how Θ_t has changed over time, particularly following the financial crisis, which can speak to debates about weak productivity growth in the post-crisis period.

The baseline estimates are reported in Columns (1) through (3) in Table 1.6.2 and assume that $\alpha = \frac{1}{3}$ (a 66.7% labour share). This is a standard macro-estimate of the labour share. Columns (4) through (6) in Table 1.6.2 use empirical estimates of the labour share.

Columns (1) and (4) in Table 1.6.2 contain our estimates of Θ_t while Columns (2) and (5) give implications of this for the percentage loss in GDP calculated from Equation (1.4.5).[36] Columns (3) and (6) look directly at the implications of the change in Θ_t for labour productivity using the estimates in Columns (2) and (5) respectively along with Equation (1.4.7), i.e. they contain an estimate of $\frac{1-\eta}{1-\alpha\eta}\left[\ln \Theta_t - \ln \Theta_{t-1}\right]$. This tells us what the model implies for the pattern of productivity growth. We can compare those patterns with what has actually happened.

Table 1.6.2 contains three notable findings. First, financial frictions matter. In Column (2) we estimate that UK output would have been on average 8.6% higher each year over our sample period in the absence of such frictions in each year. The overall impact of credit frictions is slightly lower in Column (5) compared to Column (2) with an average effect of frictions of 6.6%.[37] We are not aware of previous estimates of the impact of credit frictions against which to benchmark these. But they are a natural corollary of the fact that default risk in our model leads to less investment and hence a lower level of the aggregate capital stock. Below, we will discuss how these effects vary by types of firms.

[36] In our baseline calibration, $\alpha = \frac{1}{3}$ and $\eta = \frac{3}{4}$, so that Θ is raised to the power of one third.

[37] This is mainly because data suggest an empirical labour share of 78%, closer to three quarters than two-thirds.

Table 1.6.2: **The Effect of Credit frictions on Aggregate Output and Productivity**

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline: $\alpha = \frac{1}{3}$			Empirical value of industry labour share		
	Credit Friction Θ_t	**Percentage Output loss**	**Contribution to productivity growth**	**Credit Friction Θ_t**	**Percentage Output loss**	**Contribution to productivity growth**
2004	0.819	6.5		0.848	4.8	
2005	0.842	5.6	0.9	0.863	4.3	0.5
2006	0.805	7	-1.5	0.832	5.4	-1.1
2007	0.795	7.4	-0.4	0.825	5.6	-0.2
2008	0.764	8.6	-1.4	0.791	6.8	-1.2
2009	0.734	9.8	-1.3	0.767	7.7	-0.9
2010	0.729	10	-0.2	0.768	7.6	0
2011	0.702	11.1	-1.2	0.74	8.6	-1.1
2012	0.704	11.1	0.1	0.743	8.5	0.1
Average	0.766	8.6	-0.6	0.8	6.6	-0.5

Note: All estimates assume that $\eta = \frac{3}{4}$. The credit friction, Θ_t, is the estimate of aggregate financial market frictions derived in Equation (1.4.3). Output loss is the proportionate fall in output as a result of credit frictions calculated using Equation (1.4.5). The variable in Columns (3) and (6) is the annual % change in productivity resulting from changes in Θ_t estimated using Equation (1.4.7). Columns (1)-(3) assume $\alpha = \frac{1}{3}$ and columns (4)-(6) use the empirical labour share in each three-digit industry.

Second, there is an increase in these frictions over time, almost doubling between the first and last years in Column (2). In 2012, output was 11.1% lower than it would have been in the absence of these frictions compared to a 6.5% loss in 2004. The effects documented in Column (2) were particularly large in the depths of the financial crisis in 2007-08 and 2008-09 cumulatively lowering output by about 2.7%. This is almost a third of the actual change in labour productivity over this time period (31% = 2.7%/8.7%). Interestingly, our model suggests that financial frictions continued to worsen after 2009 which is consistent with the aggregate pattern of productivity shown in Figure 1.1.1 and Table 1.5.2.[38] In 2010 productivity rose, only to fall back again in the following two years. The last three columns of Table 1.6.2 show the same three broad stylized facts using empirical estimates of the labour share, and an average change of 0.5 percentage points in Column (6) compared to 0.6 percentage points in Column (3).

Third, the estimates in Column (2) of Table 1.6.2 suggest that labour productivity would be 3.7% higher in 2012 had financial frictions remained at their 2007 level (11.1% - 7.4%). Since data suggest that UK productivity would have been 11% higher in 2012 if growth had remained on its pre-crisis trend after 2007, this means that, using the estimates in Columns (1) through (3), financial frictions can account for about 34% (= 3.7%/11%) of this productivity puzzle. Using the estimates in Columns (4) to (6) with the empirical labour share, credit frictions account for about a quarter of the productivity fall in the financial crisis - 24% (=2.1%/8.7%) and 26% (=2.9%/11%) of the potential productivity gap. Either way, this does leave a substantial fraction of the weak productivity performance accounted for by other factors, such as weak demand (Summers, 2016) or a global slowdown of technological change (Gordon, 2016). Nonetheless, a quarter to a third of lower productivity related to ongoing problems in credit markets suggests an economically substantial effect.

Taken together, these results reinforce the idea that looking at the impact of credit market frictions through the lens of firm-level estimated default probabilities is a useful way of thinking about the aggregate performance of the UK economy since the financial crisis. The approach provides a novel way of looking at the role of financial frictions in shaping the trajectory of the economy. However, it also allows us to think about the loss in output due to such frictions in "normal times".

[38] One somewhat surprising finding in Table 1.6.2 is that there is a loss of productivity due to financial frictions of between -1.1% and -1.5% in 2006. This was the peak of the credit boom and we show below that this may have been due to increased misallocation associated with lax credit standards.

1.6.2.2 Extensions

We now exploit the fact that we have firm-level estimates to look at the findings in Table 1.6.2 in a more disaggregated way. We will also explore the robustness of the findings to alternative methods of estimation following Equation 1.5.3.

SMEs versus Large Firms We now decompose the aggregate estimate of Θ_t into two subgroups reflecting firm size (See Appendix 1.D.2 for more details). This is of interest since we have already seen from Figure 1.5.2 that there are substantial differences in the default probabilities of large and small firms, including how they have evolved since the financial crisis.

The results split by size are presented in Table 1.6.3, assuming that $\alpha = \frac{1}{3}$ and hence parallel the findings in Columns (1) through (3) of Table 1.6.2[39]. The left hand panel contains estimates for SMEs while the right hand panel is for large firms. These results show that, as we would expect from Figure 1.5.2, that the output losses due to credit frictions among SMEs are much larger than for large firms. In particular, the friction measure, Θ_t, is about twice as severe for SMEs (on average 8.5% vs. 4.3%), reducing their overall output by 11% in 2012 compared to 4.6% for large firms.[40] The worsening of financial frictions is also mainly due to credit access for SMEs. In 2004 the effect of such frictions was only a 6.3% output loss for SMEs and 3.9% for large firms, but by 2012 the size of the effect had risen to 11% and 4.6% respectively. While large firms did experience some deterioration in credit conditions during the financial crisis, these were less severe than the problems faced by SMEs. Moreover, conditions improved slightly in the recovery for large firms whereas they continued to get worse for SMEs.

[39] Results which parallel Columns (4) through (6) of Table 1.6.2 using the empirical labour share are in Table 1.D.8

[40] It is worth noting that the numbers in Table 1.6.2 are not simply a weighted average of those in Table 1.6.3 as there is also an effect from the allocation of credit between the SME and large firm sectors as a whole which will reflect the average default probabilities in the two sectors.

Table 1.6.3: **Table 6: The Effect of Credit frictions on Aggregate Output and Productivity: Broken down by firm size ($\alpha = \frac{1}{3}$)**

	(1)	(2)	(3)	(4)	(5)	(6)
	SMEs			Large firms		
	Credit Friction Θ_t	**Percentage Output loss**	**Contribution to productivity growth**	**Credit Friction Θ_t**	**Percentage Output loss**	**Contribution to productivity growth**
2004	0.822	6.3		0.887	3.9	
2005	0.840	5.6	0.7	0.890	3.8	0.1
2006	0.799	7.2	-1.7	0.898	3.5	0.3
2007	0.802	7.1	0.1	0.892	3.7	-0.2
2008	0.769	8.4	-1.4	0.863	4.8	-1.1
2009	0.733	9.8	-1.6	0.861	4.9	-0.1
2010	0.735	9.8	0.1	0.869	4.6	0.3
2011	0.707	10.9	-1.3	0.866	4.7	-0.1
2012	0.705	11.0	-0.1	0.869	4.6	0.1
Average	0.768	8.5	-0.7	0.877	4.3	-0.1

Note: All estimates assume that $\eta = \frac{3}{4}$. The credit friction, Θ_t, is the estimate of aggregate financial market frictions derived in Equation (1.4.3). Output loss is the proportionate fall in output as a result of credit frictions calculated using Equation (1.4.5). The variable in Columns (3) and (6) is the annual % change in productivity resulting from changes in Θ_t estimated using Equation (1.4.7). Columns (1)-(3) assume $\alpha = \frac{1}{3}$ and columns (4)-(6) use the empirical labour share in each three-digit industry. SMEs are defined as having under 250 employees, whereas large firms have 250 or more employees.

Misallocation of Capital Across Firms There are two aspects to the credit frictions that are studied here. First, there is the aggregate effect of shifts in perceptions of default in the economy as would occur in the face of a generalised financial crisis affecting all firms and lenders. The second concerns distortions in the allocation of credit across firms which can result in productive firms getting less credit than would be ideal. The latter has been the main focus of the recent literature on capital misallocation such as Hsieh and Klenow (2009). Here, we can explore the relative importance of these, both in terms of cross-sectional patterns across firms and in the dynamics of the financial crisis. This will make further use of the fact that we are using firm-level data. We investigate this issue in two ways, both of which are reported in Table 1.6.4. First, we decompose credit frictions into a mean and a covariance term. Second, we perform a counterfactual exercise where all firms in the same industry-year cell are assigned the *same* default probability. We describe those steps before turning to the results.

Decomposing Θ into a mean and a covariance term Omitting time subscripts for brevity, Θ in Equation 1.4.3 can be written as

$$\Theta = \sum_{n=1}^{N} \left[\omega_n - \frac{1}{N} \right] \phi_n^{1+\frac{\alpha\eta}{1-\eta}} + \frac{1}{N} \sum_{n=1}^{N} \phi_n^{1+\frac{\alpha\eta}{1-\eta}}. \tag{1.6.2}$$

When all firms are equally productive, $\sum_{n=1}^{N} \left[\omega_n - \frac{1}{N} \right] \phi_n^{1+\frac{\alpha\eta}{1-\eta}} = 0$. The first term is the covariance term - it captures how the productivity weights vary with the probabilities of repayment. The second term is the mean term - it captures the mean probability of repayment. See Appendix 1.D.3 for more details.

Column (1) in Table 1.6.4 reports the overall credit friction term, from Table 1.6.2 Column (1), for reference. We then decompose Θ_t into two components (i) a covariance (between firm) term in Column (2) and (ii) a mean (within firm) term in Column (3). The striking finding from this exercise is that the mean term is quantitatively much more important than the covariance term. Although the latter is mainly positive (i.e. firms with higher repayment probabilities are relatively more productive), it is always small by comparison. Moreover, the covariance term shows no consistent pattern of change throughout the sample period 2004-2012. Thus, the lion's share of the effect of financial frictions is due to the general level of perceived default rather than the way in which it is distributed across firms with heterogeneous productivity levels.

Counterfactual exercise Assume that each firm is assigned its industry average scaled probability of repayment, i.e. the mean of $\phi_{nt}^{1+\frac{\alpha\eta}{1-\eta}}$ (by industry-year) instead of its own probability of repayment. The resulting counterfactual industry-level Θ is

$$\Theta_{jt}\left(\sigma_t, \rho_t\right) = \sum_{n=1}^{N_{jt}} \omega\left(\theta_{njt}\right) \frac{1}{N} \sum_{n=1}^{N_{jt}} \phi_{njt}^{1+\frac{\alpha\eta}{1-\eta}} \tag{1.6.3}$$

When each firm is assigned its industry-level average probability of repayment, inter-industry variation in default probabilities drives all of the effects with no firm-level heterogeneity between firms within an industry.

Column (4) of Table 1.6.4 reports the implied effect on productivity growth from this counterfactual exercise. As a point of comparison, Column (5) gives the baseline productivity contributions (from Table 1.6.2 Column (3)) with the difference between Columns (4) and (5) reported in Column (6). This can be interpreted as the contribution to productivity growth of changes in the between-firm allocation of credit frictions. A negative number in Column (6) means that allocation would have been better had all firms within an industry had the same default probability. The results in Column (6) of Table 1.6.4 suggest that, on average, these between-firm effects within an industry depressed labour productivity by only 0.01% over 2005-2012. We find a larger effect in 2009, with larger within-industry misallocation effects reducing productivity growth by just under 0.9 percentage points. After a rebound in 2010, within-industry credit frictions continued to depress productivity in 2011-12, by 0.7% cumulatively. It is also interesting to note that within-industry credit frictions depressed productivity by 1.4% in 2006, at the height of the credit boom and account for essentially all of the negative aggregate effect of credit frictions (1.5%) in that year.

The main conclusion from these exercises is that our main findings in Table 1.6.2 are driven by a generalized deterioration in credit conditions across the broad swathe of firms (particularly SMEs), rather than credit markets failing to allocate capital to the more productive enterprises within industries. This conclusion is consistent with the findings of Gopinath et al (2015) that capital misallocation worsened in Southern Europe in the 2000s, but not in Northern EU countries like the UK. It is also consistent with the conclusions of Riley et al (2015) that the within-firm component accounts for most of the fall in UK productivity.

Calculations using employment data Since there are many measurement issues with firm-level data, particularly as regards calculating the capital stock (e.g. De Loecker, Jan and A. Collard-Wexler, 2016), we also estimate productivity differences across firms using only employment data by implementing Equation 1.5.3. This approach uses the theoretical structure of the model to obtain an estimate of underlying TFP without using information on capital or value added.

The results from this exercise are presented in Table 1.6.5 which mirrors Table 1.6.2. The effects of credit frictions on the level of output are very similar to those of Table 1.6.2, ranging between 8% in Column (2) and 6% in Column (5) on average. Using this approach to measuring firm-level productivity, the increase in credit market imperfections is also visible, especially during the financial crisis. The overall deterioration over 2004-2012 is somewhat smaller than in the baseline results however (about 60% from 6.3% in 2004 to 9.9% in 2012 compared to 70% in Table 1.6.2, from 6.5% to 11.1%). This gives some comfort for future research which does not have access to rich data sets which include capital information of the kind that we use here. The methodology that we suggest could still be implemented using a credit scoring model and, at least in our context, seems to generate similar qualitative results.

Table 1.6.4: **The Effect of Credit frictions on Aggregate Output and Productivity - Mean-covariance decomposition ($\alpha = \frac{1}{3}$)**

	(1)	(2)	(3)	(4)	(5)	(6)
	Credit Friction Θ_t	**Covariance term**	**Mean term**	**Contribution to productivity growth (Every firm gets its industry average) probability of default)**	**Contribution to productivity growth (Baseline)**	**Contribution of (mis)allocation to productivity growth relative to (4)**
2004	0.819	-0.012	0.830			
2005	0.842	0.022	0.820	-0.4	0.9	1.3
2006	0.805	-0.011	0.817	-0.1	-1.5	-1.4
2007	0.795	0.006	0.789	-0.9	-0.4	0.5
2008	0.764	0.015	0.748	-2.1	-1.4	0.7
2009	0.734	0.005	0.729	-0.4	-1.3	-0.9
2010	0.729	0.004	0.725	-0.6	-0.2	0.4
2011	0.702	0.006	0.696	-0.8	-1.2	-0.4
2012	0.704	0.014	0.690	0.4	0.1	-0.3
Average	0.766	0.005	0.760	-0.6	-0.6	-0.01

Note: All estimates assume that $\eta = \frac{3}{4}$ and $\alpha = \frac{1}{3}$. The credit friction, Θ_t, is the estimate of aggregate financial market frictions derived in the text. TFP is calculate based on a Solow residual. The credit friction is decomposed into a covariance term in Column (2) and a mean term in Column (3) as outlined in the text. As an alternative way of gauging misallocation across firms we give every firm the average default probability for the three digit industry in the relevant year and re-calculate the contribution to productivity growth as we did in Table 5 in Column (4). Column (5) reproduces the baseline. Column (6) is the difference between Columns (5) and (4) and measures the contribution of credit frictions between firms within an industry to productivity growth.

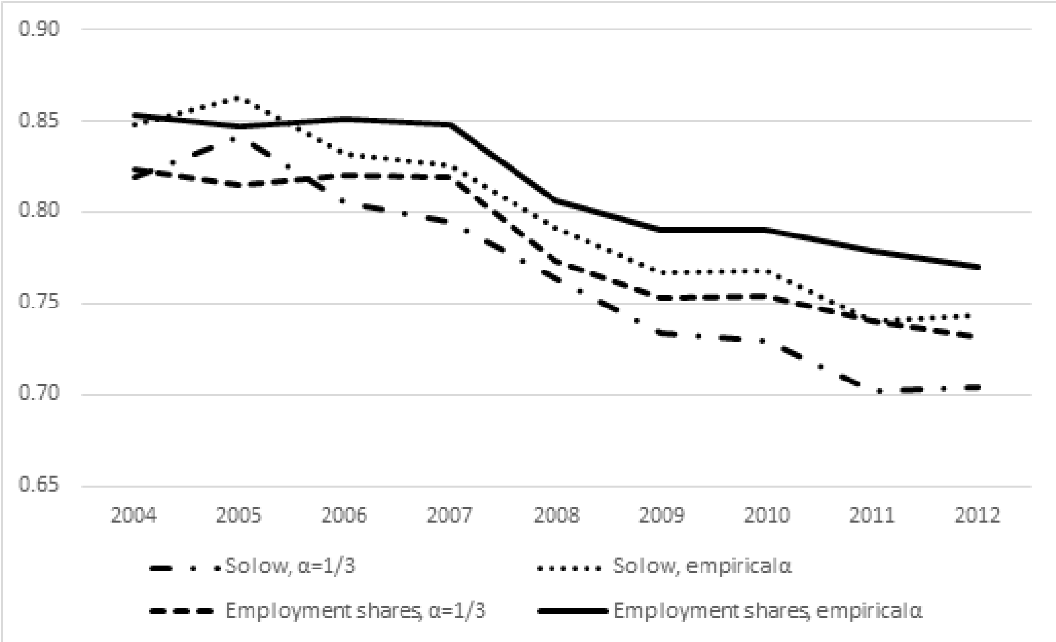
Table 1.6.5: **The Effect of Credit frictions on Aggregate Output and Productivity Growth Using Employment Data to Estimate Productivity**

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline: labour share $\alpha = \frac{1}{3}$			Empirical value of industry labour share		
	Credit Friction Θ_t	Percentage Output loss	Contribution to productivity growth	Credit Friction Θ_t	Percentage Output loss	Contribution to productivity growth
2004	0.823	6.3		0.853	4.6	
2005	0.815	6.6	-0.3	0.847	4.9	-0.2
2006	0.820	6.4	0.2	0.851	4.7	0.1
2007	0.819	6.4	-0.1	0.848	4.8	-0.1
2008	0.773	8.2	-1.9	0.806	6.3	-1.5
2009	0.753	9.0	-0.9	0.790	6.8	-0.6
2010	0.754	9.0	0.0	0.790	6.8	0.0
2011	0.740	9.5	-0.6	0.779	7.2	-0.4
2012	0.732	9.9	-0.4	0.770	7.5	-0.3
Average	0.781	7.9	-0.5	0.815	6.0	-0.4

Note: All estimates assume that $\eta = \frac{3}{4}$ The credit friction, Θ_t, is the estimate of aggregate financial market frictions derived in the text. Output loss is the proportionate fall in output as a result of credit frictions and is calculated using Equation 1.4.5. The variable in Columns (3) and (6) is the annual difference in the output loss. Columns (1)-(3) use $\alpha = \frac{1}{3}$ and columns (4)-(6) use a value based on the labour share in the three-digit industry.

Figure 1.6.1 gives an overview of our various estimates of financial frictions and shows that the qualitative features of our approach are robust to different estimation methods.

Figure 1.6.1: **Estimates of Θ_t - Comparing Approaches**



Note: Estimates of Θ_t based on the four estimation methods. "Solow, $\alpha = 1/3$" refers to TFP estimates based on a Solow residual with$\alpha = 1/3$. "Employment shares, $\alpha = 1/3$" refers to TFP estimates based on Equation 1.5.3 with $\alpha = 1/3$. "Solow, empirical α" refers to TFP estimates based on a Solow residual with labour shares calculated at the 3-digit industry level. "Employment shares, empirical α" refers to TFP estimates based on Equation 1.5.3 with labour shares calculated at the 3-digit industry level.

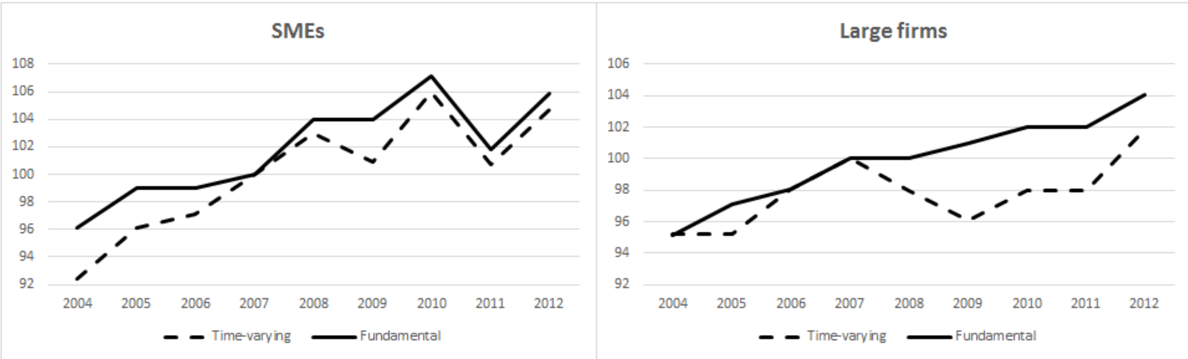
The Role of Demand Effects Table 1.6.3 showed that financial frictions appear to matter mainly in accounting for the poor productivity performance of SMEs compared to that of larger firms. This may seem puzzling since the productivity performance of larger firms does also appear to have been poor since the financial crisis. We now explore one possible explanation for this, namely that demand conditions weighed more heavily on larger firms. This is plausible since they are more exposed to international trade and weaknesses in the world economy.

Figure 1.6.2 plots aggregate TFP trends broken down by firm size in two different ways. First we aggregate the time-invariant firm-specific TFP estimates θ_n (the solid line)[41]. Changes in this over time are driven purely by changes in the size of firms with different (fixed) productivity levels and changes in the population of firms. Second, we aggregate the time-varying firm-specific TFP estimates θ_{nt} (the dotted line). The time invariant measure is intended to capture fundamental underlying TFP, whereas the time varying measure will also be influenced by demand shocks. Hence, the difference between the two lines gives a sense of the magnitude of any demand shock which is treated as exogenous in our model since it focuses exclusively on

[41] We first aggregate firm-level TFP at the industry level using sampling weights and then obtain an economy-wide estimate by aggregating industry-level TFP using each sector's share in total employment.

supply-side factors.

Figure 1.6.2: **Evolution of TFP based on Solow residual with $\alpha = \frac{1}{3}$ - SMEs versus Large firms, Index 2007=100**



Note: Estimates of aggregate TFP allowing firm-level efficiency to change over time (dashed line) vs. keeping it fixed over time (solid line).

In the right-hand Panel of Figure 1.6.2, we show the results for large firms. It shows that in the years 2008-2009 the actual TFP fall is large whereas there is little change in our measure of fundamental underlying TFP. This is suggestive of the idea that the fall in the measured productivity of large firms was in fact due to the fall in demand which would be part of $\Delta \ln \left(\hat{\theta}_t\right)$ in Equation 1.4.7. In the left-hand panel, we show parallel estimates for SMEs. It appears that any demand shock, as measured by the difference between the fundamental and time-varying TFP, was less severe for SMEs during and after the financial crisis.

1.7 Conclusion

This paper develops an approach to studying the role of credit frictions in affecting the aggregate performance of an economy. Beginning from a simple model of credit contracts with endogenous default driven by firm-level managerial effort, it shows how the default probability of a firm is a useful sufficient statistic for distortions in the allocation of capital. This motivates an empirical approach with a direct focus on assessments of default by lenders. This is measured by the "PD model" of Standard and Poor's that assesses each firm based on financial information. It gives an important window on the assessment of default given that such tools are part of the due diligence process used by lenders prior to making loans. Having incorporated financial data on firms along with the PD model, we merge this with a representative sample of UK firms' employment, investment and value added. This provides a unique data set with which we can assess the role of credit frictions since we can aggregate to provide a picture of the whole economy.

The approach confirms that credit frictions are important in the aggregate but weigh more heavily on SMEs rather than large firms. On average SMEs suffer output losses of around 8.5% from credit frictions while it is around half as big for large firms. The role of credit frictions came into sharp relief following the financial crisis. Our analysis based on the assessment made using the PD model suggests that the output loss increased overall to 11% from around 6% prior to the crisis. Moreover, this accounts for between a quarter and a third of the loss in productivity experienced in the UK. SMEs were particularly hard hit by the banking crisis and the increase in frictions has largely been driven by the SME sector. This suggests that the productivity problems of large firms are more likely to be related to other factors such as weak demand.

Another key finding is that most of the cost of credit frictions comes from the average assessment of expected default rather than the way in which it is distributed across firms within industries. The big story of the financial crisis as told through the lens of our approach is one of an aggregate shock to perceived default risk which drove down investment and real wages. That is not to say that credit frictions do not matter at the micro level. Along the way, we have shown that our default probability estimates predict firm-level decisions, even when we include firm fixed-effects. But across-firm misallocation does appear relatively unimportant in explaining macroeconomic effects compared to the core macroeconomic shock.

Our focus on the UK has been driven by the availability of data on firms' real decisions, their financial accounts and the output from a credit-scoring model. The general approach is of wider applicability especially given the importance of automated tools for assessing firm-level credit risk in many economies. This allows us to open up the "black box" of credit frictions in a specific way which is linked to an underlying theory and is relevant to a range of contexts and country experiences.

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Appendix

1.A Proof of Proposition 1

We have already shown that credit contracts are fully characterized once $\{\theta, A, u\}$ are known. It should also be clear that $u \geqslant u^a(\theta, A, \rho)$. Otherwise, the firm will choose self-finance. Now consider what happens when this constraint is not binding. The firm's bank needs to offer sufficient surplus to prevent the firm moving to another bank. Any other bank, will be willing to offer a contract up to point where it makes zero profit, i.e.

$$S(\hat{u}(\theta, A, \rho) + A, \theta, A, \rho) = \hat{u}(\theta, A, \rho).$$

Hence each firm has an outside option of $\hat{u}(\theta, A, \rho) - \sigma$, i.e. the maximum that another lender will offer less the switching cost. Otherwise, the firm will leave. (We assume, with loss of generality, that a firm will remain if they are indifferent.) Suppose that $\hat{u}(\theta, A, \rho) + A > \bar{v}(\theta, \rho)$, then $\hat{u}(\theta, A, \rho) = S(\bar{v}(\theta, \rho), \theta, A, \rho)$ and the inside bank will offer $S(\bar{v}(\theta, \rho), \theta, \rho) - \sigma$ and still retain the firm. Now suppose that $S(\underline{v}(\theta, \rho), \theta, A, \rho) + A < \underline{v}(\theta, \rho)$. Now $\hat{u}(\theta, A, \rho) = \underline{v}(\theta, \rho) - A$. It will never be optimal for the inside lender to offer a payoff less than this, so $u^b(\theta, A, \rho, \sigma) = \underline{v}(\theta, \rho) - A$ as claimed. Finally, consider the case where $\hat{u}(\theta, A, \rho) \in [\underline{v}(\theta, \rho) - A, \bar{v}(\theta, \rho) - A]$, then $u^b(\theta, A, \rho, \sigma) = \hat{u}(\theta, A, \rho) - \sigma$ as claimed.

1.B Derivation of the output loss

The output loss is $1 - \frac{Y_t^e}{Y_t^*}$, where $Y_t^e = \psi(w_t, \rho_t)\, \hat{\theta}_t^{\frac{1}{1-\eta}} \Theta(\sigma_t, \rho_t)$ and by definition $Y_t^* = \psi(w_t^*, \rho_t)\, \hat{\theta}_t^{\frac{1}{1-\eta}}$. Hence $\frac{Y_t^e}{Y_t^*} = \frac{\psi(w_t, \rho_t)}{\psi(w_t^*, \rho_t)} \Theta(\sigma_t, \rho_t)$. Remember that by definition $\psi(w_t, \rho_t) = \left(\frac{w_t}{\eta(1-\alpha)}\right)^{-\frac{\eta(1-\alpha)}{1-\eta}} \left(\frac{\rho_t}{\eta\alpha}\right)^{-\frac{\eta\alpha}{1-\eta}}$. Solving for w_t, we get:

$$w_t = (1-\alpha)\, \eta \psi(w_t, \rho_t)^{\frac{-(1-\eta)}{\eta(1-\alpha)}} \left(\frac{\rho_t}{\alpha\eta}\right)^{\frac{-\alpha\eta}{\eta(1-\alpha)}}$$

Substituting this into the wage equation (Equation 1.4.4) and solving for $\psi(w_t, \rho_t)$ we get:

$$\psi(w_t, \rho_t) = \left(\frac{\hat{\theta}_t^{\frac{1}{1-\eta}}}{L}\right)^{\frac{-\eta(1-\alpha)}{1-\alpha\eta}} \left(\frac{\rho_t}{\alpha\eta}\right)^{\frac{-\alpha\eta}{1-\alpha\eta}} \Theta(\sigma_t, \rho_t)^{\frac{-\eta(1-\alpha)}{1-\alpha\eta}} \tag{1.B.1}$$

Note that the first two terms are aggregate entities not affected by financial frictions. Similarly, it is easy to see that

$$\psi\left(w_t^*, \rho_t\right) = \left(\frac{\hat{\theta}_t^{\frac{1}{1-\eta}}}{L}\right)^{\frac{-\eta(1-\alpha)}{1-\alpha\eta}} \left(\frac{\rho_t}{\alpha\eta}\right)^{\frac{-\alpha\eta}{1-\alpha\eta}}$$

Hence $\frac{Y_t^e}{Y_t^*} = \frac{\psi(w_t,\rho_t)}{\psi(w_t^*,\rho_t)}\Theta\left(\sigma_t, \rho_t\right) = \Theta\left(\sigma_t, \rho_t\right)^{1+\frac{-\eta(1-\alpha)}{1-\alpha\eta}} = \Theta\left(\sigma_t, \rho_t\right)^{\frac{1-\eta}{1-\alpha\eta}}$ as claimed in Equation 1.4.5. Using the wage equation (Equation 1.4.4) and the solution for $\psi\left(w_t, \rho_t\right)$ (Equation 1.B.1), we have:

$$\log\left(w_t\right) = \text{constant} - \frac{\eta\alpha}{1-\alpha\eta}\log\left(\rho_t\right) + \frac{1-\eta}{1-\alpha\eta}\left[\log\left(\Theta\left(\sigma_t, \rho_t\right)\right) + \frac{1}{1-\eta}\log\left(\hat{\theta}_t\right)\right].$$

1.C Data Appendix

1.C.1 ABI/ABS data

1.C.1.1 Sampling frame

The sampling frame for the ABI and ABS surveys is the Inter-Departmental Business Register (IDBR), a list of all UK incorporated businesses and other businesses registered for tax purposes. The survey has been the ABS since 2007 and was the ABI prior to this. This register includes basic information for all businesses in the sampling frame, such as employment and industry. The population in the sectors that we consider ("IDBR market sector") includes on average 1.4 million establishments covering employment of around 16 million people (see Tables 1.D.1 and 1.D.2). The ABI/ABS include all non-farm businesses. The main industries excluded from the surveys are the crop and animal production part of agriculture, public administration and defence, activities of households as employers; undifferentiated goods and services-producing activities of households for own use, and activities of extraterritorial organizations and bodies.

We define the "market sector" in the ABI (SIC 1992 or 2003 sections) as: D Manufacturing, F Construction, G Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods, H Hotels and restaurants, I Transport, storage and communication, and K real estate, renting and business activities (but excluding real estate SIC 2-digit 70). Sectors we cover in the ABS (SIC 2007 sections) are: C Manufacturing, F Construction, G

Wholesale and retail trade; repair of motor vehicles and motorcycles, H Transport and storage, I Accommodation and food service activities, J Information and communication , M Professional, Scientific and Technical Activities, N Administrative and Support Service Activities. Our sectoral coverage is comparable to that of Riley et al (2015). The sectors we drop are those where output is very hard to measure, namely: financial services, non-market service sectors (e.g. education, health, social work and the public sector), agriculture, mining and quarrying, utilities, real estate, and non-profit organizations.

1.C.1.2 Sampling weights

The ABI and ABS surveys contain grossing weights which reflect the survey design. Sample selection is carried out using a stratified random sample design. Groups of reporting units (sampling cells) are defined by three strata: employment size band, industry, and geographical region. We use a combination of probability weights (the inverse of the sampling probability) and employment weights provided by the ONS. Denote with N_{pi} the number of firms in the population of sampling cell i, and N_{si} the sample of firms surveyed in sampling cell i. Total GVA in cell i is

$$\sum_{n=1}^{N_{si}} GVA_n \frac{N_{pi}}{N_{si}} \frac{\text{Average population employment in cell } i}{\text{Average sample employment in cell } i}$$

Since our sample on which we estimate the efficiency loss from credit frictions is only a subset of the entire ABI/ABS universe of firms, mainly due to requiring positive values of the capital stock, we adjust the ONS weights to reflect extra selection. The weights are to ensure that the sample is representative of the market sector as a whole (IDBR market sector in Table 1.5.1). In grossing up the ONS weights, sampling strata are defined in terms of industry (SIC 1992 and SIC 2007 at the 4-digit level) and employment size bands (1-9; 10-19; 20-49; 50-99; 100-249; 250 or more). As other researchers before us, we ignore regions in defining the sampling strata due to small cell sizes.

1.C.2 Capital Stock Calculation and Perpetual Inventory Method

We apply the Perpetual Inventory Method (PIM) on establishment-level data from the ABI/ABS surveys. This is the standard way in which the ONS calculates establishment level capital stocks and we follow their procedures as closely as possible. The PIM is:

$$K_{nt} = (1 - \delta)K_{nt-1} + I_{nt}$$

where K_{nt} is the establishment n's capital stock at the beginning of period t, K_{nt-1} is the capital stock at the beginning of period $t-1$, I_{nt} is real net investment (capital expenditure minus proceeds from disposal of capital) deflated by an industry specific deflator, and δ is the depreciation rate. We allow for three types of investment: Plant and Machinery, Buildings, and vehicles with depreciation rates of 8%; 2% and 20% respectively. We do a separate PIM calculation for each type of capital, then sum them to obtain the total capital stock in every period.

Although our sample starts in 2005 we have ABI/ABS data back to 1979 for manufacturing which we can use for the PIM. However, small establishments are not sampled every year. Because the ABI/ABS is a stratified random sample there are gaps in the establishment's investment series making it hard to implement the PIM. Hence, we impute missing investment values using each establishment's average ratio of real net capital expenditures to employment (which is always available from the IDBR if the establishment is alive). The imputation of investment values will be more of a problem when there are many missing values. So we set a "tolerance level", i.e. a maximum ratio of imputed to actual values. If we increase the tolerance level, we will get more establishments with capital stock data, but mis-measurement may worsen. In the baseline data set, we apply a ratio of 10 (so not more than 10 investment values are imputed for an establishment with only one valid investment number), but we change the tolerance level to check robustness.

We need to impute an initial capital stock for entrants and for establishments that are sampled for the first time but are not genuine entrants (i.e. they were born before the year in which they were first sampled). To do so, we apportion to those establishments part of the aggregate industry-level capital stock. Our measure of aggregate industry-level capital stocks is the Volume index of capital services (VICS) produced by the ONS. The VICS is a measure of capital input to economic production which takes account of the quality and use of the capital stock across time and different types of assets. VICS weights together the growth of the net stock of assets using a user cost of capital. The VICS data sets contain data on capital stocks, investment, and deflators at the industry level, by asset category.

The apportioning procedure has two steps. First, the VICS is apportioned to the entire population of selected establishments in the sample based on their share of capital expenditures in the sectoral aggregates. The resulting capital stock is what we call "selected capital". Second, each establishment is allocated part of this selected capital based on its share of total purchases in the sectoral sample aggregate. Missing data on total purchases are imputed in the same way as they were for employment.

There are some observations with zero or negative values of the capital stock after this procedure, for which we cannot calculate a valid TFP number. These are not used in the core sample.

1.C.3 Matching ABI/ABS and PD data

The linking between CRNs (Company Registration Numbers at Companies House) in the Orbis data set and the enterprise reference numbers (ENTREF) in the IDBR was performed by the UK Data Service at the University of Essex. The mapping is done with a lookup table provided by the ONS.

The matching process consists of two steps: (i) mapping CRNs which identify firms in Orbis to the ENTREF identifiers in the IDBR; (ii) mapping ENTREFs to reporting unit numbers (RUREF). A company's CRN can be mapped to an ENTREF on the IDBR.

There are several issues with the mapping process, over which we have little control. First, the ONS relies on name matching for some records. This can be problematic if different names or spellings are used. Second, the CRN and IDBR systems are maintained independently. Hence, the same business may be represented differently in either register. The IDBR identifies business units based on their relevance for the computing of government statistics. By contrast, a CRN number is created whenever a company's management registers a new business name. Hence there is no necessary one-to-one concordance between ENTREF and CRNs. Third, although the vast majority of ENTREFs only encompass one RUREFs, some larger enterprises will have several RUREF and CRNs. This creates duplicates in the data set. For ENTREFs corresponding to several CRNs, we compute a weighted average probability of default using weights based on total assets at the CRN level. Subsequently, all reporting units belonging to the same enterprise are assigned this weighted average PD.

Despite these issues we obtain 11.7m ENTREF-year matches on approximatelt 2.3m separate ENTREFs in the IDBR (only 25,093 of those are ENTREFs had multiple CRNs). This compares to a population of around 13m observations in Orbis.

To illustrate the matching process Table 1.D.3 begins with our core sample which is comprised of ABI/ABS establishments with strictly positive values of the capital stock and value added. Column (1) shows that we have 216,540 observations between 2004-2012. Through the matching process we were able to obtain data on PDs for 168,512 of these establishments ranging between a 73% and 85% match rate depending on the year. Unmatched firms are smaller than matched firms.

We impute the approximately 22% of missing PDs using regressions with ABI/ABS control variables including employment, value added, division-level industry dummies, year fixed effects, and year-industry fixed effects. We checked that the results were robust to alternative functional forms of the imputation and dropping the imputed PDs completely.

1.D Further Technical details

1.D.1 Total Factor Productivity estimates and empirical factor shares

Given the production function

$$Y_{nt} = \theta_{nt}\left(L_{nt}^{1-\alpha}K_{nt}^{\alpha}\right)^{\eta}$$

the Solow residual is constructed in the standard way from:

$$\ln(\theta_{nt}) = \ln(Y_{nt}) - \eta\,(1-\alpha)\ln(L_{nt}) - \eta\alpha\ln(K_{nt}) \tag{1.D.1}$$

where Y_{nt} is real gross value added, L_{nt} is the wage bill (real labour costs) and K_{nt} is the real capital stock estimated using the perpetual inventory method. In all our of estimates, we set η equal to $\frac{3}{4}$ as in Bloom (2009). In our baseline estimates, α is set equal to $\frac{1}{3}$. In the empirical value of industry labour share (e.g. last three columns of Table 1.6.2) we use the actual levels of labour costs divided by value added from the ABI/ABS. Since we have abstracted away from frictions in labour, the first order condition for employment generates that the labour share is:

$$\frac{w_t L_{nt}}{Y_{nt}} = \eta(1-\alpha)$$

We use the share of labour costs in value added in each three-digit industry and average this between 2004 and 2012 to estimate $\eta(1-\alpha)$. As above, we set $\eta = \frac{3}{4}$ and recover an industry-specific estimate of α. Note that although these are not directly relative to a time varying industry average, the way TFP enters the formula for Θ_t is relative to industry means, so we are not making TFP comparisons across industries.

1.D.2 Decomposing Θ by size: SMEs versus large firms

Omitting time subscripts for brevity, Θ in Equation (1.4.3) for industry j can be written as

$$\Theta_j = \sum_{n=1}^{N_j} \omega_{nj} \phi_{nj}^{1+\frac{\eta\alpha}{1-\eta}}$$

which can be re-written as the weighted sum of an SME component Θ_{jS} and a large-firm component Θ_{jL} as follows

$$\begin{aligned} \Theta_j &= \lambda_{jS}\Theta_{jS} + \lambda_{jL}\Theta_{jL} \\ &= \left(\frac{\hat{\theta}_{jS}}{\hat{\theta}_j}\right)^{\frac{1}{1-\eta}} \sum_{n=1}^{N_{jS}} \omega_{njS} \phi_{nj}^{1+\frac{\eta\alpha}{1-\eta}} + \left(\frac{\hat{\theta}_{jL}}{\hat{\theta}_j}\right)^{\frac{1}{1-\eta}} \sum_{n=1}^{N_{jL}} \omega_{njL} \phi_{nj}^{1+\frac{\eta\alpha}{1-\eta}} \end{aligned}$$

where

- N_{jS} is the number of SMEs in industry j, N_{jL} the number of large firms in industry j, and N_j the total number of firms in industry j;
- $\omega_{njS} = \left(\frac{\theta_{nj}}{\hat{\theta}_{jS}}\right)^{\frac{1}{1-\eta}}$ and $\hat{\theta}_{jS} = \left(\sum_{n=1}^{N_{jS}} \theta_{nj}^{\frac{1}{1-\eta}}\right)^{1-\eta}$;
- $\omega_{njL} = \left(\frac{\theta_{nj}}{\hat{\theta}_{jL}}\right)^{\frac{1}{1-\eta}}$ and $\hat{\theta}_{jL} = \left(\sum_{n=1}^{N_{jL}} \theta_{nj}^{\frac{1}{1-\eta}}\right)^{1-\eta}$;
- $\hat{\theta}_j = \left(\sum_{n=1}^{N_j} \theta_{nj}^{\frac{1}{1-\eta}}\right)^{1-\eta}$.

We implement this decomposition at the industry level and then aggregate using industry employment shares by size category to obtain an aggregate estimate of Θ for SMEs and large firms separately.

1.D.3 Decomposing Θ into a mean and a covariance term

Omitting time subscripts for brevity, and denoting $\mu \equiv 1 + \frac{\eta\alpha}{1-\eta}$, the covariance between the productivity weights and the scaled probabilities of repayment is

$$cov(\omega_n, \phi_n^{\mu}) = \frac{1}{N} \sum_{n=1}^{N} (\omega_n - \overline{\omega}) \left(\phi_n^{\mu} - \overline{\phi^{\mu}}\right)$$

It can be shown that

$$\Theta = Ncov(\omega_n, \phi_n^\mu) + \overline{\phi^\mu}$$

where $\overline{\phi^\mu} = \frac{1}{N}\sum_{n=1}^N \phi_n^\mu$ and $\overline{\omega} = \frac{1}{N}\sum_{n=1}^N \omega_n$. It can also be shown that

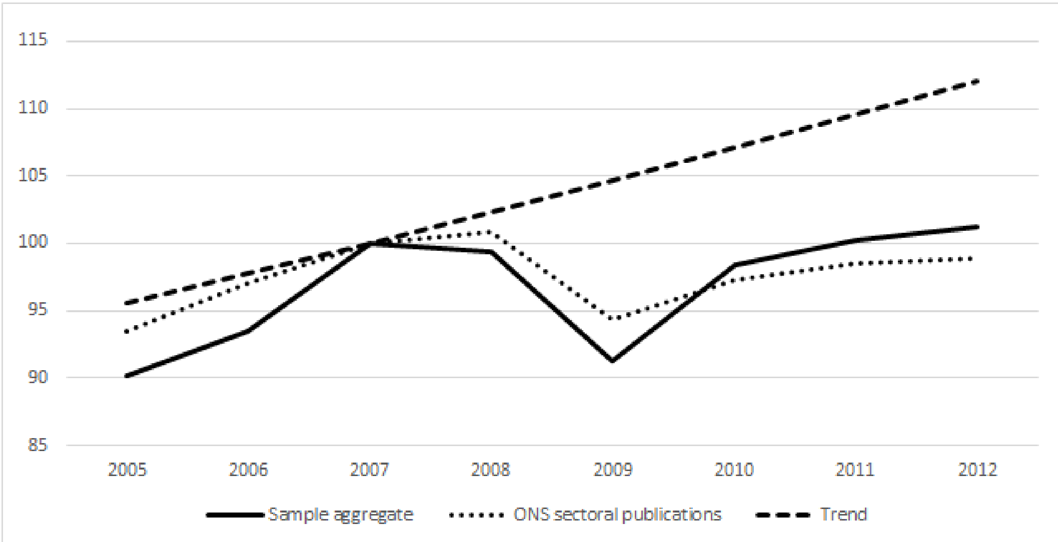
$$Ncov(\omega_n, \phi_n^\mu) = \sum_{n=1}^N \left(\omega_n - \frac{1}{N}\right)\phi_n^\mu$$

Hence the decomposition becomes

$$\Theta = \sum_{n=1}^N \left(\omega_n - \frac{1}{N}\right)\phi_n^\mu + \frac{1}{N}\sum_{n=1}^N \phi_n^\mu.$$

1.D.4 Appendix Tables and Figures

Figure 1.D.1: **Labour productivity in the "market sector" (2007=100)**



Notes: "Market sector" is all sectors in the ABI/ABS, except financial services, education, health, social work, agriculture, mining and quarrying, utilities, real estate, and non-profit organizations. The solid line refers to our estimates based on the calibration sample ("Sample aggregate"). The dashed line ("Trend") is the trend assuming a historical average growth of 2.3% per annum (the average over the period Q1-1979 to Q2-2008). The dotted line refers to the estimates based on "ONS sectoral publications" (See ONS UK non-financial business economy Statistical bulletins, for example: http://www.ons.gov.uk/businessindustryandtrade/business/businessservices/ data sets/uknonfinancialbusinesseconomyannualbusinesssurveysectionsas). Note that the sectoral publication numbers include the real estate sector (which we drop in our sample) because it cannot be disentangled from the rest of SIC 1992 section K. Our numbers are roughly in line with those of other papers, e.g. Riley et al (2015).

Table 1.D.1: **IDBR market sector employment and number of establishments by size category (average 2004-2012)**

		Employment (millions)	Number of establishments (thousands)
Micro firms	**(0-9)**	3.2	1,298
Small firms	**(10-49)**	2.6	132
Medium sized firms	**(50-249)**	2.4	24
Large firms	**(250+)**	7.6	5

Source: IDBR and authors' calculations. Note: average 2004-2012; non-farm non-financial market sectors excl. mining and quarrying, utilities, and real estate activities.

Table 1.D.2: **Number of establishments and total employment in the IDBR market sector**

	Employment (millions)	Number of establishments (thousands)
2004	15.34	1,322
2005	15.53	1,372
2006	15.60	1,410
2007	15.43	1,457
2008	16.20	1,549
2009	15.92	1,488
2010	15.29	1,470
2011	15.45	1,517
2012	15.71	1,520

Source: IDBR and authors' calculations.

Table 1.D.3: **Match rates between ABI/ABS and PD data**

(1)	(2)	(3)	(4)
Year	**Calibration sample**	**Matched PD data**	**% of calibration sample**
2004	26,155	19,106	73.05
2005	25,358	19,214	75.77
2006	21,989	17,247	78.43
2007	24,363	18,220	74.79
2006	23,614	17,428	73.8
2009	23,283	18,385	78.96
2010	23,010	18,163	78.94
2011	24,048	19,810	82.38
2012	24,720	20,939	84.7
TOTAL	*216,540*	*168,512*	*77.82*

Table 1.D.4: **Firm performance and lagged default probabilities - Table 4 on winsorized data**

PANEL A: Industry fixed effects								
	Ln(N)	**Ln(GVA)**	**Ln(Purchases)**	**Ln(TA)**	**Ln(Net capex)**	**Ln(K)**	**Ln(FA)**	**Ln(TFP)**
Lag of 1-year PD	-3.273***	-4.116***	-3.920***	-5.070***	-4.585***	-4.136***	-5.708***	-0.383***
	(0.067)	(0.072)	(0.084)	(0.092)	(0.093)	(0.087)	(0.105)	(0.028)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	80,942	80,942	80,942	80,942	80,942	80,942	80,942	80,942
R^2	0.112	0.123	0.179	0.141	0.135	0.202	0.162	0.212
PANEL A: Firm fixed effects								
	Ln(N)	**Ln(GVA)**	**Ln(Purchases)**	**Ln(TA)**	**Ln(Net capex)**	**Ln(K)**	**Ln(FA)**	**Ln(TFP)**
Lag of 1-year PD	-0.103***	-0.612***	-0.215***	-0.394***	-0.912***	-0.083***	-0.390***	-0.463***
	(0.025)	(0.045)	(0.041)	(0.037)	(0.095)	(0.021)	(0.057)	(0.036)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	60,798	60,798	60,798	60,798	60,798	60,798	60,798	60,798
R^2	0.98	0.941	0.961	0.982	0.825	0.992	0.968	0.824

Notes: **N**=Employees; **TA**=Total assets; **K**=Capital stock estimate in real terms; **FA**=Fixed assets; **Purchases**=Total purchases of goods and materials; **TFP**=TFP estimate; **Net capex**=Real net capital expenditures; **GVA**=Real gross value added. OLS estimates with standard errors clustered by firm in parantheses; *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. Data are winsorized at the top and bottom 1%. Data runs from 2004-2012. Data on employment, value added, purchases, investment, capital and TFP are from the ABI/ABS. Data on total assets and fixed assets from BVD Orbis. "Lagged Default Probability" is the firm's estimated one year ahead probability of default from Standard and Poor's PD model. Full set of year dummies in all models. Both panels condition on a sub-sample with non-missing values on all left-hand side variables. Panel B also conditions on a sub-sample with at least two firm-level observations (in order to be able to include firm fixed effects).

Table 1.D.5: **Firm performance and lagged default probabilities, not conditioning on common sample of non-missing dependent variables in ABI/ABS**

PANEL A: Industry fixed effects									
	Ln(N)	**Ln(Real GVA)**	**Ln(Purchases)**	**Ln(TA)**	**Ln(Net capex)**	**Ln(K)**	**Ln(FA)**	**Ln(TFP)**	**Ln(△debt)**
Lag PD	-3.804***	-4.571***	-4.484***	-5.609***	-4.795***	-4.753***	-6.585***	-0.287***	-0.157***
	(0.051)	(0.055)	(0.064)	(0.069)	(0.099)	(0.074)	(0.080)	(0.021)	(0.051)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	142,887	142,887	142,289	142,846	82,173	142,887	137,500	142,864	49,333
R^2	0.143	0.146	0.226	0.17	0.135	0.226	0.202	0.168	0.002
PANEL B: Firm fixed effects									
	Ln(N)	**Ln(Real GVA)**	**Ln(Purchases)**	**Ln(TA)**	**Ln(Net capex)**	**Ln(K)**	**Ln(FA)**	**Ln(TFP)**	**Ln(△debt)**
Lag PD	-0.094***	-0.610***	-0.250***	-0.390***	-0.927***	-0.102***	-0.439***	-0.440***	-0.672***
	(0.022)	(0.038)	(0.039)	(0.051)	(0.096)	(0.018)	(0.052)	(0.029)	(0.110)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	96,747	96,747	96,457	96,733	61,437	96,747	95,003	96,725	38,171
R^2	0.982	0.947	0.96	0.962	0.826	0.995	0.97	0.842	0.201

Notes: **Lag PD**=Lag of 1-year default probability; **N**=Employees; **TA**=Total assets; **K**=Capital stock estimate in real terms; **FA**=Fixed assets; **Purchases**=Total purchases of goods and materials; **TFP**=TFP estimate; **Net capex**=Real net capital expenditures; **GVA**=Real gross value added; and △**debt**=Change in total debt. OLS estimates with standard errors clustered by firm in parentheses; *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. Data runs from 2004-2012. Data on employment, value added, purchases, investment, capital and TFP are from the ABI/ABS. Data on total assets and fixed assets from BVD Orbis. "Lagged Default Probability" is the firm's estimated one year ahead probability of default from Standard and Poor's PD model. Full set of year dummies in all models. Both panels condition on a sub-sample with non-missing values on all left-hand side variables. Panel B also conditions on a sub-sample with at least two firm-level observations (in order to be able to include firm fixed effects).

Table 1.D.6: **Probability of survival and lagged default probabilities**

	Exit: dummy=1 if firm exits in the following year
Lag of 1-year PD	0.014***
	(0.005)
Year FE	Yes
Firm FE	Yes
N	96,734
R^2	0.386

Notes: OLS estimates with standard errors clustered by firm in parentheses; *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. Data runs from 2004-2012. The dependent variable is a dummy which is equal to one if the firm exits in the following year, and zero otherwise. Exit indicates that the firm is not longer active and hence no longer registered in the IDBR. "Lagged Default Probability" is the firm's estimated one year ahead probability of default from Standard and Poor's PD model. Full set of year dummies.

Table 1.D.7: **Firm performance and lagged default probabilities, ORBIS Data before matched to ABI/ABS**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ln(EBIT)	**Ln(FA)**	**Ln(N)**	**Ln(Net assets)**	**Ln(EBIT)**	**Ln(FA)**	**Ln(N)**	**Ln(Net assets)**
Lag of Ln(1-y PD)	-1.081***	-0.640***	-0.222***	-0.275***	-0.254***	-0.080***	-0.013***	-0.070***
	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Industry FE	Yes	Yes	Yes	Yes	No	No	No	No
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,662,977	8,048,545	602,053	8,260,230	5,220,840	7,661,775	576,023	7,941,916
R^2	0.399	0.246	0.190	0.093	0.884	0.936	0.965	0.901

Notes: **EBIT**=Earnings before interest and tax; **FA**=Fixed assets; **N**=Employees; **Net assets**=Total assets minus total liabilities. OLS estimates with standard errors clustered by firm in parantheses; *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. Data runs from 2004-2012. All data from BVD Orbis. "Lagged Default Probability" is the firm's estimated one year ahead probability of default from Standard and Poor's PD model. Full set of year dummies in all models. Right-hand side panel conditions on a sub-sample with at least two firm-level observations (in order to be able to include firm fixed effects).

Table 1.D.8: **The Effect of Credit frictions on Aggregate Output and Productivity Broken Down by Firm Size (using the Solow residual and empirical labour share)**

	(1)	(2)	(3)	(4)	(5)	(6)
	SMEs			Large Firms		
	Credit Friction Θ_t	Percentage Output loss	Contribution to productivity growth	Credit Friction Θ_t	Percentage Output loss	Contribution to productivity growth
2004	0.849	4.8		0.907	2.9	
2005	0.861	4.4	0.4	0.908	2.8	0.1
2006	0.826	5.6	-1.2	0.917	2.6	0.3
2007	0.829	5.5	0.1	0.913	2.7	-0.1
2008	0.794	6.7	-1.3	0.885	3.6	-0.9
2009	0.762	7.8	-1.3	0.887	3.6	0.1
2010	0.765	7.7	0.1	0.893	3.3	0.2
2011	0.738	8.7	-1.1	0.886	3.6	-0.2
2012	0.740	8.7	0.1	0.890	3.4	0.1
Average	0.796	6.7	-0.5	0.898	3.2	-0.1

Note: All estimates assume that $\eta = \frac{3}{4}$. The credit friction, Θ_t is the estimate of aggregate financial market frictions derived in the text. Output loss is the proportionate fall in output as a result of credit frictions and is calculated using Equation 1.4.5. The variable in Columns (3) and (6) is the annual difference in the output loss. All columns use a value based on the labour share in the three-digit industry. SMEs are defined to have under 250 employees, whereas large firms have 250 or more employees.

Chapter 2

Management practices, precautionary savings, and company investment dynamics

Abstract

This paper investigates a potential channel behind the well-documented positive correlation between the quality of management practices and firm performance. The main hypothesis of the paper is that financially constrained firms accumulate larger cash reserves when they are better managed. This allows them to avoid the costs of underinvestment when future profitable investment opportunities arise. The theoretical analysis predicts that well managed firms which face financial constraints save relatively more out of their cash flows and accumulate more cash when their cash flows are more volatile. This enhanced precautionary behaviour arises because management quality alleviates agency problems between equity holders and managers. The empirical analysis provides evidence to support these predictions using data from the World Management Survey and administrative and accounting data on UK firms. A direct consequence of this enhanced precautionary behaviour is that well managed firms invest more efficiently. Specifically, they adjust more quickly towards their long-run equilibrium capital stock when their current capital stock falls short of the latter. The paper provides evidence of this using a dynamic model of investment.

2.1 Introduction

There are large and persistent productivity differentials between firms and between countries. Hall and Jones (1999) and Jones and Romer (2010) show that these explain a significant fraction of the differences in average incomes. Differences in productivity are also large within narrowly defined industries and very homogeneous goods industries (See e.g. Foster, Haltiwanger and Syverson, 2008; and Syverson, 2011)[1]. The main explanation put forward is that these productivity differences are due to technological factors such as R&D, patents and the adoption of information and communications technology (ICT). Another, more recent, explanation is that these differences reflect variations in the quality of management practices across firms and countries[2]. Since managers control the use of labour, capital, and intermediate inputs, it is intuitive that they may drive productivity differences. But for years, data limitations on managerial inputs have precluded the systematic study of this issue. The World Management Survey (WMS) has recently started to close this measurement gap (Bloom and Van Reenen, 2007). The WMS defines 18 basic management practices and scores firms from 1 (worst practice) to 5 (best practice). The practices cover four broad areas: operations, monitoring, targets, and incentives (See Appendix 2.B).

Bloom and Van Reenen (2007) document that higher-quality management practices as measured by the WMS are positively correlated with firm performance, using measures including sales growth, labour productivity, total factor productivity (TFP), return on capital, Tobin's Q, and the probability of survival. These correlations are statistically and economically significant. Bloom, Sadun, and Van Reenen (2016) provide further evidence of this link. They argue that management practices are a "technology" in the sense that they raise TFP. These results highlight correlations. However, Bloom et al (2013) establish a causal link between management practices and productivity using a field experiment on Indian firms, whereby free consulting on management practices was provided to randomly chosen treatment plants. In brief, the evidence that management and productivity are related has been piling up rapidly with the launch of the WMS.

I provide further evidence that management practices as measured by the WMS are positively correlated with firm performance using administrative data on UK firms. This is mainly for the purpose of confirming the relationship in my sample, but the use of administrative data is still

[1] See Bartelsman, Haltiwanger and Scarpetta (2013) for a general survey.
[2] Syverson (2011) provides a survey of the recent literature.

rather novel. To the best of my knowledge, the only existing study linking UK administrative data to the WMS is Bloom et al (2010). The authors estimate an establishment level production function and show that there is a significantly positive correlation between management and real gross output. I expand the set of dependent variables to include real gross value added, the capital stock, and capital expenditures. I also estimate a simple production function and show that better management raises TFP.

Despite the clear link between management and performance, the potential corporate finance channels behind it have remained largely unexplored. The main contribution of the paper is to start filling this gap. This paper investigates whether better management practices may help prevent underinvestment by financially constrained firms. The specific hypothesis of the paper is that better management practices promote more prudent cash policies that allow firms to build "financial flexibility" and react to unexpected cash flow shocks and investment opportunities in the future. Financial flexibility matters for investment when there are financing frictions. In a world without frictions, firms are always able to reach their first-best levels of investment. When capital markets are frictional, firms' investments will depend on the availability of finance (internal or external)[3]. Firms with greater flexibility are better able to meet their funding needs when they experience unanticipated earnings shortfalls. They can therefore avoid suboptimal investment. This idea dates back to seminal corporate finance papers. According to the pecking order theory of capital structure (Myers, 1984, and Myers and Majluf, 1984), firms preserve financial slack to avoid having to rely on external funds to finance future investment projects. Similarly, Froot, Scharfstein and Stein (1993) suggest that firms maintain financial flexibility to avoid the costs of underinvestment. Financial flexibility can be achieved through conservative leverage policies and large cash reserves[4]. In this paper I focus on cash holdings and their relationship with management. The analysis shows that well managed firms which face financial constraints save relatively more out of their cash flows and accumulate more cash when their cash flows are more volatile.

A direct consequence of this enhanced "precautionary behaviour" is that well managed firms should adjust more quickly towards their long-run equilibrium capital stock when their current capital stock falls short of the latter. I provide evidence of this in a dynamic investment

[3] See Bond and Van Reenen (2007) for a survey.

[4] Studies examining financial flexibility through low leverage policies include Byoun, 2008; Lins, Servaes and Tufano, 2010; Billet, King and Mauer, 2007; and Campello, Graham and Harvey, 2010. Studies focussing on cash balances include Opler et al, 1999; Billet and Garfinkel, 2004; Almeida, Campello and Weisbach, 2004; Faulkender and Wang, 2006; Acharya, Almeida and Campello, 2007; Dittmar and Mahrt-Smith, 2007; Kalcheva and Lins, 2007; Harford, Mansi and Maxwell, 2008; and Riddick and Whited, 2008.

model (Error Correction Model) with asymmetric adjustment speed. The model suggests that well managed firms are indeed better prepared to deal with financial constraints or cash flow shortfalls when investment opportunities present themselves. This could be an important channel in the translation of management practices into better corporate performance.

The paper is related to the corporate governance literature, which has extensively studied the role of strategic choices made at the executive level. The literature focusses on the separation of ownership and control and the agency conflicts between managers and shareholders. CEOs have been shown to have an impact on corporate investment decisions and performance (e.g. Adams, Almeida, and Ferreira, 2005, 2009; Bertrand and Schoar, 2003). The information on corporate strategy that managers disclose to stakeholders, such as employees and suppliers, also affects a firm's investments. When managers disseminate information about their future plans for the firm, they provide stakeholders with valuable information for assessing the profitability of strategy-specific investments (Ferreira and Rezende, 2007). Finally, Dittmar and Mahrt-Smith (2007) show that the value of cash holdings is higher in well-governed firms.

However, the present paper is concerned with a different layer of managerial governance, namely the management of day-to-day operations, rather than high-level corporate governance institutions. The role of mid-level management and their impact on firms' financial policies has not been studied extensively in the literature. There are several reasons why management practices may matter in a way that is similar to governance institutions. By "tying the hands of managers", management practices may serve as an informational, commitment, and monitoring device which prevents managers from wasting money or aligns their incentives with those of shareholders. Well managed firms may plan ahead better to meet their future financing needs because they closely monitor progress and the achievement of targets. Therefore, there are a lot of interesting avenues of research which could link corporate finance, corporate governance and management practices.

The structure of the paper is as follows. In Section 2.2, I develop a theoretical framework which imbeds agency problems in the cash saving model of Almeida, Campello, and Weisbach (2004), henceforth ACW (2004). The main friction is the possibility of cash diversion or wasteful activities by managers who are in charge of day-to-day operations. The cash saving policy of the firm is determined at the executive level and takes into account this agency problem. On the basis of this model, I develop the central hypotheses of the paper. In Section 2.3, I present the data sources and some descriptive statistics on the sample. In Section 2.4, I provide evidence that management practices are positively correlated with firm performance using administrative data for a sample of UK firms. In Sections 2.5 and 2.6, I explore the central hypotheses of the paper based on the predictions of the model presented in Section 2.2. In Section 2.7, I estimate a dynamic investment model to study the impact of management on the speed at which firms adjust to their target capital stocks. I allow management to have an asymmetric impact on adjustment speed in order to provide evidence that better management helps firms avoid underinvestment. Section 2.8 concludes.

2.2 A theory of management and precautionary behaviour

In this section I develop a model of precautionary cash holdings based on the model of ACW (2004). I incorporate the possibility of "cash diversion" (or wasteful behaviour) by managers in charge of day-to-day operations. High-level executives (equivalent to equity holders in my model) choose how much equity to inject in the firm taking this agency problem into account. They also determine the financial policies of the firm, including the cash saving policy. Cash diversion is not necessarily intended to represent stealing by managers, but rather organizational slack and inefficiencies in the running of the business that result in some non-pecuniary benefits for managers, for example more free time and less hard work broadly defined. This rationale is related to the idea that weak corporate governance allows managers to enjoy the "quiet life" (Bertrand and Mullainathan, 2003). There is also an indirect link to short-termism. I assume that operational managers are "short-sighted" and do not internalize the impact of cash diversion on the decisions taken by high-level executives. Theoretical work predicts that managers with shorter horizons will engage in value-destroying actions, such as delaying profitable investments[5]. Managerial myopia is particularly relevant for corporate investment because its benefits usually arise in the long term. Managers may be short-sighted for many reasons, but it seems plausible that they are remote enough from high-level decisions (CEO, board of directors) to actually ignore the impact of their behaviour on those decisions - which they may not even understand[6]. By tying the hands of managers, better management practices not only make daily operations more efficient but they also decrease the level of discretion that managers have in spending cash. Most importantly, they provide a framework for setting

[5]See for example Holmström (1999) and Shleifer and Vishny (1990).

[6]Another possibility would be to introduce finite managerial tenure so that managers have shorter time horizons than equity holders. This is left for future research.

targets and monitoring outcomes. The WMS management score is well suited for measuring these kinds of operational inefficiencies and the scope for short-termism (See Appendix 2.B).

2.2.1 Model set-up

There are two sets of agents: operational managers and high-level executives (equivalent to equity holders in my simple set-up). They are responsible for different "governance tasks" within the firm. Managers look after the day-to-day operations of the firm, while equity holders are responsible for higher-level decisions. In this model, high-level decisions include the cash saving, dividend, debt and hedging policies of the firm. By running day-to-day operations, managers have an impact on how efficiently cash reserves are put to use in the production and investment process. Equity holders take this into account when deciding on the cash policy of the firm.

The model has three dates, 0, 1, and 2. At time 0, the manager raises equity c_0 from equity holders with initial wealth W[7]. For simplicity, assume that this equity injection generates cash flows from existing operations in an equal amount c_0. Equity holders keep the remainder of their wealth $(W - c_0)$ in the form of cash which is not made available to managers for use in production or investment (call this "non-productive cash"). The cash flows generated by the initial equity injection c_0 are used partly for current investment and the remainder is kept within the firm in the form of cash reserves (precautionary savings). Denote the cash stock with C. I call these cash reserves "productive cash". As opposed to $(W - c_0)$, they are put at the disposal of operational managers for use in investment at time 1. While C is determined by equity holders, its use is determined by mid-level managers in charge of operations.

Investment opportunities are modelled as in ACW (2004). At time 0, the firm invests I_0 in a project that pays off $F(I_0)$ at time 2. At time 1, the firm receives an exogenous cash flow draw c_1 and invests I_1 in a project that pays off $G(I_1)$ at time 2. The functions $F(.)$ and $G(.)$ are increasing, concave, and continuously differentiable. With probability p, the time 1 cash flow is high, c_1^H, and with probability $(1 - p)$ it is low, c_1^L, with $c_1^L < c_1^H$. The discount factor is 1, equity holders are risk neutral, and the cost of investment goods at dates 0 and 1 is normalised to 1. In addition to generating payoffs at time 2, the investments I_0 and I_1 can be liquidated at time 2. The payoff from liquidation is $q(I_0 + I_1)$, where $q \leqslant 1$, and $I_0, I_1 > 0$. Define total cash flows from investments at time 2 as $f(I_0) \equiv F(I_0) + qI_0$, and $g(I_1) \equiv G(I_1) + qI_1$.

[7]This is a departure from ACW (2004), where c_0 is the firm's *exogenous* cash flow from current operations.

The firm has access to debt markets. Cash flows are not verifiable so the firm cannot pledge those cash flows to outside investors. However, the firm can raise debt finance using its productive assets as collateral. The collateral value of assets I that can be captured by creditors is given by $(1-\tau)qI$. The parameter τ captures the degree of external financing constraints. Equity holders choose how much equity to invest, and determine the debt, hedging, dividend, and cash policies of the firm - denoted $\{B^*, h^*, d^*, C^*\}$ in short-cut notation. B^* denotes the optimal debt policy at times 0 and 1 in both states. C^* denotes the optimal cash policy at time 0. h^* denotes the optimal hedging policy at time 1, and d^* is the optimal dividend policy at times 0, 1, and 2 in both states. As in ACW (2004) I assume that the firm can fully hedge future earnings at a fair cost[8].

There is potential cash diversion by managers, i.e. they may allocate part of the "productive cash" C towards purposes that do not benefit investment. Assume that managers can divert a fraction s of the stock of cash C and receive a net benefit $\left(s - \frac{m}{2}s^2\right)C$. The parameter m denotes the quality of management practices. It is known to all agents. s is the endogenous behaviour of managers, and m is the exogenous managerial framework in which the manager operates (monitoring, oversight, etc.). Higher values of m lower the net benefits of diversion. As managerial practices improve, it becomes more difficult or costly to slack or divert cash. Managers maximize their expected utility and take the high-level decisions of equity holders as given. I assume that operational managers are "short-sighted" and do not internalize the impact of cash diversion on the decisions of equity holders. While this is a simplifying assumption, it is not implausible that operational managers do not understand the impact of their behaviour on higher-level decisions[9]. The optimal investment policy at time 0 and 1 results from the optimal equity injection, the optimal financial policies and the manager's optimal cash diversion.

[8] A binding financial constraint creates a motive for hedging future cash flows (Froot, Scharfstein, and Stein, 1993).

[9] Another possibility would be to introduce finite managerial tenure so that managers have shorter time horizons than equity holders. This is left for future research.

2.2.2 Equity holders' problem

2.2.2.1 Equity injection, dividend, hedging, debt and cash policies

The equity holders' objective is to maximize the expected sum of dividends subject to the firm's budget and financial constraints, and the behaviour of managers:

$$\max_{C,h,d,B,c_0} \left\{ d_0 + pd_1^H + (1-p)d_1^L + pd_2^H + (1-p)d_2^L + (W - c_0) \right\} \text{ s.t.}$$

$$W \geqslant c_0 \geqslant C \geqslant 0$$

$$d_0 = c_0 + B_0 - I_0 - C \geqslant 0$$

$$d_1^S = c_1^S + h^S + B_1^S - I_1^S + (1-s)C \geqslant 0 \text{ for S =H, L}$$

$$d_2^S = f(I_0) + g(I_1^S) - B_0 - B_1^S \geqslant 0 \text{ for S =H, L}$$

$$B_0 \leqslant (1-\tau)qI_0$$

$$B_1^S \leqslant (1-\tau)qI_1^S$$

$$ph^H + (1-p)h^L = 0.$$

The first constraint specifies that the initial equity injection c_0 must be positive and less than the initial wealth of the equity holders. In addition to choosing c_0, equity holders decide how much of their initial equity injection to stock away in the form of precautionary savings C. The second, third and fourth constraints restrict dividends d_t to be non-negative at times $t = \{0, 1, 2\}$ in both states. The terms B_0 and B_1^S are the debt amounts borrowed at time 0 and 1 in both states. The firm cannot borrow more than the collateral value generated by its investments at times 0 and 1 in both states. Debt is repaid at time 2 when investments pay off. Hedging payments in states H and L are denoted by $h_H < 0$ and $h_L > 0$, respectively. The firm aims to increase cash flows in state L at the expense of reducing cash flows in state H. This can be achieved, for example, with a futures contract which pays off $c_1^S + h^S$ in state S. Hedging is fairly priced. Therefore, the firm will choose full insurance, leading to equal cash flows in both states (equal to $E[c_1]$)[10]. The optimal amount of hedging is given by $h^L = p(c_1^H - c_1^L)$.

In what follows, I focus on the case of the financially constrained firm, i.e. a firm that cannot always attain its first-best level of investment[11]. A financially constrained firm under-invests. It will not pay dividends in order to exhaust its capacity to take available positive NPV projects. The firm will also exhaust its debt capacity. In other words:

[10] See Froot, Scharfstein, and Stein (1993).

[11] Appendix 2.C discusses the case of unconstrained firms.

$$
\begin{aligned}
d_0 &= d_1 = 0 \\
B_0 &= (1-\tau)qI_0 \\
B_1^S &= (1-\tau)qI_1^S
\end{aligned}
$$

Hence

$$
\begin{aligned}
I_0 &= \frac{c_0 - C}{\lambda} \\
I_1^S &= \frac{c_1^S + (1-s)C}{\lambda}
\end{aligned}
$$

where $\lambda \equiv 1 - q + \tau q$. Together with full insurance, the objective function of the firm becomes:

$$
\begin{aligned}
\max_{C, c_0} \Bigg\{ & F\left(\frac{c_0 - C}{\lambda}\right) + G\left(\frac{E[c_1] + (1-s^*)C}{\lambda}\right) \\
& + \tau q \frac{c_0 - C + E[c_1] + (1-s^*)C}{\lambda} + (W - c_0) \Bigg\}
\end{aligned}
$$

Equity holders take into account the manager's optimal cash diversion behaviour, denoted by s^*. There exist optimal cash and equity injection policies, C^* and c_0^*, because injecting equity and holding cash entail both costs and benefits. Injecting equity in the firm increases cash flows at time 0 (c_0), enables the firm to set aside more "productive cash" (C), and to invest more at time 1. By contrast, there is no return to holding "non-productive cash" ($W - c_0$). However, holding cash (C) is costly because a proportion s^* of it will be wasted. This results in $c_0 < W$. In addition, holding cash requires reducing I_0 today. The benefit is the increase in the firm's ability to finance future projects (higher I_1). The first-order condition (FOC) for the time 0 equity injection c_0 is:

$$
F'\left(\frac{c_0 - C}{\lambda}\right) = 1 - q. \tag{2.2.1}
$$

Similarly, the optimal cash policy C^* is determined by the equality between the marginal cost and the marginal benefit of increasing cash holdings:

$$
F'\left(\frac{c_0 - C}{\lambda}\right) + \tau q = (1 - s^*)\left(G'\left(\frac{E[c_1] + (1-s^*)C}{\lambda}\right) + \tau q\right) \tag{2.2.2}
$$

Equation (2.2.2) captures the central result of ACW (2004): Financially constrained firms will keep more cash today if future investment opportunities are more profitable relative to current ones.

2.2.2.2 Comparative statics

In this section I examine how the firm's optimal policies C^* and c_0^* depend on the quality of management practices m. Taking the total differential of Equation (2.2.1) with respect to m, it follows that

$$F''\left(\frac{c_0 - C}{\lambda}\right)\left(\frac{dc_0}{dm} - \frac{dC}{dm}\right) = 0. \tag{2.2.3}$$

Hence $\frac{dc_0}{dm} = \frac{dC}{dm}$. Taking the total differential of Equation (2.2.2) with respect to m, it follows that better managed firms will hold more cash, i.e. $\frac{dC}{dm} > 0$ if $\frac{ds}{dm} < 0$ and[12]:

$$G'\left(\frac{E[c_1] + (1 - s^*)C}{\lambda}\right) + \tau q > -\frac{C(1 - s^*)}{\lambda} G''\left(\frac{E[c_1] + (1 - s^*)C}{\lambda}\right) \tag{2.2.4}$$

The first condition ($\frac{ds}{dm} < 0$) states that better management should address the agency problem and discourage cash diversion. I will show in the next section that this is always the case. The second condition 2.2.4 indicates that there is a trade-off between a substitution effect and two income effects. An increase in m is akin to a reduction in the cost of "productive cash" (and hence equity injection) since equity holders expect lower diversion. Keeping the value of the firm constant, equity holders substitute away from "non-productive cash" ($W - c_0$) into "productive cash" (C). Lower diversion also has an income effect, which increases firm value. However, the resulting increase in cash holdings also has a negative income effect as the amount of cash diverted is proportional to C. The overall income effect can be either negative or positive. If it is positive, cash holdings are a "normal good". If it is negative, they are an "inferior good". The condition can be satisfied if both the substitution effect and the overall income effect are positive, or if the substitution effect is positive and the income effect is negative but small. Note that this condition is more likely to be satisfied when future investment opportunities are relatively more profitable than current ones. Finally, if $\frac{dC}{dm} > 0$ it follows that[13]:

$$\frac{d\left(\frac{C}{c_0}\right)}{dm} = \frac{1}{c_0}\frac{dC}{dm}\left(1 - \frac{C}{c_0}\right) > 0 \tag{2.2.5}$$

In other words, better managed firms have a higher propensity to save out of cash flows if they hold more "productive cash". Using the insights from Han and Qiu (2007), it can be

[12] See Proof in Appendix 2.A.
[13] See Proof in Appendix 2.A.

shown that if the constrained firm cannot fully hedge cash flow risk at fair prices, it will have an additional motive to save an amount of cash above that predicted by ACW (2004). By Jensen's inequality:

$$E\left(G'\left(\frac{c_1+(1-s^*)C}{\lambda}\middle|F\right)+\frac{\tau q(1-s^*)}{\lambda}\right)>G'\left(\frac{E[c_1|F]+(1-s^*)C}{\lambda}+\frac{\tau q(1-s^*)}{\lambda}\right)$$

for all C, where F is the probability distribution of cash flows at time 1. When future cash flow risk cannot be fully hedged, financially constrained firms will hold more cash for any given distribution of future cash flows. In addition, Han and Qiu (2007) show that they accumulate larger cash holdings in response to higher cash flow volatility[14].

2.2.3 Managerial decision on cash diversion

The manager of day-to-day operations maximizes his expected utility from running the firm, with utility function U such that $U' > 0$ and $U'' < 0$. Given the high-level policies $\{C, B, h, d, c_0\}$, the manager's objective function is:

$$\max_s \left\{ pU(d_2^H) + (1-p)U(d_2^L) + \left(s - \frac{m}{2}s^2\right) C \right\} \tag{2.2.6}$$

where, for $S = H, L$

$$\begin{aligned} d_2^S &= F\left(\frac{c_0 - C}{\lambda}\right) + \tau q\left(\frac{c_0 - C}{\lambda}\right) \\ &+ G\left(\frac{c_1^S + (1-s)C}{\lambda}\right) + \tau q\left(\frac{c_1^S + (1-s)C}{\lambda}\right) \end{aligned}$$

The manager derives utility from the dividends at time 2 and enjoys the benefits of diversion. His utility from time 2 dividends can be understood as the benefits from running the firm. The benefits of cash diversion could take different shapes: perks, increased free time, the "quiet life", for example. Note that the manager does not derive utility from the non-productive cash $(W - c_0)$ kept by equity holders. This cash is not at his disposal. Since the manager is short-sighted, the first-order condition for s is:

[14] See Han and Qiu (2007) for details.

$$
\begin{aligned}
&pU'\left(d_2^H\right)\left(G'\left(I_1^H\right)+\tau q\right)\\
&+(1-p)U'\left(d_2^L\right)\left(G'\left(I_1^L\right)+\tau q\right)=\lambda(1-ms).
\end{aligned}
\tag{2.2.7}
$$

Taking the total differential with respect to m, it can be verified that $\frac{ds}{dm} < 0$[15]. In other words, the equilibrium rate of diversion or wastage s^* depends negatively on m. Better management practices (e.g. greater monitoring and better targeting) lead to a lower level of diversion. It follows that $\frac{dC}{dm} > 0$ and $\frac{d\left(\frac{C}{c_0}\right)}{dm} > 0$ if Equation (2.2.4) is satisfied.

2.2.4 Hypothesis development

Hypothesis 1: High management scores are associated with better firm performance.

There is by now a lot of empirical evidence supporting this hypothesis, and from experimental evidence the management effect appears to be causal (Bloom et al, 2013). In terms of the model of Section 2.2, a well managed firm will be able to attract more equity and invest more efficiently because management quality alleviates an agency problem whereby operational managers can divert or waste some of the cash reserves set aside for future investment. The initial equity injection which allows the firm to produce cash flows at time 0 (c_0) and the firm's cash reserves increase in the quality of management practices ($\frac{dc_0}{dm} = \frac{dC}{dm} > 0$). This means that the firm will be able to invest more at time 0, but also at time 1 due to increased cash holdings (See Hypothesis 2). As a result, management should be positively correlated with the efficiency of a firm's investment dynamics - ultimately leading to better performance.

To probe Hypothesis 1 in my sample, I run a series of regressions akin to those in Bloom, Sadun, and Van Reenen (2016) but using administrative data on UK firms instead of using accounting measures of performance. I use administrative data from the ONS Annual Business Inquiry and Annual Business Survey to confirm that management improves performance along several dimensions, namely real gross value added, capital expenditures, the capital stock, and employment. I also estimate a simple production function and show that management is positively correlated with TFP. The full analysis is in Section 2.4.

[15]See Proof in Appendix 2.A.

Hypothesis 2: Financially constrained firms save more out of their cash flows if they have higher management scores.

When firms face financial constraints, their capacity to invest will vary with the availability of internal funds. When short of cash, they may have to pass up on profitable investment opportunities. Firms that expect to face financing constraints in the future respond by stocking cash today. Holding cash is costly, since higher cash savings require reductions in current investments. As in ACW (2004), the optimal cash policy is the one that balances the profitability of current investments relative to future ones. The comparative statics from the cash saving model of Section 2.2 yield additional predictions for empirical analysis. Since better management practices mitigate cash diversion or wasteful behaviour, a well managed firm will also save more out of its cash flows for given current and future investment opportunities. Equity holders feel more at ease with giving managers discretion over the use of cash reserves. In other words, cash holdings and their sensitivity to cash flows are increasing in managerial capital. In terms of the model, $\frac{dC}{dm} > 0$ and $\frac{d\left(\frac{C}{c_0}\right)}{dm} > 0$ (under mild conditions). Using an empirical model similar to that of ACW (2004), I provide evidence that well managed firms indeed save more out of their cash flows. The full analysis is in Sections 2.5 and 2.6.

Hypothesis 3: Financially constrained firms save more out of their cash flows in response to cash flow volatility if they have higher management scores.

Financial constraints are not the only motive for cash hoarding. Han and Qiu (2007) argue that the cash holdings of financially constrained firms react to cash flow volatility. When future cash flow risk cannot be fully diversified, the inter-temporal trade-off between current and future investment opportunities gives constrained firms the incentives to accumulate precautionary savings. The model of Section 2.2 predicts that good management practices will encourage this precautionary behaviour. Equity holders face a trade-off between incentives to be prudent and the fact that some of the savings will be directed towards unproductive uses. Since better management ties the hands of operational managers, it alleviates agency problems and reduces the opportunity cost of saving cash. Using an empirical model similar to that of Han and Qiu (2007), I provide evidence that well managed firms indeed save more when their cash flows are more volatile. The full analysis is in Sections 2.5 and 2.6.

Hypothesis 4: High management scores are associated with a higher speed of adjustment towards a firm's optimal capital stock.

Hypotheses 2 and 3 deliver a rationale for why better managed firms that face financial constraints and volatile cash flows will be more able to undertake profitable investment opportunities when they arise (e.g. when they receive positive shocks to their fundamental productivity). Precautionary savings leave them better prepared for tightening credit constraints and/or unexpected negative earnings shocks. A direct consequence of this is that well managed firms should be able to invest more efficiently. Put differently, well managed firms are expected to adjust more quickly towards their long-run frictionless optimal capital stocks, which is equivalent to facing lower adjustment costs. I use an Error Correction Model (ECM) which follows the specification of Bloom, Bond, and Van Reenen (2007) to test this hypothesis. I find that the speed of adjustment increases in the Management score. The traditional ECM for investment dynamics assumes symmetry of adjustment speed, i.e. the same adjustment speed whether the firm's deviation from its long-run frictionless optimal capital stock is positive or negative. However, I want to test whether adjustment is faster when the firm falls *short* of its frictionless equilibrium level of capital. When this is the case, the firm needs to accumulate capital. By contrast, when a firm is above its long-run equilibrium, it needs to divest. Should the adjustment speed be symmetric, then it could be that well managed firms are simply more flexible, in the sense that they accumulate *and* divest faster. However, the results point to a significant asymmetry supporting the precautionary savings story. The full analysis is in Section 2.7.

2.3 Data

The dataset is based on several sources. Specifically, I obtain data on company accounts from Bureau van Dijk's Orbis database, administrative data from the Office for National Statistics, and management data from the WMS.

2.3.1 World Management Survey

The WMS is an interview-based survey that defines 18 management practices and scores firms from 1 (worst practice) to 5 (best practice). A high score represents better practices: a firm with a higher score will, on average, be more productive. The measured practices pertain to day-to-day operations rather than decisions of a more strategic nature taken at the executive level. Specifically, the practices cover four broad dimensions: operations, monitoring, targets, and incentives. Appendix 2.B gives a few more details on the survey, but I refer to Bloom and Van Reenen (2007) for details on the specific practices, and to Bloom, Sadun, and Van Reenen (2016) for details on the survey design.

Throughout the analysis, I use the overall Management z-score. The overall score is the average of the scores across all 18 questions. This average is z-scored so that the management index has a standard deviation of unity. The WMS has a panel dimension, so one could a priori use a time-varying measure of firm-level management quality. However, the panel dimension of the UK data set is growing but still too limited to provide robust econometric results in this paper. To maximise the number of observations, I use a firm's Management z-score in the first year in which it was surveyed, henceforth the "initial Management z-score". I then look at the firm's future performance given these "initial conditions" in managerial capital. In other words, the management score used in the analysis is always dated earlier than the outcome variables of interest. This also helps addressing potential issues of endogeneity as firms invest in their managerial capital over time in a way which may be endogenous to their performance. My sample covers the manufacturing sector for the period 2001-2013. Most of the management data is post 2004, and the results are robust to excluding 2001-2003. While the WMS contains data for 2014, I exclude this year due to data limitations in my administrative sample[16].

2.3.2 Administrative data and company accounts for UK firms

The main source of information on firm performance is administrative data collected by the UK's Office for National Statistics (ONS). I use two surveys, the Annual Business Inquiry (ABI) and the Annual Business Survey (ABS). These are establishment-level surveys that are primarily used in the construction of various national account aggregates. They are increasingly used in empirical studies of productivity (e.g. Barnett et al, 2014, and Riley et al, 2015)[17]. The sampling frame for the surveys is the Inter-Departmental Business Register (IDBR), a register of all UK incorporated businesses and other businesses registered for tax purposes. The surveys are a census of larger businesses and a stratified random sample (by industry, region and employment size) of businesses with fewer than 250 employees (SMEs). The surveys cover the non-financial

[16] In particular, I do not have the data on aggregate capital stocks and capital expenditures by assets and industries that are necessary to estimate firm-level capital stocks in 2014.

[17] Details of the ABI and ABS data can be found in Griffith (1999), Bovill (2012), Barnett et al (2014), and Riley et al (2015).

non-farm market sector for 1994-2014.

I measure labour productivity as real gross value added (GVA) per head. The ABI and ABS data are published in current values. To obtain real GVA, I compute implied GVA deflators coded to the UK Standard Industrial Classification (SIC) 2007 at the section level. I construct firm-level measures of capital stocks (including machinery & equipment, buildings, and vehicles) using information on investment net of disposals of these assets available in the ABI/ABS. Investment is deflated using investment deflators by asset and industry obtained from the ONS Volume of Capital Services (VICS). Firm-level capital stocks are estimated using the Perpetual Inventory Method (See Appendix 2.D for details). Initial capital stocks are imputed using ONS VICS data by asset and industry. I derive a simple measure of TFP using a Solow residual with industry-specific empirical labour shares. To the best of my knowledge the only existing paper linking ABI/ABS data to the WMS is Bloom et al (2010). Appendix 2.E gives information on how the two data sets were linked.

I complement the ONS data with company accounts from Bureau van Dijk's Orbis database. I collect data on total assets, cash flows from operations, cash holdings, and short-term debt (loans). All data are winsorized (top and bottom 1%) to ensure the results are not driven by extreme values.

2.3.3 Descriptive statistics

I describe the full sample with the maximum number of observations for each variable. The sample size will vary across regressions due to data limitations. However, the descriptive statistics are robust across regression sub-samples. After matching ONS and WMS data, the final sample consists of 4,284 observations on 928 firms from the UK. Of those, 1,573 observations are for SMEs (firms with fewer than 250 employees) and 2,711 for large firms. The sample period is 2001-2013. Table 2.3.1 presents the number of observations, by size, as well as the average number of observations per firm for each size category.

Table 2.3.1: **Number of observations**

	Number of obs	Average no. of obs per firm
All	4,284	6.30
SMEs	1,573	4.65
Large	2,711	7.26

Notes: Full 2001-2013 sample. SMEs are firms with strictly fewer than 250 employees. Large firms are firms with 250 employees or more.

Table 2.3.2 summarizes the basic descriptive statistics for the key variables. The mean cash ratio is 9% and the median value is 5%. These values are in line with those previously reported for UK (public) firms. Ozkan and Ozkan (2004) report that the mean and median values of the cash ratio are 9.9% and 5.9% respectively. They are also surprisingly in line with those reported for US firms. For example, in Kim et al (1998) the mean and median values of the cash ratio are 8.1% and 4.7%. In Han and Qiu (2007) the sample firms hold on average 8.4% of their assets in cash (with a median of 3.3%).

Table 2.3.2: **Descriptive statistics**

	N	Stdev	Mean	p50	p25	p75
Initial Management z-score	4,284	1.03	0.24	0.28	-0.45	1.01
Real gross I/K	3,445	0.13	0.09	0.05	0.02	0.1
Real GVA (in th)	4,284	56,718	34,476	15,199	6,636	35,955
Employment	4,284	924	591	319	177	577
Real K (in th)	4,276	52,771	31,808	15,057	5,564	32,596
Real gross capex (in th)	4,191	4,648	2,233	645	178	1,985
Ln(TFP)	4,100	0.69	2.48	2.47	2.06	2.87
Cash flow/TA	2,993	0.38	0.16	0.08	0.04	0.15
TA (in th)	4,065	185,396	93,182	28,184	10,718	81,125
Cash/TA	2,979	0.12	0.09	0.05	0.01	0.13

Notes: Full 2001-2013 sample with maximum number of observations for each variable. SMEs are firms with strictly fewer than 250 employees. Large firms are firms with 250 employees or more. All variables are winsorized (top and bottom 1%) except the initial Management z-score. Total factor productivity (TFP) is measured using a simple Solow residual with industry-level empirical labour shares. The capital stock has been computed on the entire ABI/ABS sample using the Perpetual Inventory Method. **Initial Management z-score** is the Management z-score in the first year in which the firm is surveyed. **Real gross I/K** stands for real gross investment divided by the capital stock estimate. **Real GVA** is real gross value added in thousands. **Employment** is the number of employees. **Real K** is the real capital stock estimate in thousands. **Real gross capex** stands for real gross capital expenditures in thousands. **Ln(TFP)** is the logarithm of the TFP estimate. **Cash flow/TA** is cash flows from operations divided by total assets. **TA** is total assets in thousands. **Cash/TA** is the ratio of cash holdings to total assets.

2.4 Management practices and firm performance

In this section, I provide evidence that management is positively correlated with firm performance in terms of real gross value added, investment, the use of capital, and survival. I perform a similar analysis to that of Bloom, Sadun, and Van Reenen (2016) but use administrative data. The advantage of administrative data is that I can work with good measurements of real gross value added and capital expenditures. I estimate firms' capital stocks using the perpetual inventory method. The management score is the initial Management z-score with a standard deviation of unity. The models I estimate are of the general form:

$$ln(Y_{i,t}) = \alpha_M M_i + \alpha_S S_{i,t} + \alpha_X X_{i,t} + B_t + B_j + u_{i,t} \tag{2.4.1}$$

$ln(Y_{i,t})$ is the natural logarithm of the dependent variable. M_i is firm i's Management z-score in the first year it was surveyed. $S_{i,t}$ is the natural logarithm of the number of employees, a measure of firm size. Larger firms are better managed than smaller ones and it is an important control to include. $X_{i,t}$ is a vector of controls including noise controls, namely the tenure and seniority of the interviewee, the duration of the interview, the day and hour of the day when the interview took place, and a measure of the reliability of the interviewee based on his/her knowledge and willingness as perceived by the analyst. It also includes the proportion of employees with a college degree. B_t and B_j are year and (3-digit) industry fixed effects respectively. $u_{i,t}$ is the error term. I do not include firm-fixed effects as I use the initial Management z-score throughout the analysis.

Using administrative data I uncover a significant relationship between management, size and performance, which complements the results of the existing literature relying on accounting measures. Column (1) of Table 2.4.1 shows that a higher initial Management z-score is significantly positively associated with a firm's number of employees. A coefficient of 0.132 suggests that one standard deviation of the management score is associated with 13.2 log points higher employment (i.e. about 14%=$(exp(0.132) - 1) * 100$). This confirms previous findings in the literature that larger firms have better management practices. Columns (2), (3) and (4) suggest that one standard deviation of the management score is associated with 5.6 log points higher real GVA (i.e. about 5.8%), 10.5 log points higher real capital stock (i.e. about 11%), and 13.6 log points higher real capital expenditures (i.e. about 14.6%) conditional on employment. This indicates that better management is associated with higher labour productivity, a higher capital intensity of production (capital-labour ratio), and higher capital expenditures. These numbers are economically significant and the correlation is particularly strong for investment and the use of capital.

In Column (5) I estimate a simple production function, regressing the logarithm of real GVA on the logarithm of the number of employees and the capital stock in real terms. The coefficient on the initial Management z-score is positive but insignificant. I re-run the regression in Column (6) allowing the Management z-score to vary over time. Accordingly, the number of observations drops substantially as the panel dimension of the UK sample is still limited. The coefficient is 0.064 and is significant at the 10% level. This suggests that better management practices are positively correlated with TFP. A coefficient of 0.064 implies that a one standard deviation of the Management z-score is associated with a 6.4 log point increase in TFP (about 6.6%).

Table 2.4.1: **Management and performance OLS regressions on ABI/ABS data**

PANEL A	(1)	(2)	(3)
	Ln(Empl)	Ln(Real GVA)	Ln(K)
Initial M z-score	0.132***	0.056**	0.105***
	(0.037)	(0.026)	(0.038)
Ln(Empl)		0.935***	0.948***
		(0.032)	(0.036)
Industry FE (3d)	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	4,284	4,133	4,269
PANEL B	**(4)**	**(5)**	**(6)**
	Ln(Real Inv)	Ln(Real GVA)	Ln(Real GVA)
Initial M z-score	0.136***	0.031	
	(0.043)	(0.026)	
Ln(Empl)	1.094***	0.708***	0.734***
	(0.042)	(0.035)	(0.040)
Ln(K)		0.239***	0.186***
		(0.030)	(0.035)
Management z-score			0.064*
			(0.036)
Industry FE (3d)	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	4,042	4,123	2,293

Notes: *** indicates significance at the 1% level, ** indicates significance at the 5% level and * indicates significance at the 10% level. All estimations by OLS with standard errors in parentheses and clustered by firm. Each model is estimated on the largest number of observations. Results are robust to running all estimations on a common sample. All regressions contain noise controls. Industry (3-digit) and year fixed effects included. **Initial M z-score** is the Management z-score in the first year the firm was surveyed (a constant at the firm level). **Management z-score** is the time-varying Management z-score. **Empl** stands for employees. **K** stands for the real capital stock estimate. **Real GVA** stands for real gross value added. **Real Inv** is real gross capital expenditures.

Table 2.4.2 examines resilience to the financial crisis and finds that better managed firms were significantly more likely to survive after 2008, even after controlling for size and profitability. The dependent variable is a dummy equal to 1 if a firm survived after 2008, and zero otherwise. The dummy is built using the Inter-Departmental Business Register, which allows me to track firms from birth to death. The financial crisis represents an exogenous shock to financial constraints and earnings. The results suggest that better managed firms were more resilient to this shock. Of course, all the results presented here are conditional correlations, and are not to be taken as causal.

Table 2.4.2: **Management and post-2008 survival**

Dependent variable: **Dummy for post-2008 survival**	**(1)**	**(2)**	**(3)**
Initial Management z-score	0.024**	0.024**	0.024**
	(0.010)	(0.011)	(0.010)
Ln(Employees)		0.001	
		(0.010)	
EBIT/TA			0.053**
			(0.025)
N	3,157	3,157	3,157

Notes: *** denotes significance at the 1% level, ** denotes 5% significance and * denotes 10% significance. The dependent variable is a dummy equal to 1 if a firm survived after 2008, and zero otherwise. All columns estimated by OLS with standard errors in parentheses and clustered by firm. Each model is estimated on the largest number of observations available for the independent and dependent variables. Results are robust to running all estimations on larger samples (without controlling for data availability). All regressions contain noise controls. No fixed effects are included. **Initial Management z-score** is the Management z-score in the first year the firm was surveyed. **Ln(Employees)** is the log of employees. **EBIT/TA** is the ratio of EBIT to total assets and proxies for the firm's profitability.

The probability of survival goes up by 2.4% for an increase of one standard deviation in the initial Management z-score. However, I cannot control for the severity of demand shocks suffered by firms of various management quality. One factor that may work against these results is that better managed firms are more export oriented and may therefore have been relatively more affected by the international demand shock.

2.5 Management and cash policies

In this Section I probe Hypotheses 2 and 3 and examine whether well managed firms are more prudent. Almeida, Campello, and Weisbach (2004) argue that firms that face frictions in raising outside finance save a greater portion of their cash flows as cash holdings. This is supported by recent studies such as Lins et al (2008) and Hadlock and Pierce (2010). But financial constraints may not be the only reason why firms may wish to save out of their cash flows. Han and Qiu (2007) show that firms may also have a precautionary motive to accumulate cash in the face of cash flow volatility. I examine the correlation between management and cash holding policies along those two dimensions.

2.5.1 Management and the cash flow sensitivity of cash

I use a model of cash flow retention similar to that of ACW (2004). Bearing in mind data limitations and the fact that my sample mainly consists of private firms, I cannot exactly replicate their augmented empirical model. In particular, I do not have a measure of growth opportunities such as Tobin's Q. The model I estimate is:

$$\begin{aligned}\triangle\left(\frac{CASH_{i,t}}{TA_{i,t}}\right) &= \beta_1\frac{CF_{i,t}}{TA_{i,t}} + \beta_2\triangle ln(GVA_t) + \beta_3\frac{I_{i,t}}{TA_{i,t-1}} + \beta_4\frac{D_{i,t}}{TA_{i,t-1}} + \beta_5 ln(TA_{i,t}) \\ &+ \beta_6\triangle ShortDebt_{i,t} + \beta_7 M_i + \beta_8 M_i\left(\frac{CF_{i,t}}{TA_{i,t}}\right) + B_t + \{B_i\} + B_j + u_{i,t}\end{aligned}$$

$\frac{CASH_{i,t}}{TA_{i,t}}$ is the ratio of cash holdings to total assets. $\frac{CF_{i,t}}{TA_{i,t}}$ is the ratio of cash flows from operations to total assets. Firms that are financially constrained are likely to increase their cash reserves following an increase in cash flows so β_1 is expected to be positive. Since the sample mainly consists of private firms, I do not have a measure of growth opportunities based on the firm's stock market valuation. I exploit administrative data to use a non-accounting proxy, namely the growth rate of a firm's gross value added ($\triangle ln(GVA_t)$). β_2 is expected to be positive. $\frac{I_{i,t}}{TA_{i,t-1}}$ is the ratio of gross capital expenditures to lagged total assets. β_3 is expected to be negative since a firm that invests today may disburse cash to do so. $\frac{D_{i,t}}{TA_{i,t-1}}$ is the ratio of disposals to lagged total assets, defined as the difference between the gross and the net investment ratios. Since disposals and sales of assets provide alternative sources of liquid funds to the firm, β_4 is expected to be negative. I control for firm size as measured by the natural logarithm of total assets, $ln(TA_{i,t})$. I control for size because of possible economies of scale in cash management and the strong positive correlation with management. If there are economies of scale β_5 should be negative, i.e. the propensity to save decreases in size. $\triangle ShortDebt_{i,t}$ is the ratio of the change in short-term debt (loans) normalised by total assets. Short-term debt is another source of liquid funds for the firm and hence may influence its cash holding behaviour. A firm with better access to debt finance may want to hoard less cash since it has lower precautionary saving incentives. On the other hand, higher debt levels increase the likelihood of financial distress. Therefore, firms that use debt finance could increase their cash holdings to decrease this likelihood. The sign of the coefficient β_6 is therefore an empirical issue. B_t, B_j, and B_i are year, industry and firm fixed effects. M_i is the initial Management z-score. Finally, $M_i\left(\frac{CF_{i,t}}{TA_{i,t}}\right)$ is an interaction term between cash flows and the initial Management z-score. It is the key variable of interest. I also re-run the estimations with an additional interaction term between the initial Management z-score and size, M_i $(ln(TA_{i,t}))$.

I first estimate the model with year and industry fixed effects using OLS[18]. I then use a system GMM estimator (Arellano and Bover, 1995, and Blundell and Bond, 1998). This technique extends the first-differenced GMM estimator by combining a system of equations in first differences with equations in levels. In the system of equations in first differences, lagged levels of the endogenous variables are used as instruments. In the system of equations in levels, lagged differences of the endogenous variables are used as instruments. System GMM allows me to obtain a coefficient on time invariant variables such as M_i, although this is not the key variable of interest. The additional requirement of system GMM relative to first-differenced GMM is that the additional instruments used in the levels equations should be uncorrelated with the unobserved firm-specific effects. This can be tested with the Sargan-Hansen difference test of over-identifying restrictions. If these extra instruments are valid, the system GMM estimator is more efficient and has a smaller finite sample bias than the first-differenced GMM estimator. Standard errors are clustered by firm and hence robust to arbitrary autocorrelation and heteroscedasticity. All GMM coefficients are one-step estimates. The reported results treat all control variables as endogenous except the initial Management z-score. Interactions between the initial Management z-score and endogenous variables are treated as endogenous. The validity of the instruments is tested by reporting both a Hansen test of the over-identifying restrictions and the Sargan-Hansen test for the additional instruments required for system GMM. I also report the test for second-order autocorrelation in the differenced residuals (Arellano and Bond, 1991).

[18] Appendix 2.F contains the results of OLS with and without fixed effects for comparison.

Table 2.5.1: **Cash saving behaviour - OLS and system GMM**

Dependent variable	**OLS**		**GMM**	
△Cash/TA	**(1)**	**(2)**	**(3)**	**(4)**
CF/TA	0.019**	0.019**	0.019*	0.022**
	(0.008)	(0.008)	(0.011)	(0.011)
△Ln(GVA)	0.002	0.002	-0.013	-0.015
	(0.004)	(0.004)	(0.011)	(0.011)
Ln(Total assets)	0.001	0.001	-0.006**	-0.005**
	(0.001)	(0.001)	(0.002)	(0.002)
Gross investment/TA	0.014***	0.014***	0.019	0.017
	(0.005)	(0.005)	(0.013)	(0.012)
Disposals/TA	-0.042***	-0.041***	-0.031	-0.034*
	(0.013)	(0.013)	(0.022)	(0.020)
△Loans/TA	0.072***	0.071***	0.170***	0.165***
	(0.018)	(0.018)	(0.042)	(0.041)
Initial Management score	-0.005***	0.003	-0.003**	-0.015
	(0.002)	(0.007)	(0.002)	(0.029)
Management score x (CF/TA)	0.016**	0.015**	0.016*	0.019*
	(0.007)	(0.007)	(0.009)	(0.011)
Management score x TA		-0.001		0.001
		(0.001)		(0.003)
Industry FE (2d)	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
N	2,360	2,360	2,360	2,360
AR(2) test			0.666	0.66
Hansen test p-value			0.877	0.963
Sargan-Hansen diff test p-value			0.982	0.993
Number of instruments			237	269

Notes: △**CASH/TA**: change in cash holdings to total assets; **CF/TA**: cash flows from operations to total assets; △**Ln(GVA)**: growth rate of gross value added; **Ln(Total assets)**: log of total assets; **Gross investment/TA**: gross capital expenditures to lagged total assets; **Disposals/TA**: disposals to total assets; △**Loans/TA**: change in short-term debt normalised by total assets; **Initial Management score**: initial Management z-score; **Management score x (CF/TA)**: interaction between cash flows and Management; **Management score x TA**: interaction between Management and size. The first two Columns report OLS estimations with year and industry fixed effects. Standard errors are clustered at the firm level. Estimation in Columns (3) and (4) uses a (one-step) system GMM estimator and also controls for year fixed effects. The instruments are, in the first-differenced equations: lags 2 and 3 of the control variables, and in the levels equations: lags 2 and 3 of the first differences of those same variables. The managerial score is assumed exogenous. All other controls are treated as endogenous. Hansen test for instrument validity and AR(2) test in the first-differenced residuals are reported.

Table 2.5.1 has two key results. First, the coefficient on cash flows is significantly positive in all specifications, implying that the firms in the sample save out of their cash flows. According to Fazzari et al (1988, 2000), this is an indication that the firms in the sample are financially constrained. Second, the interaction term between cash flows and management is positive and significant across all estimations. The magnitudes of the coefficients are robust across OLS and GMM. The results are also robust to including an interaction term between size and management (Columns (2) and (4)). Better managed firms are more prudent in the sense that they save more out of their cash flows. The magnitude of the interaction coefficient is robust across estimations and ranges between 0.015 and 0.019. With a mean ratio of cash flows to assets equal to 0.16, the estimates suggest that a one standard deviation of the management score increases a firm's savings (normalised by assets) by between 24 and 30 percentage points on average. This is economically significant because the coefficients on the standalone cash flow term ranges between 0.019 and 0.022. A one standard deviation of the management score is associated with almost a doubling of the saving propensity in the sample. Given a mean (median) cash ratio of 0.09 (0.05), this is economically significant.

The coefficient on disposals is negative and significant (except for Column (3)), suggesting that firms substitute between sources of liquid funds. An increase in short-term debt attracts a positive coefficient, qualitatively in line with the results in ACW (2004) and the argument that higher debt levels can increase the likelihood of financial distress. In response firms increase their cash holdings to decrease the likelihood of distress. The magnitude of the coefficient on debt is large and significant at the 1% level. This suggests that firms in the sample are financially constrained. The standalone coefficient on the initial Management z-score is significantly negative in OLS and GMM (Columns (1) and (3)), but loses its significance when I control for the interaction between management and size. The interaction term between size and management is itself insignificant and does not affect the magnitude of the coefficients on the interaction between cash flows and managerial capital. It renders the standalone coefficient on management insignificant though. Size attracts an insignificant coefficient in OLS and a significantly negative coefficient in GMM, which suggests economies of scale in cash management. Surprisingly the coefficient on the growth rate of gross value added is insignificant. In addition, the coefficient on gross investment is positive (but only significant in OLS). Instead of divesting funds, firms which invest today seem to accumulate more cash. This could suggest that current investment captures growth opportunities: firms that invest today expect to grow tomorrow and hence accumulate cash to finance continued opportunities. It is well-established that measuring growth opportunities is problematic.

In the GMM estimations, the test for second-order autocorrelation of the differenced residuals does not indicate any problems with the specification. The Hansen test does not reject the exogeneity of the entire set of instruments. Finally, the Sargan-Hansen difference test does not reject the exogeneity of the additional instruments for the levels equations in system GMM.

2.5.2 Management and precautionary behaviour when cash flows are volatile

In this section, I estimate the previous model but also include the standard deviation of a firm's cash flows in the set of control variables. I replace the interaction term between management and cash flows with an interaction term between management and cash flow volatility. The model I estimate is:

$$\begin{aligned}\triangle\left(\frac{CASH_{i,t}}{TA_{i,t}}\right) = \beta_1\frac{CF_{i,t}}{TA_{i,t}} + \beta_2\triangle ln(GVA_t) + \beta_3\frac{I_{i,t}}{TA_{i,t-1}} + \beta_4\frac{D_{i,t}}{TA_{i,t-1}} + \beta_5 ln(TA_{i,t}) \\ + \beta_6\triangle ShortDebt_{i,t} + \beta_7 CFV_{i,t} + \beta_8 M_i \\ + \beta_9 M_i(CFV_{i,t}) + B_t + \{B_i\} + B_j + u_{i,t}\end{aligned}$$

All the variables are defined as in the model of Section 2.5.1. $CFV_{i,t}$ is the standard deviation of a firm's cash flows normalised by assets over the past three years (3-year rolling average), and $M_i(CFV_{i,t})$ is an interaction term between cash flow volatility and the initial Management z-score. I expect a positive coefficient on cash flow volatility in line with the ideas of Minton and Schrand (1999) and Han and Qiu (2007). In line with the model of Section 2.2, I expect β_9 to be positive. Again, I first estimate the model with year and industry fixed effects using OLS[19] and then use system GMM.

In Table 2.5.2 I find that cash flow volatility induces firms to save. The coefficients on cash flow volatility are all positive and significant. Using a similar measure of cash flow volatility, Ozkan and Ozkan (2007) also find evidence that UK (public) firms with more volatile cash flows hold more cash. Their estimated coefficient is 0.035. My coefficients range between 0.032 in OLS and 0.070 in GMM. The higher coefficients I obtain in GMM could be related to the fact that 50% of the firms in my sample are private. Since private firms have more restricted access to external finance, they may have stronger precautionary incentives.

More importantly I find a significantly positive interaction between management and cash

[19] Appendix 2.F contains the results of OLS with and without fixed effects for comparison.

flow volatility. The coefficients are robust to controlling for potential interaction between management and size. The interaction coefficient is economically significant when compared to the standalone coefficient on volatility. It ranges between 0.052 in OLS and 0.069 in GMM. Given a mean cash flow volatility of 0.076, this suggests that a one standard deviation of the management score is associated with an increase in savings (normalised by assets) of between 39 and 52 percentage points on average. The coefficients are all significant at the 1% level. A one standard deviation of the management score is associated with (more than) a doubling of the saving propensity in the sample in response to cash flow volatility. These empirical results indicate systematic differences in cash holding behaviour between poorly and well managed firms in response to cash flow volatility, and support Hypothesis 3. The other coefficients are in line with the results in Section 2.5.1.

In the GMM estimations, the test for second-order autocorrelation of the differenced residuals does not indicate any problems with the specification. The Hansen test does not reject the exogeneity of the entire set of instruments. Finally, the Sargan-Hansen difference test does not reject the exogeneity of the additional instruments for the levels equations in system GMM.

Table 2.5.2: **Cash saving behaviour and cash flow volatility, OLS and GMM**

Dependent variable	**OLS**		**GMM**	
△ Cash/TA	**(1)**	**(2)**	**(3)**	**(4)**
CF volatility	0.032**	0.032**	0.070***	0.069***
	(0.015)	(0.015)	(0.025)	(0.025)
CF/TA	0.013*	0.013*	-0.004	-0.002
	(0.007)	(0.007)	(0.011)	(0.010)
△Ln(GVA)	0.003	0.003	-0.002	-0.006
	(0.004)	(0.004)	(0.010)	(0.010)
Ln(Total assets)	0.001	0.001	-0.004**	-0.004**
	(0.001)	(0.001)	(0.002)	(0.002)
Gross investment/TA	0.012**	0.012**	0.017*	0.014
	(0.005)	(0.005)	(0.010)	(0.009)
Disposals/TA	-0.030**	-0.030**	-0.024	-0.026
	(0.012)	(0.012)	(0.018)	(0.018)
△Loans/TA	0.069***	0.069***	0.168***	0.165***
	(0.018)	(0.018)	(0.038)	(0.037)
Initial Management score	-0.006***	-0.003	-0.005***	-0.028
	(0.001)	(0.007)	(0.001)	(0.024)
Management score x CF vol	0.053***	0.052***	0.063***	0.069***
	(0.011)	(0.011)	(0.013)	(0.013)
Management score x TA		0.000		0.002
		(0.001)		(0.002)
Industry FE	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
N	2,360	2,360	2,360	2,360
AR(2) test			0.671	0.665
Hansen test p-value			0.904	0.977
Sargan-Hansen diff test p-value			0.911	0.989
Number of instruments			269	301

Notes: **△Cash/TA**: cash holdings to total assets; **CF volatility**: standard deviation of a firm's cash flows over the past 3 years; **CF/TA**: cash flows from operations to total assets; **△Ln(GVA)**: growth rate of gross value added; **Ln(Total assets)**: log of total assets; **Gross investment/TA**: gross capital expenditures to lagged total assets; **Disposals/TA**: disposals to lagged total assets; **△Loans/TA**: change in short-term debt normalised by total assets; **Initial Management score**: initial Management z-score; **Management score x CF vol**: interaction between cash flow volatility and Management; **Management score x TA**: interaction between Management and size. The first two Columns report OLS estimations with year and industry fixed effects. Standard errors clustered at the firm level. Estimation in Columns (3) and (4) uses a (one-step) system GMM estimator and also controls for year fixed effects. The instruments are, in the first-differenced equations: lags 2 and 3 of the control variables, and in the levels equations: lags 2 and 3 of the first differences of those same variables. The managerial score is assumed exogenous. All other controls are treated as endogenous. Hansen test for instrument validity and AR(2) test in the first-differenced residuals are reported.

2.6 Financially constrained versus unconstrained firms

The story put forward in this paper is that better management practices alleviate under-investment by financially constrained firms. The models of ACW (2004) and Han and Qiu (2007) make predictions for financially constrained firms only. This applies to my model too, with the starker conclusion that unconstrained firms will hold no cash at all to smooth investment (See Appendix 2.C). The results of the empirical analysis point to the presence of financial constraints in the sample. First, the significant cash flow sensitivity of cash found in Table 2.5.1 is evidence of financial constraints according to ACW (2004), and so is the sensitivity of cash to cash flow volatility according to Han and Qiu (2007) (Table 2.5.2). The results in Tables 2.5.1 and 2.5.2 also suggest that firms feel the need to accumulate more cash when their debt levels increase. This suggests that the likelihood of financial distress is a concern among sample firms. To provide more rigorous evidence, however, I differentiate between a priori constrained and unconstrained firms on the basis of their size. I distinguish between small and large firms. A small (large) firm is defined as having a logarithm of total assets below (above) the sample median.

2.6.1 Sensitivity of cash to cash flows

Table 2.6.1 reproduces the estimations of Table 2.5.1 by size category. There are two key results. First, the coefficient on cash flows remains significantly positive in all specifications. This is in contradiction with the results of ACW (2004) that the cash holdings of a priori unconstrained firms are not sensitive to their cash flows. However, their sample is based on US public firms and our results are in line with work on European firms. Using data on firms in the Euro area, Ferrando and Pál (2006) find that the propensity to save cash out of cash flows is significantly positive regardless of firms' financing conditions. Even firms with favourable external financing conditions use internal funds for the inter-temporal allocation of capital. Cash flow sensitivity appears to be a flawed measure of financial constraints.

Second, and more importantly, the coefficient on the interaction term between management and cash flows is only significantly positive for small firms. The enhanced precautionary behaviour resulting from better management practices seems to be a small-firm phenomenon - in line with the hypothesis that the mechanism only applies to financially constrained firms. In stark contrast with the results for small firms, the coefficient on the interaction term between management and cash flows is significantly negative both in OLS and GMM in the sub-sample of large firms. This is consistent with an empire-building story where excess cash accumulation is mitigated by better management practices. The corporate governance literature has shown that agency problems can lead to excess cash holdings (e.g. Gao et al, 2013; Dittmar, Mahrt-Smith, and Servaes, 2003). In line with this, Dittmar and Mahrt-Smith (2007) find that cash holdings are valued higher in firms with stronger corporate governance (measured as lower managerial entrenchment and better monitoring from institutional block holders). The results of Table 2.6.1 indicate that better management practices could alleviate value destruction through overinvestment in wasteful projects that provide managers with private benefits - but this is beyond the scope of the present paper as the model pertains to financially constrained firms and value destruction through underinvestment.

Table 2.6.1: Cash saving behaviour by size - OLS and GMM

Dependent variable	**OLS**		**GMM**	
△Cash/TA	**Small firms**	**Large firms**	**Small firms**	**Large firms**
	(1)	**(2)**	**(3)**	**(4)**
CF/TA	0.017*	0.053**	0.021*	0.084*
	(0.009)	(0.025)	(0.011)	(0.046)
△Ln(GVA)	-0.005	0.006	-0.003	-0.006
	(0.007)	(0.005)	(0.009)	(0.010)
Ln(Total assets)	-0.002	0.002	-0.007	-0.002
	(0.004)	(0.001)	(0.005)	(0.001)
Gross investment/TA	0.011*	-0.015	0.013	0.015
	(0.006)	(0.026)	(0.008)	(0.017)
Disposals/TA	-0.039***	0.002	-0.040**	-0.087
	(0.014)	(0.044)	(0.016)	(0.081)
△Loans/TA	0.083***	0.044**	0.175***	0.105**
	(0.027)	(0.021)	(0.043)	(0.046)
Initial Management score	0.047**	0.009	-0.019	0.02
	(0.023)	(0.017)	(0.051)	(0.025)
Management score x(CF/TA)	0.013*	-0.037**	0.022**	-0.091**
	(0.007)	(0.018)	(0.010)	(0.039)
Management score x TA	-0.006**	-0.001	0.002	-0.001
	(0.003)	(0.001)	(0.006)	(0.002)
Industry FE (2d)	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
N	842	1,518	842	1,518
AR(2) test			0.611	0.389
Hansen test p-value			0.995	0.992
Sargan-Hansen diff test p-value			0.995	0.975
Number of instruments			235	258

Notes: △**CASH/TA**: change in cash holdings to total assets; **CF/TA**: cash flows from operations to total assets; △**Ln(GVA)**: growth rate of gross value added; **Ln(Total assets)**: log of total assets; **Gross investment/TA**: gross capital expenditures to lagged total assets; **Disposals/TA**: disposals to total assets; △**Loans/TA**: change in short-term debt normalised by total assets; **Initial Management score**: initial Management z-score; **Management score x (CF/TA)**: interaction between cash flows and Management; **Management score x TA**: interaction between Management and size. A small (large) firm is defined as having a logarithm of total assets below(above) the sample median. The first two Columns report OLS estimations with year and industry fixed effects. Standard errors are clustered at the firm level. Estimation in Columns (3) and (4) uses a (one-step) system GMM estimator and also controls for year fixed effects. The instruments are, in the first-differenced equations: lags 2 and 3 of the control variables, and in the levels equations: lags 2 and 3 of the first differences of those same variables. The managerial score is assumed exogenous. All other controls are treated as endogenous. Hansen test for instrument validity and AR(2) test in the first-differenced residuals are reported.

2.6.2 Sensitivity of cash to cash flow volatility

Table 2.6.2 reproduces the estimations of Table 2.5.2 by size category. There are two key results. First, the standalone coefficient on cash flow volatility is insignificant in the sub-sample of large firms, while it remains significantly positive for small firms. This is in line with the results of Han and Qiu (2007) that the cash holdings of a priori unconstrained firms are not sensitive to the volatility of their cash flows. Second, the enhanced precautionary behaviour induced by better management practices again seems to be a small-firm phenomenon - in line with the hypothesis that the mechanism only applies to financially constrained firms. The coefficient on the interaction term between management and cash flow volatility is insignificant for large firms but significantly positive for small firms.

Table 2.6.2: Cash saving behaviour and cash flow volatility by size , OLS and GMM

Dependent variable	**OLS**		**GMM**	
△ Cash/TA	**Small firms**	**Large firms**	**Small firms**	**Large firms**
	(1)	**(2)**	**(3)**	**(4)**
CF volatility	0.047***	-0.056	0.071***	-0.018
	(0.017)	(0.041)	(0.025)	(0.061)
CF/Total assets	0.005	0.040*	0.002	0.02
	(0.008)	(0.021)	(0.009)	(0.032)
△Ln(GVA)	-0.003	0.007	0.006	-0.005
	(0.006)	(0.005)	(0.010)	(0.009)
Ln(Total assets)	-0.001	0.002	-0.004	-0.002
	(0.004)	(0.001)	(0.004)	(0.001)
Gross investment/TA	0.011*	0.032**	0.009	0.026
	(0.006)	(0.012)	(0.006)	(0.016)
Disposals/TA	-0.028**	-0.037	-0.025	-0.088
	(0.013)	(0.034)	(0.017)	(0.080)
△Loans/TA	0.083***	0.057***	0.169***	0.103**
	(0.029)	(0.021)	(0.042)	(0.047)
Initial Management score	0.036*	-0.005	-0.017	-0.021
	(0.020)	(0.015)	(0.047)	(0.027)
Management score x CF vol	0.057***	0.047	0.071***	0.041
	(0.011)	(0.029)	(0.014)	(0.063)
Management score x TA	-0.005**	0	0.001	0.001
	(0.002)	(0.001)	(0.005)	(0.002)
Industry FE (2d)	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
N	842	1518	842	1518
AR(2) test			0.622	0.349
Hansen test p-value			0.999	0.985
Sargan-Hansen diff test p-value			0.999	0.949
Number of instruments			254	283

Notes: **△Cash/TA**: cash holdings to total assets; **CF volatility**: standard deviation of a firm's cash flows over the past 3 years; **CF/TA**: cash flows from operations to total assets; **△Ln(GVA)**: growth rate of gross value added; **Ln(Total assets)**: log of total assets; **Gross investment/TA**: gross capital expenditures to lagged total assets; **Disposals/TA**: disposals to lagged total assets; **△Loans/TA**: change in short-term debt normalised by total assets; **Initial Management score**: initial Management z-score; **Management score x CF vol**: interaction between cash flow volatility and Management; **Management score x TA**: interaction between Management and size. A small (large) firm is defined as having a logarithm of total assets below(above) the sample median. The first two Columns report OLS estimations with year and industry fixed effects. Standard errors clustered at the firm level. Estimation in Columns (3) and (4) uses a (one-step) system GMM estimator and also controls for year fixed effects. The instruments are, in the first-differenced equations: lags 2 and 3 of the control variables, and in the levels equations: lags 2 and 3 of the first differences of those same variables. The managerial score is assumed exogenous. All other controls are treated as endogenous. Hansen test for instrument validity and AR(2) test in the first-differenced residuals are reported.

2.7 Management and investment dynamics

In this section, I examine the impact of managerial capital on the dynamics of the investment process. Firms adjust their capital stocks according to their expectations about future investment opportunities. However, adjustment costs imply that this process is gradual. Hypothesis 4 posits that well managed firms are able to adjust their capital stocks more quickly towards their long-run optimal levels. I rely on a reduced-form Error Correction Model as in Bloom, Bond, and Van Reenen (2007) to probe this hypothesis.

Bloom (2000) shows that, in the long run, the actual capital stock chosen by a firm facing adjustment costs grows at the same rate as the hypothetical capital stock that the firm would choose in the absence of those costs. This implies cointegration I(1) between the logarithms of the actual capital stock and the target capital stock:

$$k_{i,t} = k^*_{i,t} + e_{it} \tag{2.7.1}$$

where k_{it} is the logarithm of the actual capital stock for firm i in period t, k^*_{it} is the logarithm of the capital stock the firm would choose in the absence of adjustment costs, and e_{it} is a stationary I(0) error term. Equation 2.7.1 can be considered a steady-state relation. The hypothetical frictionless level of the capital stock is specified as

$$k^*_{i,t} = y_{i,t} + A^*_i + B^*_t \tag{2.7.2}$$

where $y_{i,t}$ is the log of real sales and A^*_i and B^*_t are unobserved firm-specific and time-specific effects reflecting differences across firms in the user cost of capital and how they respond to it.

A parsimonious Error Correction representation of the dynamic relationship between $k_{i,t}$ and $k^*_{i,t}$, using Equations 2.7.1 and 2.7.2, takes the form

$$\triangle k_{i,t} = \beta \triangle y_{i,t} + \theta(k_{i,t-1} - y_{i,t-1}) + A_i + B_t + \nu_{i,t} \tag{2.7.3}$$

where $\nu_{i,t}$ is a serially uncorrelated error term, and A_i and B_t are unobserved firm and time fixed effects. The key property of the model is that the coefficient θ on the Error Correction term should be negative, so that firms with a capital stock level above their long-run equilibrium will eventually adjust downwards and vice versa.

Denote gross investment with $I_{i,t}$, the capital stock with $K_{i,t}$, and the depreciation rate with

$\delta_{i,t}$. One can use the approximation $\triangle k_{i,t} = \left(\frac{I_{i,t}}{K_{i,t-1}} - \delta_{i,t}\right)$ to obtain an ECM specification for the investment rate $\frac{I_{i,t}}{K_{i,t-1}}$[20]. I include a cash flow term $\frac{CF_{i,t}}{K_{i,t-1}}$ to reflect the fact that a firm's investment will depend on its ability to generate internal funds in the presence of financial constraints. To probe Hypothesis 4, I also include a firm's initial Management z-score (subsumed in the firm fixed effects in the OLS regressions) and more importantly an interaction term between the latter and the Error Correction term. The ECM becomes:

$$\begin{aligned} \frac{I_{i,t}}{K_{i,t-1}} &= \beta_1 \triangle y_{i,t} + \beta_2 (k_{i,t-1} - y_{i,t-1}) + \beta_3 M_i + \\ \beta_4 M_i (k_{i,t-1} - y_{i,t-1}) &+ \beta_5 \frac{CF_{i,t}}{K_{i,t-1}} + A_i + B_j + B_t + \nu_{i,t} \end{aligned} \tag{2.7.4}$$

If the Error Correction Model is an adequate representation of investment dynamics, then a firm whose capital stock falls short of equilibrium in the last period should increase investment to move towards target. In other words, the coefficient β_2 should be negative and smaller than one. This coefficient reflects the speed of adjustment. It can be interpreted as the share of the deviation from equilibrium eliminated on average in each period. In the presence of capital market imperfections, β_5 is expected to be positive. I have no *a priori* expectation on the sign of the coefficient on the Management z-score β_3. The coefficient of interest is β_4. A negative coefficient would imply that well managed firms adjust more quickly towards equilibrium. I estimate the ECM with OLS with industry (B_j) and year (B_t) fixed effects[21], and with system GMM with firm (A_i) and year fixed effects. Table 2.7.1 reports the results. In Columns (2) and (4) I add an interaction term between management and the logarithm of GVA to account for the significant interaction between management and size.

I find that the coefficient on the Error Correction term in Table 2.7.1 is negative as expected and statistically significant. This means that in the long run firms adjust their capital stocks towards a target that is proportional to real sales. The coefficient on the error correction term ranges from -0.022 to -0.036. An Error Correction coefficient of -0.036 implies that a deviation from the long-term target is corrected by 3.6% the following year. This is quite a sluggish speed of adjustment - about a third to a half of the magnitude of the adjustment speed in Bloom et al (2007) for a sample of UK public firms. However, note that the latter use real gross output rather

[20] The term, $\triangle k_{i,t}$, is the change in $ln(K_{i,t})$ which is roughly equal to the percent change in $K_{i,t}$. This, in turn, is approximately equal to $\left(\frac{I_{i,t}}{K_{i,t-1}} - \delta_{i,t}\right)$. The depreciation rate, $\delta_{i,t}$, can be subsumed into the time fixed effects, the firm fixed effects and the error term. Therefore, $\triangle k_{i,t}$ can be replaced with $\frac{I_{i,t}}{Ki,t-1}$.

[21] Appendix 2.G contains the results of OLS with and without fixed effects for comparison.

than real GVA. A slower adjustment speed could also be related to the fact that most firms in my sample are not public. Public firms typically have better access to external finance and hence may be able to more quickly adjust their capital stocks.

I find a short-run effect of real GVA growth that is positive and statistically significant, although considerably smaller than the long-run elasticity of unity in Equation 2.7.2. Assuming that the firm is in equilibrium and there are no disturbances, the growth rate of the capital stock should equal the growth rate of real GVA for equilibrium to be maintained. However, I find that when real GVA rises, investment tends to lag behind, creating a disequilibrium.

I find significant effects from the cash-flow terms in all the specifications. The positive coefficient associated with the cash flow to capital ratio suggests that a drop in cash flow is associated with a drop in investment - a potential (but flawed) indication of financial constraints. The coefficient on the standalone Management z-score is always insignificant. The main result of interest is the significantly negative coefficient on the interaction term between Management and the Error Correction term. This is evidence of a long-run effect of management practices in the sense that better managed firms adjust more quickly towards their target capital stocks. The magnitude of the interaction term ranges between -0.008 (Columns (1) and (2)) and -0.019 (Column (4)). For comparison, the effect ranges between 22% (Columns (1) and (2)) and 77% (Column (3)) of that of the standalone EC term. The coefficient implies that if a firm improves its Management score by one standard deviation, the adjustment process speeds up by about 1% to 2% each period. This is economically significant given that I find a sluggish adjustment speed of between 2.2% and 3.6%.

In the GMM estimations, the test for second-order autocorrelation of the differenced residuals does not indicate any problems with the specification. The Hansen test does not reject the exogeneity of the entire set of instruments. Finally, the Sargan-Hansen difference test does not reject the exogeneity of the additional instruments for the levels equations in system GMM.

Table 2.7.1: **Error Correction Model for investment dynamics - OLS and system GMM**

Dependent variable:	**OLS**		**GMM**	
I/K	**(1)**	**(2)**	**(3)**	**(4)**
△Ln(real GVA)	0.034***	0.034***	0.046**	0.050***
	(0.006)	(0.006)	(0.018)	(0.017)
Error Correction term	-0.036***	-0.036***	-0.022*	-0.030***
	(0.004)	(0.004)	(0.011)	(0.010)
CF/K	0.012***	0.012***	0.016**	0.015**
	(0.004)	(0.004)	(0.007)	(0.007)
Initial Management score	0.004	-0.002	0.002	0.014
	(0.003)	(0.023)	(0.003)	(0.070)
Management score x EC term	-0.008**	-0.008**	-0.017**	-0.019**
	(0.003)	(0.003)	(0.008)	(0.008)
Management score x GVA		0.001		-0.001
		(0.002)		(0.007)
Industry FE	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
N	2,842	2,842	2,842	2,842
AR(2) test			0.176	0.154
Hansen test p-value			0.535	0.552
Sargan-Hansen diff test p-value			0.491	0.567
Number of instruments			173	205

Notes: The dependent variable **I/K** is the ratio of gross capex to the capital stock. **△Ln(real GVA)** is the growth rate of real GVA. **Error Correction term** is the difference between the current capital stock and its long-run equilibrium level. **CF/K** is the ratio of cash flows from operations to the capital stock. **Initial Management score** is the Management z-score in the first year the firm was surveyed. **Management score x EC term** is an interaction term between the initial Management z-score and the EC term. **Management score x GVA** is an interaction term between the initial Management z-score and the log of real GVA. Columns (1) and (2) are estimations with OLS with industry and year fixed effects. Standard errors are clustered at the firm level. Columns (3) and (4) are one-step system GMM coefficients with year fixed effects. The instruments are, in the first-differenced equations: lags 2 and 3 of $\frac{I_{i,t}}{K_{i,t-1}}$ and all the control variables, and in the levels equations: lags 2 and 3 of the first differences of those same variables. The managerial score is assumed exogenous but its interactions are treated as endogenous. Instrument validity is tested using the Hansen test of the over-identifying restrictions and the Sargan-Hansen difference test. AR(2) serial correlation in the first-differenced residuals is also tested (Arellano and Bond, 1991).

A caveat with the traditional ECM is that it assumes symmetry of adjustment speed whether the firm's deviation from long-run frictionless optimum capital stock is positive or negative. But the test here should be one of faster positive adjustment, and not faster shrinking when a firm gets a negative shock and has excess capacity. Should the adjustment speed be symmetric, then it could be that well managed firms are simply more flexible and hence make fewer "mistakes" -

both positive and negative. Granger and Lee (1989) extend the ECM specification to allow for asymmetric adjustments. They decompose the cointegration residuals into positive and negative values. Therefore, the ECM can be written as:

$$\begin{aligned}\frac{I_{i,t}}{K_{i,t-1}} &= \beta_1 \triangle y_{i,t} + \beta_2 EC^+ + \beta_3 EC^- + \beta_4 M_i + \beta_5 M_i(EC^+) \\ &+\beta_6 M_i(EC^-) + \beta_7 \frac{CF_{i,t}}{K_{i,t-1}} + A_i + B_j + B_t + \nu_{i,t}\end{aligned} \tag{2.7.5}$$

The variable EC^+ is defined as the product of the EC term $(k_{i,t-1} - y_{i,t-1})$ and a dummy for a positive deviation from the long-run equilibrium (excess capacity). In other words $EC^+ = (k_{i,t-1} - y_{i,t-1})$ if $(k_{i,t-1} - y_{i,t-1}) > 0$. Similarly, $EC^- = (k_{i,t-1} - y_{i,t-1})$ if $(k_{i,t-1} - y_{i,t-1}) < 0$. The Management z-score is interacted with EC^+ and EC^- separately. If the impact of management on adjustment is asymmetric and better management practices help alleviate underinvestment, I would expect β_5 to be insignificant and β_6 to be significantly negative. Note that I assume symmetry in the short-run dynamics. I estimate the ECM with OLS with industry (B_j) and year (B_t) fixed effects[22], and with system GMM with firm (A_i) and year fixed effects. The results are in Table 2.7.2.

Simple inspection of the signs, magnitudes and statistical significance of the estimated coefficients offers some indication that there is an asymmetry, not only in the adjustment process but also in the impact of management on the adjustment speed. The absolute value of the coefficient on EC^+ is systematically smaller than that on EC^-. In addition, the absolute value of the coefficient on $M_i(EC^+)$ is systematically smaller than that on $M_i(EC^-)$. In fact the GMM coefficients on EC^+ and the OLS and GMM coefficients on $M_i(EC^+)$ are all insignificant. By contrast, all the coefficients on EC^- and $M_i(EC^-)$ are significant, most of them at the 1% level. The results point to asymmetric adjustment to the long-run equilibrium, giving more credence to the conjecture that precautionary savings behaviour may be behind the link between management and investment dynamics. In other words, better management helps firms avoid underinvestment.

In the GMM estimations, the test for second-order autocorrelation of the differenced residuals does not indicate any problems with the specification. The Hansen test does not reject the exogeneity of the entire set of instruments. Finally, the Sargan-Hansen difference test does not reject the exogeneity of the additional instruments for the levels equations in system GMM.

[22] Appendix 2.G contains the results of OLS with and without fixed effects for comparison.

The results are consistent with some of the findings of the existing literature. von Kalckreuth (2004) shows theoretically and empirically that financing constraints slow down the speed of adjustment. There is evidence that firms with cash shortfalls fail to take up some of their valuable growth opportunities (Minton and Schrand, 1999) and that cash holdings mitigate this problem (Denis and Sibilkov, 2010). In addition, the results may be linked to the literature on resource misallocation. Firm-specific distortions to the price of capital lead to deviations between actual and optimal capital stocks, with negative consequences for *aggregate* output and productivity (e.g. Hsieh and Klenow, 2009). Prudent firms guard themselves against such distortions by accumulating precautionary savings. This could explain why management also matters when explaining cross-country productivity differences.

In order to be rigorous I need to formally test the hypotheses that $\beta_2 \neq \beta_3$ and $\beta_5 \neq \beta_6$. Cook et al (1999) show that standard tests of symmetry are affected by low power in an ECM framework. In particular such tests typically have low power in *rejecting the null of symmetric adjustment*. The power increases in sample size and with the variance of the independent variable relative to the dependent variable. Using standard F-tests, I find that the null hypothesis of symmetry cannot be rejected in GMM. In OLS, $\beta_2 \neq \beta_3$ is rejected at the 1% level while $\beta_5 \neq \beta_6$ is rejected at close to the 5% level. I leave it for further research to implement a better test for asymmetry.

Table 2.7.2: **Asymmetric EC Model for investment dynamics - OLS and system GMM**

Dependent variable:	**OLS**		**GMM**	
I/K	**(1)**	**(2)**	**(3)**	**(4)**
$\triangle$Ln(real GVA)	0.033***	0.033***	0.028*	0.036**
	(0.006)	(0.006)	(0.014)	(0.014)
EC^{+}	-0.015**	-0.015**	0.017	0.009
	(0.006)	(0.006)	(0.026)	(0.023)
EC^{-}	-0.052***	-0.052***	-0.040**	-0.049***
	(0.007)	(0.008)	(0.018)	(0.016)
CF/K	0.009***	0.009***	0.013**	0.008
	(0.004)	(0.004)	(0.006)	(0.006)
Initial Management score	-0.002	-0.007	0.000	0.039
	(0.004)	(0.023)	(0.007)	(0.060)
Management score x EC^{+}	0.001	0.001	-0.017	-0.019
	(0.005)	(0.005)	(0.018)	(0.017)
Management score x EC^{-}	-0.017***	-0.017***	-0.021*	-0.027**
	(0.006)	(0.006)	(0.011)	(0.011)
Management score x GVA		0		-0.004
		(0.002)		(0.006)
Industry FE	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
N	2,842	2,842	2,842	2,842
AR(2) test			0.120	0.101
Hansen test p-value			0.245	0.829
Sargan-Hansen diff test p-value			0.217	0.894
Number of instruments			237	269

Notes: The dependent variable **I/K** is the ratio of gross capex to the capital stock. **$\triangle$Ln(real GVA)** is the growth rate of real GVA. **EC^{-}** (**EC^{+}**) is the product of the EC term $(k_{i,t-1} - y_{i,t-1})$ and a dummy for a negative (positive) deviation from the long-run equilibrium. **CF/K** is the ratio of cash flows from operations to the capital stock. **Initial Management score** is the Management z-score in the first year the firm was surveyed. **Management score x EC^{-}** (**Management score x EC^{+}**) is an interaction term between the initial Management z-score and **EC^{-}** (**EC^{+}**). **Management score x GVA** is an interaction term between the initial Management z-score and the log of real GVA. Columns (1) and (2) are estimations with OLS with industry and year fixed effects. Standard errors are clustered at the firm level. Columns (3) and (4) are one-step system GMM coefficients with year fixed effects. The instruments are, in the first-differenced equations: lags 2 and 3 of $\frac{I_{i,t}}{K_{i,t-1}}$ and all the control variables, and in the levels equations: lags 2 and 3 of the first differences of those same variables. The managerial score is assumed exogenous but its interactions are treated as endogenous. Instrument validity is tested using the Hansen test of the over-identifying restrictions and the Sargan-Hansen difference test. I also report the AR(2) test for the first-differenced residuals.

2.8 Conclusion

This paper investigates a potential channel behind the positive correlation between the quality of management practices and firm performance. The main hypothesis of the paper is that financially constrained firms have more prudent cash holding policies when they are better managed. Specifically, the theoretical analysis predicts that well managed firms which face financial constraints save relatively more out of their cash flows and accumulate more cash when their cash flows are more volatile. As a consequence, they can avoid underinvestment when future profitable investment opportunities arise. This enhanced precautionary behaviour results from the fact that management quality alleviates agency problems between equity holders and managers. The empirical analysis provides evidence to support these predictions using data from the World Management Survey and administrative and accounting data on UK firms. This points to an interesting link between management practices and the efficiency of investment dynamics. I provide evidence that well managed firms invest more efficiently. In particular, they adjust more quickly towards their long-run frictionless capital stock when their current capital stock is sub-optimal.

This paper can be improved along several dimensions. On the one hand, the theory will be modified to model short-termism explicitly, by making the manager's tenure finite. On the other hand, the empirical results will be strengthened and extended. First, a better test for asymmetry in the speed of adjustment in the error correction framework needs to be designed. Second, I will implement several instrumental variable strategies to address endogeneity.

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Appendix

2.A Proofs

Proposition 2. Better managed firms will hold more cash, i.e. $\frac{dC}{dm} > 0$ if $\frac{ds}{dm} < 0$ and

$$G'\left(\frac{E[c_1] + (1-s^*)C}{\lambda}\right) + \tau q > -\frac{C(1-s^*)}{\lambda}G''\left(\frac{E[c_1] + (1-s^*)C}{\lambda}\right) \tag{2.A.1}$$

Proof. Taking the total differential of Equation 2.2.2 with respect to m delivers:

$$\begin{aligned} &\frac{(1-s^*)^2}{\lambda}G''\left(\frac{E[c_1] + (1-s^*)C}{\lambda}\right)\frac{dC}{dm} = \\ &\frac{1}{\lambda}F''\left(\frac{c_0 - C}{\lambda}\right)\left(\frac{dc_0}{dm} - \frac{dC}{dm}\right) \\ &+ \frac{ds}{dm}\left\{G'\left(\frac{E[c_1] + (1-s^*)C}{\lambda}\right) + \frac{C(1-s^*)}{\lambda}G''\left(\frac{E[c_1] + (1-s^*)C}{\lambda}\right) + \tau q\right\} \end{aligned} \tag{2.A.2}$$

Since $G'(.) > 0$, $G''(.) < 0$, and $\frac{dc_0}{dm} = \frac{dC}{dm}$, it follows that $\frac{dC}{dm} > 0$ if $\frac{ds}{dm} < 0$ and

$$\left\{G'\left(\frac{E[c_1] + (1-s^*)C}{\lambda}\right) + \frac{C(1-s^*)}{\lambda}G''\left(\frac{E[c_1] + (1-s^*)C}{\lambda}\right) + \tau q\right\} > 0. \tag{2.A.3}$$

□

Proposition 3. If $\frac{dC}{dm} > 0$ it follows that:

$$\frac{d\left(\frac{C}{c_0}\right)}{dm} = \frac{1}{c_0}\frac{dC}{dm}\left(1 - \frac{C}{c_0}\right) > 0 \tag{2.A.4}$$

Proof.

$$\frac{d\left(\frac{C}{c_0}\right)}{dm} = \frac{\frac{dC}{dm}c_0 - \frac{dc_0}{dm}C}{c_0^2} \tag{2.A.5}$$

The result follows since $\frac{dC}{dm} = \frac{dc_0}{dm}$. □

Proposition 4. $\frac{ds}{dm} < 0$.

Proof. Taking the total differential of Equation 2.2.7 with respect to m delivers:

$$\begin{aligned}
& pU''\left(d_2^H\right)\left(\frac{C}{\lambda}\right)^2\left(G'(I_1^H)+\tau q\right)^2\frac{ds}{dm} \\
& +\left(\frac{C}{\lambda}\right)^2 pU'\left(d_2^H\right)G''(I_1^H)\frac{ds}{dm} \\
& +(1-p)U''\left(d_2^L\right)\left(\frac{C}{\lambda}\right)^2\left(G'(I_1^L)+\tau q\right)^2\frac{ds}{dm} \\
& +\left(\frac{C}{\lambda}\right)^2(1-p)U'\left(d_2^L\right)G''(I_1^L)\frac{ds}{dm} \\
& -mC\frac{ds}{dm}=sC
\end{aligned} \tag{2.A.6}$$

bearing in mind that the manager is short-sighted, i.e. $\frac{dC}{dm}=\frac{dc_0}{dm}=0$ from the manager's perspective. The result simply follows from $U'(.)>0$, $U''(.)<0$, $G'(.)>0$, and $G''(.)<0$. □

2.B World Management Survey

The World Management Survey (WMS) defines 18 management practices and scores them from one (worst practice) to five (best practice) on a scoring grid. The practices are categorised in four broad areas (Bloom and Van Reenen, 2007):

- **Operations**: This area focuses on the introduction of "lean manufacturing" techniques and processes improvements.
- **Monitoring**: This dimension focuses on how companies track and review the performance of individuals, and on "consequence management" (e.g., making sure that targets are met and appropriate sanctions and incentives are in place).
- **Target setting**: This dimension examines how companies set targets (financial or operational or more holistic), their realism (stretching, unrealistic, or non-binding) and transparency (simple or complex), and their interconnection (e.g., whether they are given consistently throughout the organization).
- **Incentives/people management**: This dimension measures whether firms promote and reward employees based on performance, and put systems in place to fire bad performers, and hire and reward the best employees.

More details on these practices are given in Bloom and Van Reenen (2007). The survey is interview based. The interviewees are plant managers, who are senior enough to understand the firm's management practices but still in touch with day-to-day operations. Production plant managers are interviewed using a double-blind technique. First, they are not told that they are being scored or shown the scoring tool. Second, the interviewers do not know anything about the performance of the firm. They only know the company name, telephone number, and industry. The questions are open, rather than [yes/no] questions. Several noise controls on the interview process were also collected - such as the time of day and the day of the week when the interview took place, and characteristics of the interviewee. Including these in the regression analysis helps to improve estimation precision by reducing random measurement error. More details on the survey design can be found in Bloom, Sadun, and Van Reenen (2016) and online at http://worldmanagementsurvey.org/.

2.C Unconstrained firms

As in ACW (2004), I define an unconstrained firm as one that can always attain its first-best level of investment. In other words, there exists a financial policy (B, d, h, C, c_0) such that

$$
\begin{aligned}
&I_0^{FB} \leqslant W + B_0 - C \\
&I_1^{FB,H} \leqslant c_1^H - \frac{1-p}{p} h^L + B_1^H + (1-s)C \\
&I_1^{FB,L} \leqslant c_1^L + h^L + B_1^L + (1-s)C
\end{aligned}
$$

In this case, the policies $\{B, h\}$ are indeterminate. Equity holders inject $c_0 = W$ into the firm but it is not optimal to hold any cash made available to managers, i.e. $C^* = 0$. Suppose the firm increases its cash holdings by a small amount, $\triangle^+ C$. There are no benefits attached to this since the firm is already able to invest at the first-best level at time 1. There is no need for smoothing. However, $\triangle^+ C$ is a negative NPV project since part of it (s) will be dissipated. Equity holders are willing to incur some degree of cash dissipation if and only if the firm is constrained and cash reserves allow the firm to invest more at time 1. So the optimal policy for an unconstrained firm is to hold no cash at all, in contrast to the irrelevance result in ACW (2004). According to this result, all firms with positive cash reserves can be understood to be facing financial constraints.

2.D Perpetual Inventory Method

I apply the Perpetual Inventory Method (PIM) on firm-level data from the ABI and ABS surveys. The basic idea of the PIM is to interpret the firm's capital stock as an inventory, which increases with capital expenditures, provides capital services perpetually, but depreciates over time.

$$k_t = k_{t-1}(1 - \delta) + i_t$$

where k_t is the firm's capital stock at the beginning of period t, k_{t-1} is the capital stock at the beginning of period $t - 1$, i_t is net capital expenditures (capex minus proceeds from disposal of capital), and δ is the depreciation rate. There are three types of capex in ABI/ABS: Plant and machinery, buildings, and vehicles. I apply the following asset-specific depreciation rates: Plant and machinery: 0.08; Buildings: 0.02; Vehicles: 0.2. I do a separate PIM calculation for each type of capital, then simply sum across them to obtain the total capital stock in every period.

Firms which are not sampled every year (randomly sampled small firms) move in and out of the sample. Hence I need to deal with gaps in the capital expenditures data. I impute missing capex values using each firm's average ratio of real net capital expenditures to employment. Where possible missing employment numbers are interpolated. Missing values at the start of the series are extrapolated using a backward rolling three-year average of employment. The imputation of missing capex values will be more of a problem when there are a lot of missing values. So I set a 'tolerance level', i.e. a maximum ratio of imputed to actual values. If I increase the tolerance level, I will get more firms with capital stock data, but mismeasurement may worsen. In the baseline dataset, I apply a ratio of 10.

I need to impute an initial capital stock for entrants and for firms that are sampled for the first time but are not genuine entrants (i.e. they were born before the year in which they were first sampled). To do so, I apportion to those firms part of the aggregate industry-level capital stock. The measure of aggregate industry-level capital stocks is the Volume index of capital services (VICS) produced by the ONS. The VICS data sets contain data on capital stocks, investment (gross fixed capital formation), and deflators at the industry level, by asset category.

The apportioning procedure has two steps. First, the VICS is apportioned to the entire population of selected firms in the sample based on their share of capital expenditures in the sectoral aggregates. The resulting capital stock is what I call 'selected capital'. Second, each firm is allocated part of this selected capital based on its share of total purchases in the sectoral sample aggregate. Missing data on total purchases are imputed in the same way as they were for employment.

2.E Linking ABI/ABS and WMS data

The WMS data set can be easily linked to Bureau Van Dijk's Orbis database on the basis of a company's CRN number. The linking between the combined WMS-Orbis data and the ONS data is a bit more complex. A CRN can be linked to an identifier called ENTREF in the Inter-Departmental Business Register. One has to note that the linking process is not straightforward. First, the ONS relies on name matching for some records. This is problematic when different names or spellings are used. Second, the CRN and IDBR systems are maintained independently. Hence, the same business is sometimes represented differently in either register. The IDBR identifies business units that are relevant for the computing of government statistics. By contrast, a CRN number is created when a new business name is registered. There may not be a 1:1 concordance between CRNs and ENTREF numbers. Finally, the lookup table is confidential. Because of confidentiality, researchers do not have access to the CRN-ENTREF linking table. The linking was performed by the UK Data Service at the University of Essex. Once the CRNs were linked to ENTREF numbers, I linked the WMS and Orbis data to reporting units (RUREF), which are the relevant units (establishments) for the ABI-ABS surveys. This was done on the basis of an ENTREF-RUREF look up table provided by the ONS.

2.F OLS cash regressions with firm fixed effects

Table 2.F.1: **Cash saving behaviour - OLS with and without firm FE**

Dependent variable:	**OLS**		**OLS with firm FE**	
△Cash/TA	**(1)**	**(2)**	**(3)**	**(4)**
CF/TA	0.019**	0.019**	0.031*	0.031*
	(0.008)	(0.008)	(0.017)	(0.017)
△Ln(GVA)	0.002	0.002	0.003	0.003
	(0.004)	(0.004)	(0.005)	(0.005)
Ln(Total assets)	0.001	0.001	0.004	0.004
	(0.001)	(0.001)	(0.006)	(0.006)
Gross investment/TA	0.014***	0.014***	0.031***	0.031***
	(0.005)	(0.005)	(0.011)	(0.011)
Disposals/TA	-0.042***	-0.041***	-0.024*	-0.026*
	(0.013)	(0.013)	(0.013)	(0.014)
△Loans/TA	0.072***	0.071***	0.079***	0.079***
	(0.018)	(0.018)	(0.022)	(0.022)
Initial Management score	-0.005***	0.003		
	(0.002)	(0.007)		
Management score x (CF/TA)	0.016**	0.015**	0.019	0.02
	(0.007)	(0.007)	(0.013)	(0.013)
Management score x TA		-0.001		0.006
		(0.001)		(0.005)
Industry FE (2d)	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
N	2,360	2,360	2,360	2,360

Notes: △**Cash/TA**: cash holdings to total assets; **CF/TA**: cash flows from operations to total assets; △**Ln(GVA)**: growth rate of gross value added; **Ln(Total assets)**: log of total assets; **Gross investment/TA**: gross capital expenditures to lagged total assets; **Disposals/TA**: disposals to lagged total assets; △**Loans/TA**: change in short-term debt normalised by total assets; **Initial Management score**: initial Management z-score; **Management score x (CF/TA)**: interaction between cash flows and Management; **Management score x TA**: interaction between Management and size measured by the log of total assets. The first two Columns report OLS estimations with year and industry fixed effects. Estimation in Columns (3) and (4) are OLS with firm fixed effects. Standard errors are clustered at the firm level.

The coefficient on the interaction term between management and cash flows remains positive but is no longer significant when firm fixed effects are included in the OLS regressions. This could result from endogeneity concerns.

Table 2.F.2: **Cash saving behaviour and cash flow volatility - OLS with and without firm FE**

Dependent variable:	**OLS**		**OLS with firm FE**	
$\triangle$Cash/TA	**(1)**	**(2)**	**(3)**	**(4)**
CF volatility	0.032**	0.032**	0.005	0.004
	(0.015)	(0.015)	(0.020)	(0.020)
CF/TA	0.013*	0.013*	0.032*	0.032*
	(0.007)	(0.007)	(0.018)	(0.018)
$\triangle$Ln(GVA)	0.003	0.003	0.003	0.003
	(0.004)	(0.004)	(0.005)	(0.005)
Ln(Total assets)	0.001	0.001	0.004	0.003
	(0.001)	(0.001)	(0.006)	(0.006)
Gross investment/TA	0.012**	0.012**	0.030***	0.030***
	(0.005)	(0.005)	(0.011)	(0.011)
Disposals/TA	-0.030**	-0.030**	-0.02	-0.023
	(0.012)	(0.012)	(0.015)	(0.016)
$\triangle$Loans/TA	0.069***	0.069***	0.079***	0.079***
	(0.018)	(0.018)	(0.022)	(0.022)
Initial Management score	-0.006***	-0.003		
	(0.001)	(0.007)		
Management score x CF vol	0.053***	0.052***	0.043***	0.048***
	(0.011)	(0.011)	(0.016)	(0.016)
Management score x TA		0.000		0.009
		(0.001)		(0.006)
Industry FE	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
N	2,360	2,360	2,360	2,360

Notes: $\triangle$**CASH/TA**: cash holdings to total assets; **CF volatility**: standard deviation of a firm's cash flows over the past 3 years; **CF/TA**: cash flows from operations to total assets; $\triangle$**Ln(GVA)**: growth rate of gross value added; **Ln(Total assets)**: log of total assets; **Gross investment/TA**: gross capital expenditures to lagged total assets; **Disposals/TA**: disposals to total assets; $\triangle$**Loans/TA**: change in short-term debt normalised by total assets; **Initial Management score**: initial Management z-score; **Management score x CF vol**: interaction between cash flow volatility and Management; **Management score x TA**: interaction between Management and size measured by the log of total assets. The first two Columns report OLS estimations with year and industry fixed effects. Estimation in Columns (3) and (4) are OLS with firm fixed effects. Standard errors are clustered at the firm level.

The coefficient on the interaction term between management and cash flow volatility remains positive and significant at the 1% level when firm fixed effects are included in the OLS regressions. The magnitude of the coefficient decreases only slightly.

2.G OLS ECM estimations with firm fixed effects

Table 2.G.1: **Error Correction Model for investment dynamics - OLS with and without firm FE**

Dependent variable:	**OLS**		**OLS with firm FE**	
I/K	**(1)**	**(2)**	**(3)**	**(4)**
△Ln(real GVA)	0.034***	0.034***	0.052***	0.048***
	(0.006)	(0.006)	(0.009)	(0.009)
Error Correction term	-0.036***	-0.036***	-0.079***	-0.075***
	(0.004)	(0.004)	(0.013)	(0.012)
CF/K	0.012***	0.012***	0.008	0.006
	(0.004)	(0.004)	(0.008)	(0.007)
Initial Management z-score	0.004	-0.002		
	(0.003)	(0.023)		
Managementz-score x EC term	-0.008**	-0.008**	-0.008	-0.081***
	(0.003)	(0.003)	(0.008)	(0.023)
Management z-score x GVA		0.001		-0.079***
		(0.002)		(0.021)
Industry FE	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
N	2,842	2,842	2,842	2,842

Notes: The dependent variable **I/K** is the ratio of gross capex to the capital stock. **△Ln(real GVA)** is the growth rate of real GVA. **Error Correction term** is the difference between the current capital stock and its long-run equilibrium level. **CF/K** is the ratio of cash flows from operations to the capital stock. **Initial Management score** is the Management z-score in the first year the firm was surveyed. **Management score x EC term** is an interaction term between the initial Management z-score and the EC term. **Management score x GVA** is an interaction term between the initial Management z-score and size measured by the log of real GVA. Columns (1) and (2) are estimations with OLS with industry and year fixed effects. Columns (3) and (4) include firm fixed effects. Standard errors are clustered at the firm level.

Table 2.G.2: **Asymmetric EC for investment dynamics - OLS with and without firm FE**

Dependent variable:	**OLS**		**OLS with firm FE**	
I/K	**(1)**	**(2)**	**(3)**	**(4)**
$\triangle$Ln(real GVA)	0.033***	0.033***	0.049***	0.045***
	(0.006)	(0.006)	(0.009)	(0.008)
EC^{+}	-0.015**	-0.015**	-0.032*	-0.029
	(0.006)	(0.006)	(0.019)	(0.020)
EC^{-}	-0.052***	-0.052***	-0.114***	-0.107***
	(0.007)	(0.008)	(0.017)	(0.017)
CF/K	0.009***	0.009***	0.006	0.004
	(0.004)	(0.004)	(0.007)	(0.007)
Initial Management z-score	-0.002	-0.007		
	(0.004)	(0.023)		
Managementz-score x EC^{+}	0.001	0.001	-0.004	-0.078***
	(0.005)	(0.005)	(0.014)	(0.026)
Managementz-score x EC^{-}	-0.017***	-0.017***	-0.024*	-0.084***
	(0.006)	(0.006)	(0.012)	(0.023)
Management z-score x GVA		0.000		-0.072***
		(0.002)		(0.020)
Industry FE	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
N	2,842	2,842	2,842	2,842

Notes: The dependent variable **I/K** is the ratio of gross capex to the capital stock. **$\triangle$Ln(real GVA)** is the growth rate of real GVA. **EC^{-}** (**EC^{+}**) is the product of the EC term ($k_{i,t-1} - y_{i,t-1}$) and a dummy for a negative (positive) deviation from the long-run equilibrium. **CF/K** is the ratio of cash flows from operations to the capital stock. **Initial Management score** is the Management z-score in the first year the firm was surveyed. **Management score x EC^{-}** (**Management score x EC^{+}**) is an interaction term between the initial Management z-score and **EC^{-}** (**EC^{+}**). **Management score x GVA** is an interaction term between the initial Management z-score and size measured by the log of real GVA. Columns (1) and (2) are estimations with OLS with industry and year fixed effects. Columns (3) and (4) include firm fixed effects. Standard errors are clustered at the firm level.

The OLS estimations with firm fixed effects continue to indicate the presence of asymmetry in the adjustment process. The majority of the coefficients on $M_i(EC^{+})$ are insignificant, whereas those on $M_i(EC^{-})$ remain significantly negative and increase in magnitude.

Chapter 3

When Does Leverage Hurt Productivity Growth? A Firm-Level Analysis[1]

Abstract

In the wake of the global financial crisis, several macroeconomic contributions have highlighted the risks of excessive credit expansion. In particular, too much finance can have a negative impact on growth. We examine the microeconomic foundations of this argument, positing a non-monotonic relationship between leverage and firm-level productivity growth in the spirit of the trade-off theory of capital structure. A threshold regression model estimated on a sample of Central and Eastern European countries confirms that TFP growth increases with leverage until the latter reaches a critical threshold beyond which leverage lowers TFP growth. This estimate can provide guidance to firms and policy makers on identifying "excessive" leverage. We find similar non-monotonic relationships between leverage and proxies for firm value. Our results are a first step in bridging the gap between the literature on optimal capital structure and the wider macro literature on the finance-growth nexus.

[1]An earlier version of the paper has been circulated as 'Excess Leverage and Productivity Growth in Emerging Economies: Is there a threshold effect?' Financial support to Nigel Driffield and Sarmistha Pal from ESRC grant RES-062-23-0986 is gratefully acknowledged. We are grateful to the Editor and the referee at the Journal of International Money and Finance for many constructive comments and to Sourafel Girma and Michael Henry for advice with the estimation of the threshold model. We thank Erik Berglof, Ralph de Haas, Bruce Hansen, Peter Sanfey, Ilya Strebulaev, Jeffrey Wooldridge, Jeromin Zettelmeyer and seminar participants at Aston Business School, UCL, EBRD and CICM conference, London for helpful comments and suggestions on an earlier draft.

3.1 Introduction

The global financial crisis has revived interest in the risks of excessive credit expansion at the macroeconomic level. In a recent paper titled "Too much finance", Arcand et al (2011) identify a threshold level of domestic credit to the economy beyond which output growth begins to fall. Reinhart and Rogoff (2010) identify a similar non-monotonic relationship between public debt and growth. In this paper we argue that there is a non-monotonic relationship between leverage and productivity growth at the firm level. Using insights from the macroeconomic and corporate finance literatures, we identify a threshold level of leverage beyond which further increases in leverage lower firm-level productivity growth.

Corporate leverage decisions are among the most important decisions made by firm executives and have been the focus of intense scrutiny since Modigliani and Miller (1958). Financial conditions in the corporate sector not only affect firm performance but, as macroeconomists have long recognized, they can have a powerful effect on macroeconomic outcomes. The literature on "financial accelerators" is concerned with the role of financial conditions in amplifying shocks to the economy (e.g. Bernanke et al, 1999) while the literature on the finance-growth nexus (e.g. Ang, 2008, for a recent survey) is concerned with their contribution to long-term growth. The present paper is a first attempt at bridging the gap between the literature on optimal capital structure and the macroeconomic literature on finance-growth linkages. We use threshold regressions to investigate the non-monotonic relationship between leverage and several indices of firm performance, and the extent to which this relationship varies across types of firms.

Among all possible measures of firm performance, our analysis particularly focuses on total factor productivity (TFP) growth for several reasons. Productivity growth is generally considered to be the main driver of growth at the macroeconomic level. A number of studies have demonstrated that TFP growth is more important for income growth than other factors such as capital accumulation, and that TFP differences explain more of the variation in cross-country per capita GDP than variables like human capital, physical capital or trade[2]. Productivity has also been used to gauge firm performance in the corporate finance literature[3], the management accounting literature[4], and the literature on corporate control[5]. It is an important determinant

[2]See for example Klenow and Rodriguez-Clare (1997), Hall and Jones (1999), Easterly and Levine (2001), and Henry et al (2009).

[3]See for example Schoar (2002), Maksimovic and Phillips (2002), McGuckin and Nguyen (1995), and Imrohoroglu and Tüzel (2014).

[4]See for example Kaplan (1983).

[5]See for example Köke and Renneboog (2005).

of how firms react to business cycle fluctuations. In the framework of Imrohoroglu and Tüzel (2011), low TFP firms are more vulnerable to business cycles and hence are riskier than firms with high TFP. Low TFP firms have a higher implied cost of capital (ICC) and both the levels of ICC and the ICC spread between low and high TFP firms are countercyclical. Therefore, understanding the effects of leverage on productivity gains is relevant both from the perspective of capital structure theory and the macroeconomic perspective of long-term growth and business cycle fluctuations.

Several papers find that productivity is positively related to firm value[6]. Intuitively, productivity growth results in the efficient use of scarce inputs. This allows the firm to reduce its output prices while maintaining or increasing profit margins, and in the long-run, to survive. This enhances shareholders' wealth. Therefore, our starting point to understand the link between leverage and productivity growth is the finance literature that relates leverage to firm value. In particular, our hypothesis is inspired by the trade-off theory of optimal capital structure, which explains firms' choice of leverage by a trade-off between the benefits and costs of debt. The second most influential theory of corporate leverage is the pecking-order theory due to Myers (1984). We however focus on the trade-off theory rather than the pecking order theory for various reasons. From a policy perspective, it is important to identify firms or sectors where leverage may be excessive. Excessiveness must be defined with respect to an optimal capital structure. However, there is no optimal debt ratio in the pecking order theory, in the sense that firms do not aim at a particular target debt ratio. Instead, the theory suggests that observed leverage is the cumulative result of hierarchical financing decisions over time (Shyam-Sunder and Myers, 1999). In addition, the US empirical evidence is not very supportive of the pecking order theory[7]. In a recent comprehensive review of the literature, Frank and Goyal (2009) conclude that the empirical evidence is rather consistent with some versions of the trade-off theory. This does not imply that the pecking order theory is irrelevant in our sample; but given our objective, we focus on the trade-off theory, which is simply the most natural starting point for a study of "excessive" indebtedness.

The trade-off hypothesis goes back to Kraus and Litzenberger (1973), who weigh bankruptcy costs against the benefits of interest tax shields. The benefits of debt also include the mitigation of agency problems. In particular, debt has a disciplining role due to the associated reduction in

[6] See for example Bao and Bao (1989), Riahi-Belkaoui (1999), Dwyer (2001), and Balasubramanyan and Mohan (2010).

[7] See for example Fama and French (2002a) and Frank and Goyal (2003).

free cash flow (Jensen, 1986). The costs of debt include debt overhang (Myers, 1977), risk-shifting (Jensen and Meckling, 1976), bankruptcy costs (Warner, 1977), and asset fire sales (Schleifer and Vishny, 1992). The trade-off theory predicts that net benefits to debt financing rise for companies with low debt but decrease as leverage becomes high, implying that net benefits are a non-monotonic function of leverage. The empirical literature tests this hypothesis (against the competing pecking order theory) by typically running cross-sectional or panel regressions of leverage on various firm-level, industry-level and market characteristics that determine optimal leverage[8]. While the literature has explored the relationship between leverage and firm value or performance[9], it has remained silent on the relationship between leverage and productivity. With both benefits and costs to leverage, we posit a hump-shaped relationship between leverage and productivity growth at the firm level[10]. At low levels of leverage, higher leverage is likely to be associated with higher TFP growth as the benefits to leverage outweigh the costs and debt is used to finance productive investment. As leverage increases, the costs of debt become larger and erode the net benefits to leverage. Highly-levered firms not only suffer from a debt overhang problem, which reduces their incentives to invest in productive investment, their attention is also diverted from productivity improvements by the need to generate cash flow in order to service their debts. While our hypothesis is clearly inspired by the trade-off theory, our analysis does not constitute a test of the theory. The trade-off theory relates the cost of capital of the firm (or its market value) to its market-value-based debt-to-equity ratio. In this paper, we relate TFP growth to the book value of leverage. The use of book values is dictated by the lack of market data for our sample countries where equity markets remain rather underdeveloped.

Our sample consists of Central and Eastern European (CEE) countries. Transition economies are an interesting sample for several reasons. First, the transition experience has long been described as a "natural experiment" (see for example, Eicher and Schreiber, 2010). While transition countries started the transition process from similar (though not identical) positions in terms of liberalisation, institutional reform has progressed in varying ways and to different degrees. Even after more than a decade of financial sector reforms, there is a growing feeling that the latter have failed to spur adequately the development of corporate financing opportunities. There is a striking proportion of firms in our sample with zero outstanding debt, including both

[8]See Frank and Goyal (2009) for a review of the literature.

[9]See for example McConnell and Servaes (1995), Berger and di Patti (2006), and Driffield, Mahambare and Pal (2007).

[10]A similar relationship can be posited between leverage and any index of firm value. While our focus is on TFP growth, we also provide evidence of a non-monotonic relationship between leverage and two proxies for firm value, namely return on assets and return on equity (see Section 3.4).

short- and long-term debt. The "mystery of zero-leverage firms" (Strebulaev and Yang, 2006) is very pronounced in transition countries. Second, this puzzle is augmented by another one: among those firms with outstanding debt, many tend to have very high, potentially excessive leverage. Unlike much of the literature on developed countries, the literature on capital structure in developing and transition countries has highlighted the importance of excessive leverage (e.g. Driffield and Pal, 2010). Many CEE countries have experienced rapid credit growth in recent years, in particular the Baltic States, Southern Eastern Europe and Ukraine. While the benefits of rapid credit growth have been recognized, the risks related to credit booms have been highlighted by the recent financial crisis, which has severely hit many CEE countries. Assessing the sustainability of firm-level credit growth and developing appropriate policy tools remains one of the priorities of policymakers and international organizations active in this region. In addition, the continued practice of soft budget constraints in this region may contribute to the negative impact of excessive leverage on TFP growth in our sample[11]. Soft budget constraints (SBCs) imply that government or financial institutions are willing to provide additional financing to firms with negative NPV projects (e.g. Dewatripont and Maskin, 1995). If firms take advantage of SBCs, borrowed funds may be used inefficiently rather than for productivity-enhancing investment. Research has for instance shown that one of the detrimental impacts of SBCs on the economy is a lack of R&D (Kornai, 2001, and Brücker et al, 2005).

Our estimates confirm that TFP growth increases with leverage until the latter reaches a critical threshold beyond which leverage becomes "excessive" and lowers TFP growth. We confirm the robustness of this result by estimating an alternative threshold model using lagged leverage. All the results point to the existence of an optimal leverage ratio where the net benefits of debt in terms of productivity gains are exhausted. Our paper reaches some qualitatively similar conclusions to Korteweg (2010). Using a different methodology and a market-based assessment of the net benefits of leverage, the author finds that as leverage increases, net benefits to leverage first increase and then decrease, and finally turn negative for distressed firms. In addition, our analysis sheds light on how optimal leverage varies with firm characteristics, particularly profitability and size. Unlike existing studies that use traditional cross-sectional or panel regressions using observed leverage ratios, the threshold model allows us to determine optimal leverage despite firms' temporary deviations from the optimum[12]. Again, we reach conclusions similar to those of Korteweg (2010).

[11] Konings et al (2003), for example, demonstrate that soft budget constraints remain into later stages of transition.
[12] See for example Korajczyk and Levy (2003).

Since our conceptual starting point is the trade-off theory, we attempted to gauge its relevance in our sample. Data limitations permit only an indirect test of the traditional trade-off theory. We employ two indices of firm value based on earnings (return on assets defined as EBIT to total assets and return on equity defined as EBIT to book value of equity) and relate these to the book value of leverage using a threshold regression. While the exact values of the thresholds are somewhat higher, the qualitative results regarding the non-monotonic relationship described above hold when the dependent variable is a proxy for firm value rather than TFP growth.

Finally, our paper also contributes to the burgeoning macro literature on the finance-growth nexus. Best practice in the recent literature on finance and growth uses industry-level data to overcome endogeneity problems typical of analyses that rely on aggregate data, and identify the channel through which finance affects growth. In their seminal contribution, Rajan and Zingales (1998) find that industries that are relatively more dependent on external finance grow disproportionately faster in countries with more developed financial markets. Our paper provides an alternative firm-level approach for studying the finance-growth nexus by directly linking firms' financial structure to TFP growth. In addition, our paper is related to the literature on the macroeconomic risks associated with lending booms. Kiyotaki and Moore (1997) show how increases in corporate leverage lead to higher costs of external financing due to a higher default probability. This could lower investment and therefore output. Kiyotaki and Moore (1997) and Bernanke et al (1999) show how high indebtedness in the corporate sector can induce severe slowdowns by amplifying and propagating adverse shocks to the economy. Our analysis provides a tool to identify the point at which corporate sector indebtedness becomes a cause for concern. Indeed, whether a firm is below or above the threshold can be seen as a measure of "sustainability" of a firm's leverage. The recent financial crisis has highlighted the risks of excessive indebtedness. Policy makers need to be able to assess the sustainability of leverage, both in order to prevent similar crises in the future and to identify those firms or sectors of the economy that need to go through a deleveraging process following a crisis. The empirical literature on lending booms has generally focused on various aggregate measures of indebtedness such as debt-to-GDP ratios (e.g. Gourinchas et al, 2001), or the growth rate of the domestic credit to GDP ratio as in the literature on banking and currency crises (e.g. Kaminsky and Reinhart, 1999). Our paper extends this literature by looking at the sustainability of credit at the firm level.

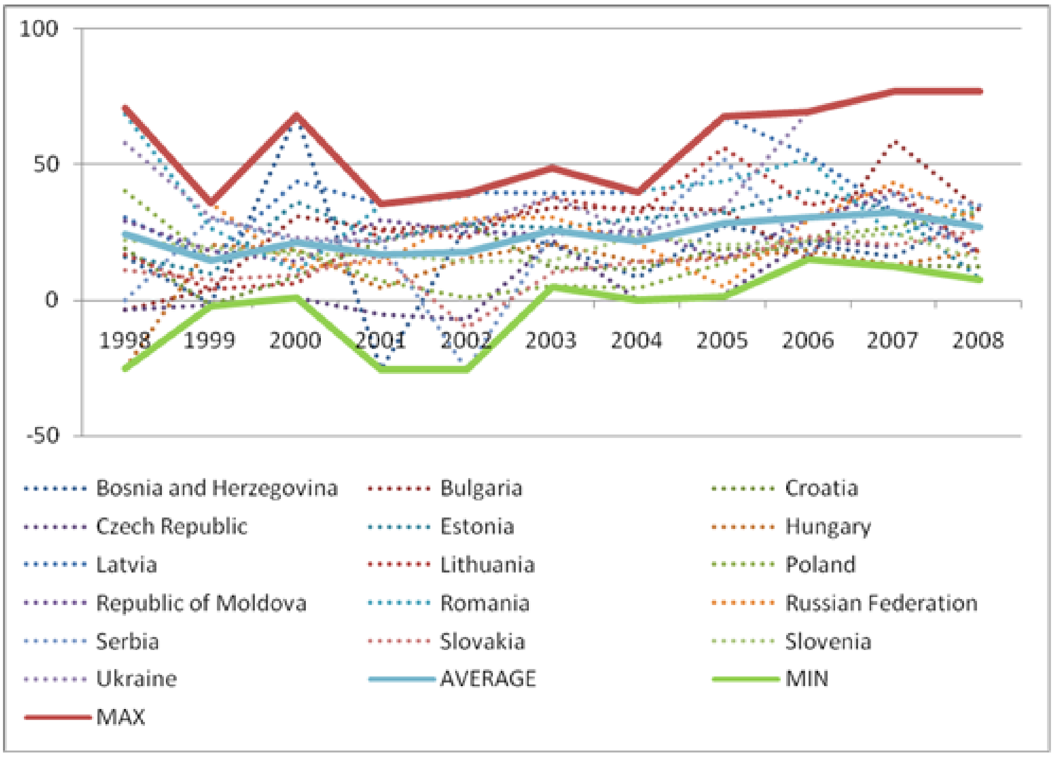
The remainder of the paper is structured as follows. In Section 3.2, we describe the data set and the variables used in the empirical analysis. In Section 3.3, we discuss the empirical methodology. Section 3.4 presents the empirical analysis. Section 3.5 concludes.

3.2 Data set and descriptive statistics

3.2.1 Sample and sources

The empirical test of our central hypothesis is based on firm-level data for a group of Central and Eastern European (CEE) countries. The data used for the analysis are primarily taken from Orbis, a rich firm-level dataset from Bureau van Dijk electronic publishing. Firm-level data have been supplemented by country-level institutional data from the European Bank for Reconstruction and Development (EBRD). Our sample consists of manufacturing firms from sixteen transition countries, namely, Bosnia and Herzegovina, Bulgaria, Croatia, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, the Republic of Moldova, Romania, Russia, Serbia, the Slovak Republic, Slovenia and Ukraine over the period 1999-2008. As can be seen from Figure 3.2.1, all these countries have on average experienced strong growth of domestic credit between 1998 and 2008. The effects of the Russian crisis, the bursting of the dotcom bubble and the financial crisis starting in 2007 visibly translated into a slowdown.

Figure 3.2.1: **Percentage changes in domestic credit in the CEE region 1998-2008**



Source: EBRD internal database.

3.2.2 Leverage measures and descriptive statistics

We consider two alternative definitions of book leverage: debt to total assets and total liabilities to total assets. These are accepted measures of leverage, especially in emerging markets where the size of equity markets is rather limited (e.g. Booth et al, 2001; Driffield and Pal, 2010). First, we use the ratio of total debt (sum of long-term debt in non-current liabilities and loans included in current liabilities) to total assets (abbreviated as TDTA). Second, we use the ratio of total liabilities (sum of total current liabilities and total non-current liabilities) to total assets (abbreviated as TLTA)[13].

[13] Data on the book value of equity of our sample firms is limited. We use the book value of total assets rather than the book value of equity in order to maximize the sample size.

Table 3.2.1: **Cross-country variation in leverage 1999-2008**

					All firms				Non-zero debt firms	
					TLTA		TDTA		TLTA	TDTA
Country	**Number of firms**	**Number of obs.**	**Percentage of zero-debt firms**	**Percentage of firms with missing debt**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**Mean**
Bosnia Herzegovina	146	1,362	19.5	20.7	0.36	0.27	0.11	0.14	0.38	0.13
Bulgaria	232	2,034	16.7	27.6	0.42	0.24	0.13	0.16	0.45	0.17
Croatia	135	1,264	5.8	87.7	0.39	0.23	0.08	0.14	0.42	0.14
Czech Republic	71	642	10.7	38.3	0.41	0.2	0.12	0.13	0.44	0.15
Estonia	10	94	2.1	40.4	0.4	0.24	0.16	0.14	0.45	0.17
Hungary	22	203	8.9	53.2	0.39	0.18	0.1	0.12	0.39	0.12
Latvia	26	239	12.1	34.3	0.45	0.24	0.2	0.22	0.52	0.25
Lithuania	30	281	3.2	49.1	0.46	0.19	0.2	0.17	0.48	0.21
Poland	159	1,467	16.4	52.1	0.47	0.19	0.1	0.13	0.52	0.15
Republic of Moldova	195	1,806	21	46.5	0.33	0.25	0.11	0.17	0.43	0.19
Romania	236	2,062	44.9	26.8	0.47	0.23	0.05	0.1	0.52	0.12
Russian Federation	656	6,021	15.4	34.5	0.46	0.25	0.15	0.18	0.5	0.2
Serbia	742	6,925	15.1	13.2	0.4	0.26	0.12	0.16	0.42	0.15
Slovak Republic	124	1,137	5.7	33	0.44	0.21	0.12	0.12	0.45	0.13
Slovenia	56	526	1.3	78.9	0.4	0.18	0.18	0.16	0.43	0.19
Ukraine	391	1,443	17.1	2.6	0.42	0.25	0.14	0.16	0.45	0.17
All	3,231	27,506	16.9	31.1	0.42	0.25	0.12	0.16	0.45	0.16

Notes: **TLTA** is the ratio of total liabilities to total assets and **TDTA** is the ratio of total debt to total assets. The sample period is 1999-2008. Non-zero debt firms refer to firms with positive outstanding debt. Source: Bureau Van Dijk's Orbis database.

As can be seen from Table 3.2.1, there is a significant proportion of zero-leverage firms, i.e. firms without any outstanding debt, as well as a significant proportion of firms for which debt data is missing. This reflects the fact that many firms still do not have access to debt markets in these economies and instead make heavy use of internal finance, trade credit and other kinds of liabilities. Accordingly, the sample size is larger when leverage is measured by TLTA.

Table 3.2.1 shows the average leverage ratios for two sub-samples, "all firms", including zero-leverage firms, and "non-zero debt firms", excluding zero-leverage firms. Among all firms, the average ratios of total liabilities to total assets range between 0.33 (Moldova) and 0.47 (Poland and Romania), while average debt ratios range between 0.05 (Romania) and 0.20 (Latvia and Lithuania). Among non-zero debt firms, the average debt ratios are unsurprisingly higher in all the sample countries, ranging from 0.12 in Romania to 0.25 in Latvia[14]. Table 3.2.2 shows the percentile distribution of debt ratios in each country. Debt ratios among the top 1% firms tend to be significantly higher than those for the median firms. Debt ratios for this group of firms exceed 50% in all but one country (Estonia). The maximum average leverage for this group is 89% in Croatia, closely followed by 85% in Latvia.

Table 3.2.2 also summarizes the distribution of debt (TDTA) by firm size. We split the sample between small and large firms, where small firms are defined as those in the first two quartiles of the distribution of total assets. The correlation between firm size and the debt ratio is mostly positive, although it is quite small in some cases. A large positive correlation is found in Bulgaria, Croatia, Moldova, Serbia, which is in line with the US and international cross-sectional evidence that large firms tend to have higher leverage ratios than small firms[15].

[14]We have also experimented with alternative leverage measures, namely, debt and liability ratios net of cash-flow, which yield comparable results to those presented here.

[15]See for example Rajan and Zingales (1995).

Table 3.2.2: **Distribution of debt among firms with positive debt 1999-2008**

	Leverage percentiles						Average leverage by size		
Country	**25%**	**50%**	**75%**	**90%**	**95%**	**99%**	**Small firms**	**Large firms**	**Correlation between size & leverage**
Bosnia and Herzegovina	0.03	0.07	0.19	0.32	0.42	0.61	0.11	0.12	0.02
Bulgaria	0.04	0.12	0.24	0.42	0.51	0.68	0.08	0.19	0.13
Croatia	0.03	0.11	0.19	0.33	0.46	0.89	0.04	0.15	0.2
Czech Republic	0.04	0.12	0.21	0.32	0.39	0.62	0.11	0.13	0.02
Estonia	0.02	0.18	0.28	0.36	0.44	0.48	0.16	0.2	0.09
Hungary	0.01	0.07	0.17	0.29	0.44	0.54	0.09	0.1	0.01
Latvia	0.07	0.19	0.35	0.62	0.71	0.85	0.22	0.15	-0.17
Lithuania	0.07	0.19	0.32	0.45	0.53	0.66	0.2	0.2	0.05
Poland	0.05	0.12	0.22	0.33	0.4	0.59	0.11	0.11	0.03
Republic of Moldova	0.04	0.13	0.3	0.46	0.56	0.72	0.06	0.18	0.21
Romania	0.04	0.08	0.17	0.28	0.34	0.55	0.04	0.06	0.12
Russian Federation	0.05	0.13	0.29	0.47	0.58	0.75	0.14	0.17	0.01
Serbia	0.03	0.09	0.21	0.38	0.49	0.69	0.09	0.17	0.17
Slovak Republic	0.04	0.1	0.18	0.29	0.35	0.58	0.1	0.16	-0.01
Slovenia	0.05	0.16	0.32	0.42	0.47	0.73	0.21	0.18	-0.13
Ukraine	0.03	0.11	0.25	0.41	0.51	0.71	0.13	0.12	-0.01

Notes: Size is measured by total assets. **Small firms** are defined as firms in the first two quartiles of the distribution of total assets. Leverage percentiles refer to the distribution of **TDTA**, i.e. total debt to total assets. The sample period is 1999-2008. Source: Bureau Van Dijk's Orbis database.

As mentioned earlier, institutional reforms in the financial sector have progressed at varying speeds across countries in our sample. Table 3.2.3 summarizes the average values of the EBRD banking sector reform index and stock market capitalization to GDP for the period 1999-2008. The extent of stock market capitalization as a share of GDP is generally limited in most of the sample countries, especially in Bulgaria, Latvia, Romania and the Slovak Republic. Therefore, firms' external financing opportunities may depend crucially on the size and efficiency of the banking sector. The extent of banking sector reforms varies widely across countries as can be seen from Table 3.2.3.

The EBRD index of banking sector reforms scores countries on a scale of 1 to 4.3 on the basis of institutional reforms implemented in the banking sector. A score of 1 indicates that little progress has been made to move away from a socialist banking system beyond the separation of the central bank and commercial banks. A score of 2 signals that internal currency convertibility has been established and both interest rates and credit allocation have been liberalised. A score of 3 means that a country has achieved substantial progress in developing effective prudential regulation and supervision. This includes the development of a framework for the resolution of insolvent banks, and importantly the elimination of soft budget constraints. A score of 4.3 represents a level of reform that meets the standards of a fully fledged market economy (For more details, see EBRD (1998), Chapter 2). A more efficient banking sector is better able to screen out bad loans while a better developed stock market not only offers an alternative source of external finance, but also contributes to improved corporate governance practices. Given the variation in the extent of institutional reforms across our sample countries, it may be important to control for the quality of financial institutions when assessing the effect of leverage on TFP growth.

Table 3.2.3: **Quality of Financial Institutions, 1999-2008**

Country	Stock market capitalization	Banking reform index
Bosnia and Herzegovina	44.54	2.53
Bulgaria	15.74	3.38
Croatia	32.62	3.70
Czech Republic	23.97	3.74
Estonia	30.03	3.85
Hungary	25.10	4.00
Latvia	9.40	3.58
Lithuania	18.18	3.34
Poland	23.87	3.46
Republic of Moldova	26.92	2.56
Romania	13.04	2.91
Russian Federation	59.49	2.15
Serbia	23.21	2.09
Slovakia	7.09	3.41
Slovenia	26.17	3.3
Ukraine	21.54	2.46
All	31.08	2.65

Notes: **Banking reform index** is the average EBRD index of banking sector reform over 1999-2008 (1 to 4.3, with a higher number indicating a better score). **Stock market capitalization** is the average stock market capitalization in per cent of GDP over 1999-2008. Source: EBRD internal database.

3.3 Empirical model of leverage and total factor productivity growth

We use the threshold regression framework of Hansen (2000) in order to test the hypothesis of a non-monotonic relationship between leverage and productivity growth[16]. In our attempt to bridge the gap between the trade-off theory and the finance-growth theory, we also examine if a similar non-monotonic relationship exists between leverage and selected measures of firm value. In the absence of data on the market value of our sample firms, the analysis relies on two earnings-based proxies of firm value, namely earnings before interest and taxes (EBIT) as a share of total assets and the book value of equity. We examine the robustness of our estimates in several ways. First, we address the potential simultaneity between leverage and TFP growth by

[16] In order to identify the non-monotonic effects of leverage on total factor productivity growth, one could use a fixed-effects regression of total factor productivity growth on leverage and its non-linear terms, after controlling for other covariates. However this conventional method does not allow one to endogenously determine the existence and significance of a threshold beyond which TFP growth is negatively affected by further increases in debt.

instrumenting leverage with its lagged value and the predicted values of leverage based on firm characteristics. Second, we examine the relationship between the identified threshold and firm characteristics, namely profitability and size. Finally, we estimate our model on the 2000-2006 sub-sample to exclude the Russian crisis of 1998-99 and the recent financial crisis.

3.3.1 Total factor productivity estimates

TFP estimates are generated using the well-known Levinsohn-Petrin method (Levinsohn and Petrin, 2003). This method allows us to address a potential endogeneity problem which arises because firms anticipate shocks to productivity and accordingly adjust inputs throughout the production process. Appendix 3.A explains how the Levinsohn-Petrin method addresses this problem.

3.3.2 A threshold regression model

The current approach to threshold analysis was pioneered by Hansen (2000). The method endogenously determines the existence and significance of one or more thresholds that split the sample into "regimes", and allows the regression coefficients on the threshold variable to vary depending on the regime. In particular, we endogenously identify three regimes of leverage (low, intermediate, and high) and show that leverage has a different impact on TFP growth depending on the regime in which a firm finds itself. This method allows us to obtain a direct estimate of optimal leverage while allowing for firms' temporary deviations from the optimum. Denoting the leverage of the i-th firm in year t by $L_{i,t}$, the simplest threshold model of TFP growth for the period $[t, t+1]$ is given by

$$\triangle TFP_{i,t+1} = \alpha_1 L_{i,t} + \beta' X_{i,t} + \nu_{i,t} \text{ if } L_{i,t} \leqslant \gamma \tag{3.3.1}$$

$$\triangle TFP_{i,t+1} = \alpha_2 L_{i,t} + \beta' X_{i,t} + \nu_{i,t} \text{ if } L_{i,t} > \gamma \tag{3.3.2}$$

where $\nu_{i,t}$ is an error term and γ is the threshold parameter to be estimated. $X_{i,t}$ is a set of lagged explanatory variables, including: firm size (dummy for small and medium firms, defined as firms in the first two quartiles of total assets), age (dummy for young firms established in or after 1995), the share of intangible assets in total assets (IFATA), foreign ownership (a dummy indicating whether the firm is foreign-owned), lagged TFP to account for convergence effects (Barro, 1998), and industry fixed effects. All regressions are estimated with OLS. As mentioned above, we also include two variables that capture the quality of financial market institutions: the EBRD index of banking sector reforms and stock market capitalization as a share of GDP. In order to minimize the potential endogeneity bias of our threshold estimates using the current period debt ratio, we also experiment with lagged and fitted leverage ratios and compare these alternative estimates. Combining 3.3.1 and 3.3.2, we can write:

$$\triangle TFP_{i,t+1} = \beta' X_{i,t} + \alpha_1 L_{i,t} I(L_{i,t} \leqslant \gamma) + \alpha_2 L_{i,t} I(L_{i,t} > \gamma) + \nu_{i,t} \tag{3.3.3}$$

$I(.)$ is an indicator function, indicating whether the leverage of the i-th firm at time t is less than, equal to, or greater than the threshold parameter. The errors $\nu_{i,t}$ are assumed to be independent and identically distributed with mean zero and finite variance. Depending on whether the actual leverage is smaller, equal to, or larger than the threshold value (γ) to be estimated, observations are divided into two regimes, where the regimes are distinguished by different regression slopes, α_1 and α_2. Let $S_n(\beta, \alpha(\gamma))$ represent the sum of squared errors for Equation 3.3.3, where n is the sample size. Given that the parameters α depend on the threshold parameter γ, we denote them by $\alpha(\gamma)$. Because of this dependence, $S_n(.)$ is not linear in the parameters but rather a step function where steps appear at some distinct values of the threshold variable γ. However, conditional on a given threshold value, say $\gamma = \gamma_0$, $S_n(.)$ is linear in β and α. Accordingly, $S_n(\beta, \alpha(\gamma_0))$ can be minimised to yield the conditional OLS estimates $\hat{\beta}(\gamma_0)$ and $\hat{\alpha}(\gamma_0)$. Among all possible values for the leverage threshold, the estimate of the threshold corresponds to that value of α, which minimises the sum of squared errors $S_n(\beta, \alpha(\gamma_0))$ for $\gamma = \gamma_0$. This minimisation problem is solved by a grid search over 393 leverage quantiles {1%, 1.25%, 1.50% ... 98.75%, 99%}. Once the sample splitting value of γ is identified, the estimates of the slope parameters are readily available. If a threshold is identified, i.e. $\alpha_1 \neq \alpha_2$, one can form a confidence interval for the particular threshold value γ. This amounts to testing the following null hypothesis:

$$H_0 : \gamma = \gamma_0 \tag{3.3.4}$$

Under the normality assumption, the likelihood ratio test statistic is routinely used in standard econometric applications to test for particular parametric values. But Hansen (2000) shows that $LR_n(\gamma)$ does not have a standard chi-square distribution in the threshold model. The correct distribution function and the appropriate asymptotic critical values need to be obtained from the bootstrapped standard errors (see Girma (2005) for further details).

On the basis of the trade-off theory of capital structure, we expect a single threshold, which is equivalent to an optimal level of leverage where TFP growth is maximized. However, the confidence interval around the point estimate allows us to identify three bands of leverage. Suppose that the limits of the confidence interval around γ_0 are given by γ_1 (lower limit) and γ_2 (upper limit). The first band corresponds to a leverage ratio below the lower limit (i.e. leverage $\leqslant \gamma_1$), the second to an intermediate leverage ratio (i.e. $\gamma_1 <$ leverage $\leqslant \gamma_2$), and the third to "excessive" leverage (i.e. leverage $> \gamma_2$). Accordingly, we modify Equation 3.3.3 as follows

$$\begin{aligned} \triangle TFP_{i,t+1} &= \alpha_1 L_{i,t} I(L_{i,t} \leqslant \gamma_1) + \alpha_2 L_{i,t} I(\gamma_1 < L_{i,t} \leqslant \gamma_2) \\ &+ \alpha_3 L_{i,t} I(L_{i,t} > \gamma_2) + \beta' X_{i,t} + \nu_{i,t} \end{aligned} \tag{3.3.5}$$

The final step in our estimation strategy is to establish the asymptotic distribution of the slope coefficients. Although these parameters depend on the estimated threshold limits γ_1 and γ_2, Hansen (2000) demonstrates that this dependence is not of first-order asymptotic importance. Consequently, the usual distribution theory (i.e. asymptotically normal) can be applied to the estimated slope coefficients so that one can use the asymptotic p-values to test whether there is a significant threshold effect, i.e. whether $\alpha_1 = \alpha_2 = \alpha_3 = 0$. Rejection of this null hypothesis would confirm the presence of a significant threshold effect[17].

3.4 Results

3.4.1 Baseline threshold estimates

The threshold estimates of Equation 3.3.5 are summarized in Tables 3.4.1 and 3.4.2 for all firms and non-zero debt firms respectively. The tables report the coefficient estimates for all the explanatory variables (except sectoral dummies), including the slope coefficients for the three bands of leverage identified by the 95% confidence interval around the threshold. We also show the corresponding point estimates for γ_0. Despite some variation depending on the sample and the measure of leverage, the confidence interval estimates seem quite robust. The upper threshold limits are 0.386 for the debt ratio and 0.403 for the liability ratio for all firms (Table 3.4.1). For indebted firms, the corresponding ratios are 0.397 and 0.429 for the debt and liability ratios respectively (Table 3.4.2). The initial value of TFP is insignificant in both tables, indicating the absence of convergence effects.

[17] This procedure is explained in detail in Girma (2005) and Henry et al (2012).

Although average observed TLTA is higher than average observed TDTA (see Table 3.2.1), the point estimates and the upper threshold levels for the liability ratio are only slightly higher than those for the debt ratio. This result suggests that non-bank liabilities, of which trade credit (accounts payable) constitutes a large part, do not significantly contribute to productivity growth in our sample countries. There is a debate in the literature regarding the impact of trade credit on productivity in transition countries. On the one hand, Schaffer (1998) argues that the use of trade credit may soften the budget constraint and therefore delay or prevent the efficient restructuring of companies in transition countries. By contrast, Coricelli (1996) argues that trade credit favours growth by providing newly established firms with access to private credit markets. The positive and negative effects of trade credit on productivity may thus offset each other, at least to some extent, so that the net effect of non-bank liabilities on productivity growth is small in our sample.

Table 3.4.1: **Threshold estimates for total factor productivity growth, all firms**

	(1) Debt ratio			**(2) Liability ratio**	
Variable	**Coefficient**	**t-statistic**	**Variable**	**Coefficient**	**t-statistic**
Initial TFP	0.1094	0.843	**Initial TFP**	0.1357	0.842
TDTA>0.386	-0.0247***	-3.424	**TLTA $>$ 0.403**	-0.1676**	-2.295
0.330⩽TDTA⩽0.386	0.0966***	2.599	**0.339⩽ TLTA⩽0.403**	0.0575**	2.006
TDTA<0.330	0.3249*	1.737	**TLTA $<$ 0.339**	0.3349**	2.424
Small/Medium firms	0.1644***	3.273	**Small/Medium firms**	0.1273***	2.887
Young firms	-0.0027	-0.087	**Young firms**	-0.0057	-0.139
Foreign firms	0.2965	1.403	**Foreign firms**	0.3415	1.309
Intangible assets	0.2535***	4.429	**Intangible assets**	0.204***	3.040
Bank Reform	0.0963**	2.383	**Bank reform**	0.0941***	2.730
Market capitalization	0.0085***	3.736	**Market capitalization**	0.0095***	4.022
Intercept	0.4183*	1.817	**Intercept**	0.4368	1.224
Industry fixed effects	Yes		**Industry fixed effects**	Yes	
R^2	0.0395		R^2	0.0436	
95% CI for γ_0	0.330-0.386 (point est.= 0.364)		**95% CI for γ_0**	0.339-0.403 (point est.=0.387)	
Observations	7,276		**Observations**	7,276	

Note: *** indicates p-value<0.01, ** indicates p-value<0.05, * indicates p-value<0.1. **Initial TFP** is lagged total factor productivity. **TDTA** is the **Debt ratio** defined as total debt to total assets. **TLTA** is the **Liability ratio** defined as total liabilities to total assets. **Small/Medium firms** is a dummy for small and medium firms, defined as firms in the first two quartiles of total assets. **Young firms** is a dummy for young firms established in or after 1995. **Foreign fims** is a dummy indicating whether the firm is foreign-owned. **Intangible assets** is the share of intangible fixed assets in total assets (IFATA). **Bank Reform** is the EBRD index of banking sector reforms. **Market capitalization** is stock market capitalization as a share of GDP. γ_0 is the threshold parameter for leverage (TDTA or TLTA).

More importantly, the slope coefficients for the three endogenously identified bands of leverage are all significant, irrespective of the sample and measure of leverage used. The slope coefficients provide evidence that moderate leverage (leverage $\leqslant \gamma_2$) boosts TFP growth (estimated α_1 and α_2 are both positive), while excessive leverage (leverage $> \gamma_2$) lowers it (estimated α_3 is negative), after controlling for firm-level, sector and market characteristics. The marginal effect of leverage on TFP growth decreases as leverage increases from the lower band through the intermediate one to the upper band where the effect finally becomes negative. In other words, at low levels of leverage an increase in leverage has a large positive impact on TFP growth. This impact diminishes as leverage increases and ultimately turns negative. Based on the estimates of Table 3.4.2, a firm with a debt ratio (liability ratio) of 0.2 (i.e. below the lower threshold), for example, reaps net benefits from leverage in the form of 4.24% (10.13%) extra TFP growth compared with an unlevered firm. For a firm with a debt ratio (liability ratio) of 0.37 (in the mid-range), the net benefits amount to 3.14% (3.73%) of extra TFP growth. Finally, a firm with a debt ratio (liability ratio) of 0.5 (i.e. an overlevered firm) has negative net benefits amounting to 23.56% (17.96%) of forgone TFP growth compared with an unlevered firm.

Clearly leverage is not the only factor affecting TFP growth. Among the firm-specific factors, firm size, share of intangible assets and ownership are significant determinants of TFP growth. In general, TFP growth is significantly higher for small and medium sized firms, foreign firms (significant at 10% level for indebted firms only) and firms with large intangible assets. The role of institutional factors is also worth highlighting. A higher efficiency of the banking sector (a higher index of banking sector reforms) significantly increases TFP growth. The marginal effect of banking sector reforms is about 10% for all firms and 5-6% for indebted firms. In comparison, the marginal effect of market capitalization is small (about 1% for both samples), but positive and statistically significant too. These estimates confirm the beneficial role of better financial institutions on TFP growth in our sample.

Table 3.4.2: **Threshold estimates for total factor productivity growth, sub-sample of firms with outstanding debt** > 0

	(1) Debt ratio			(2) Liability ratio	
Variable	**Coefficient**	**t-statistic**	**Variable**	**Coefficient**	**t-statistic**
Initial TFP	0.1246	1.434	**Initial TFP**	0.1606	1.0525
TDTA>0.397	-0.4711***	-4.4027	**TLTA >0.429**	-0.3591***	-4.1582
0.312⩽TDTA⩽0.397	0.0848***	4.0394	**0.366⩽ TLTA ⩽0.429**	0.1007**	2.2809
TDTA<0.312	0.2121***	3.9798	**TLTA < 0.366**	0.5063***	4.9196
Small/Medium firms	0.2827***	3.2036	**Small/Medium firms**	0.2183***	3.7566
Young firms	-0.0184	-0.6056	**Young firms**	-0.0104	-0.3224
Foreign firms	0.4598*	1.7453	**Foreign firms**	0.4722*	1.8367
Intangible assets	0.1461***	3.0295	**Intangible assets**	0.1103***	3.4344
Bank reform	0.0584*	1.7651	**Bank efficiency**	0.0498**	2.2909
Market capitalization	0.0144*	1.9062	**Market capitalization**	0.0079***	4.508
Intercept	0.3079	1.4412	**Intercept**	0.2503	0.5869
Industry fixed effects	Yes		**Industry fixed effects**	Yes	
R^2	0.038		R^2	0.0609	
95% CI for γ_0	0.312-0.397 (point est. = 0.368)		**95% CI for** γ_0	0.366-0.429 (point est. =0.391)	
Observations	7,276			7,276	

Note: *** indicates p-value<0.01, ** indicates p-value<0.05, * indicates p-value<0.1. **Initial TFP** is lagged total factor productivity. **TDTA** is the **Debt ratio** defined as total debt to total assets. **TLTA** is the **Liability ratio** defined as total liabilities to total assets. **Small/Medium firms** is a dummy for small and medium firms, defined as firms in the first two quartiles of total assets. **Young firms** is a dummy for young firms established in or after 1995. **Foreign fims** is a dummy indicating whether the firm is foreign-owned. **Intangible assets** is the share of intangible fixed assets in total assets (IFATA). **Bank Reform** is the EBRD index of banking sector reforms. **Market capitalization** is stock market capitalization as a share of GDP. γ_0 is the threshold parameter for leverage (TDTA or TLTA).

Since our conceptual starting point is the trade-off theory, we attempt to check for its relevance in our sample. However, we are unable to investigate the relationship between market-based measures of leverage and firm value or the cost of capital due to lack of data. Instead, we examine whether a non-linear relationship exists between book leverage and alternative measures of firm value. Since earnings growth is a primary determinant of equity value[18], we consider two proxies for firm value based on earnings, namely return on assets (ROA, defined as EBIT/total assets) and return on equity (ROE, defined as EBIT/book equity)[19]. The results are shown in Table 3.4.3. They support the existence of a leverage level that maximizes ROA as well as ROE.

Bearing in mind the fact that our results are not a formal test of the trade-off theory due to data issues, the results suggest that the optimal leverage level from a firm-value perspective is higher than the optimal level from a productivity perspective. This is likely due to the fact that value creation does not only result from productivity improvements but also increases in the capital base that supports earnings growth[20]. More importantly, the qualitative results are very similar. The thresholds exist and the effects of leverage on TFP growth within the three different bands are as follows: first positive and large, then positive but small, and finally negative when leverage is higher than the upper confidence limit. Bearing in mind the caveats of our analysis, these results can add value to the study of capital structure. In particular, it would be interesting in future research to apply our approach to a sample of firms for which market values are available (e.g. US data).

[18]Examples of valuation models which incorporate earnings growth are Campbell and Shiller (2001) and Fama and French (2002b).

[19]The availability and quality of data on the book value of equity is limited. We had to exclude about 15% of observations as outliers for the threshold model to converge.

[20]The upper threshold level of leverage is smaller for ROE than for ROA. However, given the limited availability and quality of equity data, we refrain from drawing quantitative conclusions from this result.

Table 3.4.3: **Threshold estimates for ROA and ROE - sub-sample of firms with outstanding debt** > 0

Dependent variable: ROA	**(1) Debt ratio**			**(2) Liability ratio**	
Variable	**Coefficient**	**t-statistic**	**Variable**	**Coefficient**	**t-statistic**
TDTA>0.629	-0.07611	-10.103**	**TLTA >0.578**	-0.0196	-2.989 **
0.271⩽TDTA ⩽0.629	0.0686	0.4048	**0.246⩽TLTA ⩽0.578**	0.0887	9.754 **
TDTA <0.271	0.044559	1.7081*	**TLTA<0.246**	0.4319	11.563 **
Other control variables	Yes		**Other control variables**	Yes	
Industry fixed effects	Yes		**Industry fixed effects**	Yes	
95% CI for γ_0	0.271 -0.629 (point est.=0.458)		**95% CI for γ_0**	0.246-0.578 (point est. = 0.406)	
Dependent variable: ROE	**(1) Debt ratio**			**(2) Liability ratio**	
Variable	**Coefficient**	**t-statistic**	**Variable**	**Coefficient**	**t-statistic**
TDTA>0.582	-0.0835	-3.014**	**TLTA>0.601**	-0.0676	-1.555**
0.326 ⩽ TDTA ⩽ 0.582	0.1312	2.668**	**0.331⩽TLTA ⩽0.601**	0.0196	1.634**
TDTA < 0.326	0.1473	2.812**	**TLTA<0.331**	0.0611	2.461**
Other control variables	Yes		**Other control variables**	Yes	
Industry fixed effects	Yes		**Industry fixed effects**	Yes	
95% CI for γ_0	0.326 -0.582 (point est.=0.469)		**95% CI for γ_0**	0.331-0.601 (point est. = 0.499)	

Note: *** denotes p-value< 0.01, ** denotes p-value<0.05, * denotes p-value<0.1. γ_0 is the threshold parameter for leverage (TDTA). **TDTA** is the **Debt ratio** defined as total debt to total assets. **TLTA** is the **Liability ratio** defined as total liabilities to total assets. **Other control variables** refers to all the other controls included in Tables 3.4.1 and 3.4.2. **ROA** is Return on Assets. **ROE** is Return on Equity.

3.4.2 Firm characteristics and optimal leverage

In this section we explore how the relationship between leverage and TFP growth varies by firm characteristics, namely size and profitability. These results are also used to test the robustness of our estimates. The trade-off theory predicts a positive relation between optimal leverage and profitability. An increase in earnings increases the tax advantage to debt and reduces the expected costs of distress and bankruptcy, and hence results in an increase in leverage (Strebulaev, 2007). In addition, the trade-off theory predicts a negative relation between optimal leverage and size (e.g. Kurshev and Strebulaev, 2006). However, previous studies using cross-sectional or panel regressions tend to find a negative (positive) relation between profitability (size) and leverage (e.g. Frank and Goyal, 2009). These conflicting results may be driven by the fact that studies typically rely on the implicit assumption that firms are always at their optimal level of capital structures. By contrast, the threshold model allows us to determine optimal leverage despite firms' temporary deviations from the optimum and may therefore enable us to examine the empirical validity of the theoretical relationships.

We use two alternative measures of profitability, namely, a firm's return on assets (ROA, defined as EBIT/total assets) and return on capital employed (ROCE as reported in Orbis). We split the sample based on the median values of those two profitability measures, i.e. a less (more) profitable firm is defined as one with a ROA or ROCE below (above) the sample median (approximately 0.04 for both measures). The threshold estimates for more and less profitable firms are presented in Table 3.4.4. We restrict our attention to the sample of firms with positive debt and use TDTA as the dependent variable.

These estimates confirm the significant adverse effect of excessive leverage (beyond the upper threshold limit) on TFP growth and the positive benefits of leverage below that point. Interestingly, the estimated threshold parameters differ significantly for more or less profitable firms. The upper and lower threshold values of the debt and liability ratios are significantly higher for more profitable firms. For example, the upper (lower) threshold limit is approximately 60% (47%) for more profitable firms as opposed to approximately 30% (20%) for less profitable firms when profitability is measured by ROA. Similarly, the point estimates of optimal leverage are higher for more profitable firms irrespective of the leverage measure. In addition, Table 3.4.4 shows that the negative effect of excessive leverage on TFP growth is significantly higher in absolute value for less profitable firms. In other words, more profitable firms are able to sustain significantly higher levels of debt without hurting their productivity growth. This result may be due to the fact that they have higher cash flows, as suggested by the trade-off theory. It supports a positive relationship between profitability and optimal leverage. Bearing in mind that this result is not a formal test of the trade-off theory, the conclusion is nevertheless qualitatively similar to the theoretical prediction of the trade-off theory and the empirical results of Korteweg (2010). Previous studies using cross-sectional or panel regressions tend to find a negative relation between profitability and leverage (e.g. Frank and Goyal, 2009). This is because high profits mechanically lower observed leverage ratios and previous studies rely on the implicit assumption that firms are always optimally levered. Strebulaev (2007) shows formally that cross-sectional regressions will produce misleading results on the relation between leverage and profitability. Specifically, he shows that even if firms in simulated economies follow the prescriptions of the dynamic trade-off theory, higher profitability lowers the current leverage of a firm unless it refinances in that period. Hence, the presence of frictions that result in firms diverging from their optimal capital structures may complicate empirical work on the trade-off theory. By contrast, the threshold model allows us to determine optimal leverage despite firms' temporary deviations from the optimum.

Table 3.4.4: **Threshold estimates for TFP growth for profitable and non-profitable firms - Sub-sample of firms with outstanding debt >0**

	ROA< 0.04		**ROA > 0.04**		**ROCE < 0.04**		**ROCE > 0.04**	
Variable	**Coefficient**	**t-statistic**	**Coefficient**	**t-statistic**	**Coefficient**	**t-statistic**	**Coefficient**	**t-statistic**
Initial TFP	0.0282	0.1882	0.2513	0.8998	0.0111	0.0785	0.2218	1.0221
TDTA $> \gamma_2$	-0.5383***	-2.871	-0.0205***	-3.7415	-0.6522***	-3.1142	-0.1924**	-2.5415
$\gamma_1 \leqslant$ **TDTA** $\leqslant \gamma_2$	0.7244**	2.4022	0.074*	1.8906	-0.0035	-0.0122	0.1114***	2.9813
TDTA $< \gamma_1$	0.297***	3.4799	0.1978*	1.7339	0.5892**	2.2228	0.1943*	1.7429
Small/Medium firms	0.0851	0.9762	0.1994***	3.2601	0.0995***	2.9089	0.0998**	2.4722
Young firms	-0.2595**	-2.1802	0.0105	0.1656	-0.1512**	-2.0046	0.0091	0.1824
Foreign firms	0.1295	0.4785	0.61**	2.2618	0.1606	0.6445	0.6175***	2.9946
Intangible assets	0.1692***	3.0924	0.2001***	2.6732	0.0977***	3.0465	0.3336***	4.4063
Bank reform	0.2476***	2.8049	0.0343	1.471	0.2102	1.4692	0.0243	1.0896
Market capitalization	0.0123	1.3506	0.0108***	3.7178	0.0075	0.7625	0.0066***	4.5869
Industry fixed effects	Yes		Yes		Yes		Yes	
Intercept	-0.4456	-0.6346	0.5858	1.4961	-0.3274	-0.357	0.3975	1.0763
R^2	0.0543		0.059		0.06		0.076	
95% CI for γ_0	0.207-0.314 (point est. = 0.266)		0.469-0.601 (point est.= 0.520)		0.337-0.502 (point est. = 0.411)		0.477-0.695 (point est.= 0.578)	

Note: *** denotes p-value< 0.01, ** denotes p-value<0.05, * denotes p-value<0.1.**Initial TFP** is lagged TFP. **TDTA** is the **Debt ratio** defined as total debt to total assets. **Small/Medium firms** is a dummy for small and medium firms, defined as firms in the first two quartiles of total assets. **Young firms** is a dummy for young firms established in or after 1995. **Foreign fims** is a dummy indicating whether the firm is foreign-owned. **Intangible assets** is the share of intangible fixed assets in total assets (IFATA). **Bank Reform** is the EBRD index of banking sector reforms. **Market capitalization** is stock market capitalization as a share of GDP. **ROA** is Return on Assets, defined as EBIT/total assets. **ROCE** is Return on Capital Employed. γ_0 is the threshold parameter for leverage (TDTA). γ_1 is the lower bound of the 95% confidence interval around γ_0. γ_2 is the upper bound.

Finally, we focus on the sub-sample of relatively larger firms, defined as firms with total assets above the sample median. We do not present the full set of results but summarize the optimal leverage ratios in Table 3.4.7. Again, we restrict our attention to the debt ratio (TDTA) and non-zero debt firms. The confidence interval for the debt ratio is 0.263-0.446 for larger firms, against 0.312-0.397 for all non-zero debt firms. The point estimates are approximately equal in the two samples (0.360 and 0.359). However, the lower bound of the confidence interval is significantly smaller for large firms (0.263 against 0.312 for all firms), suggesting that the beneficial effects of debt decline faster. This is consistent with available empirical evidence that suggests that the marginal benefits of debt are likely to be lower for firms with better access to debt markets (such as large firms) than for those firms that face tighter credit constraints. This argument goes back to the work of Titman and Wessels (1988) in a static framework and is also consistent with the more recent work of Strebulaev (2007) in a dynamic setting. These results are not definitive though because there was no significant threshold for smaller firms, i.e. firms with total assets below the median. Therefore we cannot directly compare the estimates for large and small firms.

3.4.3 Incidence of excess leverage

We use the leverage threshold estimates to calculate the percentage of firms above the upper threshold for the debt ratio (TDTA) in each of our sample countries. We obtain these estimates for all non-zero debt firms, but also for more and less profitable non-zero debt firms (where profitability is based on ROA). The results are summarized in Table 3.4.5. There is evidence of a significant proportion of firms in most of our sample countries with debt ratios in excess of the upper debt threshold. There is also pronounced inter-country variation: considering all non-zero debt firms, the proportion of firms with excessive leverage is the highest in Russia (above 20% of firms), closely followed by Bulgaria (about 19% of firms). In contrast, the proportion of non-zero debt firms with excessive leverage is the lowest in Hungary (little less than 3%), closely followed by Slovakia (little above 3%). These results, combined with the finding that many firms have zero leverage (see Section 3.2), highlight the presence of a double puzzle, the puzzle of zero-leverage firms and the puzzle of overlevered firms.

Table 3.4.5: **Percentage of firms above the upper threshold limits for the debt ratio (TDTA), by country**

	Non-zero debt firms		
	All firms	**Profitable firms (ROA $>$ 0.04)**	**Non-profitable firms (ROA $<$ 0.04)**
	Debt ratio $\gamma_2 > 0.399$	**Debt ratio $\gamma_2 > 0.577$**	**Debt ratio $\gamma_2 > 0.301$**
Bosnia and Herzegovina	15.2%	1.5%	4.7%
Bulgaria	18.9%	2.0%	8.6%
Croatia	10.4%	1.3%	5.4%
Czech Republic	10.9%	1.1%	5.7%
Estonia	8.4%	1.4%	4.6%
Hungary	2.9%	0.0%	1.5%
Latvia	12.8%	0.8%	11.5%
Lithuania	11.2%	2.0%	2.6%
Poland	6.3%	0.7%	1.0%
Republic of Moldova	8.8%	0.0%	8.8%
Romania	11.3%	0.9%	0.6%
Russian Federation	20.1%	5.2%	4.5%
Serbia	10.1%	0.7%	7.1%
Slovakia	3.2%	0.9%	1.2%
Slovenia	9.3%	0.8%	6.0%
Ukraine	8.3%	1.0%	4.6%

Note: *** denotes p-value$<$ 0.01, ** denotes p-value$<$0.05, * denotes p-value$<$0.1. **ROA** is Return on Assets, defined as EBIT/total assets. **TDTA** is the **Debt ratio** defined as total debt to total assets. γ_2 is the upper limit of the 95% confidence interval for γ_0.

In Columns (2) and (3) of Table 3.4.5, we split the sample to focus on more and less profitable firms. The figures suggest that the proportion of firms with excessive leverage is higher among relatively less profitable firms in most sample countries, in line with the findings in Korteweg (2010) for the US.

3.4.4 Robustness of threshold estimates

One criticism of the Hansen (2000) approach is that the variable of interest is often subject to the decision making process of the firm, and is therefore endogenous. Hence, the threshold estimates may be biased or inconsistent. In order to check the robustness of our original estimates, we use other proxies for leverage and re-estimate the threshold model.

This methodology requires one to identify appropriate instruments, in this case variables that are correlated with the current debt ratio, but uncorrelated with current productivity growth. Typically, the literature has resorted to employing lags to resolve endogeneity issues (e.g. Arellano and Bond, 1991). Accordingly we instrument the current debt ratio with its lag. In addition, we employ a two-stage method where we first obtain the predicted value of the current debt ratio using the standard cross-sectional approach (see Appendix 3.B) and then replace the current debt ratio by its fitted value[21].

The correlation between the current firm-level debt ratio and its lagged value is 0.2188 while that between the current debt ratio and its predicted value is 0.8091. In addition, both lagged and fitted debt ratios display little correlation with the error term of the TFP growth equation. This can be seen from the low correlation between these alternative leverage measures and the estimated error from Equation 3.3.5. In particular, the correlation between the lagged debt ratio and the estimated residual is 0.035 and the correlation between the predicted debt ratio and the residual is 0.0945 in the sample of all firms.

The alternative threshold estimates for the debt ratio (TDTA) are summarised in Table 3.4.6 for all firms and for the sub-sample of indebted firms. Again, they confirm the non-monotonic effects of leverage on TFP growth: while moderate leverage boosts productivity growth, excessive leverage (beyond the upper threshold limit) hampers productivity growth. The estimated confidence interval for the lagged debt ratio is 0.326-0.407 for all firms and 0.366-

[21] Note that the variables that explain the debt ratio in Appendix 3.B are not exactly the same as those determining TFP growth in Equation 3.3.5. In particular, the log of total assets and the inflation rate are included in Appendix 3.B, but not in Equation 3.3.5. In addition, Equation 3.3.5 includes initial TFP and also different bands of leverage depending on the two threshold limits obtained from the estimation of the threshold model. See further discussion in Appendix 3.B

0.437 for indebted firms. Similar threshold estimates are obtained when we replace the current debt ratio with its fitted value. These are 0.339-0.419 and 0.357-0.431 respectively for all firms and all indebted firms. The corresponding estimates from the original threshold model were 0.330-0.386 and 0.312-0.397 respectively for all firms and indebted firms. In other words, these alternative threshold estimates for the debt ratio are within less than 5 percentage points of the estimates (0.386 and 0.397) using the contemporaneous debt ratio.

When leverage is instrumented using lagged leverage (fitted leverage), ceteris paribus, a firm with a debt ratio of 0.2 (i.e. below the lower threshold) reaps net benefits from leverage in the form of 13.1% (12.1%) extra TFP growth compared with an unlevered firm. For a firm with a debt ratio of 0.37 (in the mid-range), the net benefits amount to 2.5% (3.23%) of extra TFP growth. Finally, a firm with a debt ratio of 0.5 (i.e. an over-levered firm) has negative net benefits amounting to 15.2% (16%) of forgone TFP growth compared with an unlevered firm.

Table 3.4.6: **Threshold estimates using alternative debt ratios**

	All firms				Firms with debt > 0			
	Lagged debt		**Fitted debt**		**Lagged debt**		**Fitted debt**	
Variable	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**
Initial TFP	0.252	14.720***	0.221	11.867***	0.102	0.786	0.139	0.8186
TDTA $> \gamma_2$	-0.446	-1.959**	-0.490	-2.366***	-0.303	-6.342***	-0.318	-6.393***
$\gamma_1 \leqslant$ **TDTA** $\leqslant \gamma_2$	0.487	3.868***	0.476	3.590***	0.068	2.906***	0.088	3.414***
TDTA$< \gamma_1$	1.030	4.933***	1.016	4.621***	0.655	2.351***	0.604	3.174***
Small/Medium firms	-0.181	-5.48***	-0.176	-4.910***	0.106	4.255***	0.165	3.245***
Young firms	-0.072	-1.781*	-0.079	-1.895*	-0.027	-0.531	-0.028	-0.474
Foreign firms	0.023	0.664	0.022	0.6134	0.305	1.3246	0.470	1.459
Intangible assets	0.505	1.645	0.582	1.750*	2.312	4.554***	2.339	4.075***
Bank reform	0.571	11.595	0.625	10.247***	0.048	1.782*	0.066	1.1439
Market capitalization	-0.001	-0.645	-0.001	-0.5376	0.008	4.858***	0.009	4.416***
Intercept	-0.385	-2.192**	-0.473	-2.534***	0.269	0.6791	0.392	0.7168
Industry fixed effects	Yes		Yes		Yes		Yes	
R^2	0.033		0.031		0.045		0.036	
95% CI for γ_0	0.326-0.407 (point est. = 0.354)		0.339-0.419 (point est. = 0.369)		0.366-0.437 (point est.= 0.394)		0.357-0.431 (point est. = 0.382)	

Note: *** denotes p-value< 0.01, ** denotes p-value<0.05, * denotes p-value<0.1.**Initial TFP** is lagged TFP. **TDTA** is the **Debt ratio** defined as total debt to total assets. **Small/Medium firms** is a dummy for small and medium firms, defined as firms in the first two quartiles of total assets. **Young firms** is a dummy for young firms established in or after 1995. **Foreign fims** is a dummy indicating whether the firm is foreign-owned. **Intangible assets** is the share of intangible fixed assets in total assets (IFATA). **Bank Reform** is the EBRD index of banking sector reforms. **Market capitalization** is stock market capitalization as a share of GDP. γ_0 is the threshold parameter for leverage (TDTA). γ_1 is the lower bound of the 95% confidence interval for γ_0. γ_2 is the upper bound.

Table 3.4.7 provides an overview of all the debt ratio threshold estimates (both confidence intervals and point estimates) that we have obtained so far. All the results point to the existence of a non-monotonic relationship between leverage and TFP growth. The presence of a single threshold in each case is compatible with the theory of optimal capital structure, where the threshold is associated with maximum TFP growth. The estimates are robust to alternative leverage measures. The threshold estimates vary somewhat with firm characteristics, in particular profitability and size, in a way consistent with the trade-off theory of capital structure.

3.4.5 Threshold estimates for 2000-2006

Given that the sample period 1999-2008 includes two crises, namely the Russian crisis of 1998-99 and the recent financial crisis of 2007, which both had a large impact on the CEE region, we estimate the threshold model for the sub-sample of "normal years" 2000-2006. The estimates for 2000-2006 are summarized in Table 3.4.7.

Threshold estimates for the period 2000-2006 appear to be in line with those for the full sample 1999-2008, irrespective of whether we consider all firms or only indebted firms. For example, the lower threshold estimate is 0.336 in the full sample of all firms as opposed to 0.342 in the corresponding 2000-2006 sample. Similarly, the estimate of the upper threshold is 0.386 in the full sample of all firms compared to 0.377 in the 2000-2006 sample. In conclusion, the results do not appear to be driven by the choice of sample period.

Table 3.4.7: **A summary of threshold estimates (debt ratio only)**

	Debt ratio thresholds		
	Lower limit	**Upper limit**	**Point estimate**
All firms	0.336	0.386	0.368
All firms (2000-2006)	0.342	0.377	0.364
All firms (lagged debt ratio)	0.326	0.407	0.370
All firms (fitted debt ratio)	0.339	0.419	0.372
Non-zero-debt firms	0.312	0.397	0.359
Non-zero-debt firms (2000-2006)	0.328	0.376	0.354
Non-zero-debt firms (lagged debt ratio)	0.366	0.437	0.400
Non-zero-debt firms (fitted debt ratio)	0.357	0.431	0.394
Non-zero-debt firms 2000-06 (lagged debt ratio)	0.369	0.421	0.399
Non-zero-debt firms 2000-06 (fitted debt ratio)	0.377	0.434	0.404
	Non-zero debt firms only		
More profitable firms	0.469	0.601	0.537
Less profitable firms	0.207	0.314	0.271
More profitable firms (2000-2006)	0.472	0.599	0.538
Less profitable firms (2000-2006)	0.248	0.301	0.273
Large firms	0.263	0.446	0.36

Note: **Debt ratio** (TDTA) is total debt to total assets. **Small firms** are those with total assets below the sample median. **Large firms** are those with total assets above the sample median. **Non-zero debt firms** are firms with positive outstanding debt. **More profitable firms** are firms with ROA>0.04. **Less profitable firms** are firms with ROA<0.04.

3.5 Conclusions

The paper aims to bridge the gap between the literature on optimal capital structure and the wider macroeconomic literature on the finance-growth nexus. On the basis of the trade-off theory of capital structure, we posit a non-monotonic relationship between leverage and productivity growth at the firm level. TFP growth is not only the most important metric in the macroeconomic growth literature; it has attracted increasing interest from the finance literature. We provide evidence supporting our hypothesis of non-monotonicity, using a threshold regression model (Hansen, 2000). Estimates for a sample of Central and Eastern European countries confirm that TFP growth increases with book leverage until the latter reaches a critical threshold beyond which leverage becomes "excessive" and lowers TFP growth. This result points to the existence of an optimal leverage ratio where the net benefits of debt in terms of productivity gains are exhausted. Despite some variation depending on the sample and the measure of leverage, the estimates seem quite robust. The estimates of the slope coefficients for the three bands of leverage (low, intermediate, and excessive) suggest that the productivity gains (costs) to leverage are substantial for underlevered (overlevered) firms. Leverage is found to have similar non-monotonic effects on return on assets and return on equity.

Due to data limitations, our results are not a formal test of the trade-off theory. However, they suggest that the threshold regression approach is a promising methodology for the study of optimal capital structure and how the latter varies with firm characteristics. In contrast to existing empirical evidence based on observed leverage ratios, the threshold model allows us to endogenously determine optimal leverage despite firms' temporary deviations from the optimum. Our results suggest a positive (negative) relationship between profitability (size) and optimal leverage, unlike existing studies that use traditional cross-sectional or panel regressions.

Using the leverage threshold estimates, we find evidence of a significant proportion of firms with debt ratios in excess of the upper debt threshold in our sample. Our results suggest that the proportion of firms with excessive leverage is higher among relatively less profitable firms in most sample countries, a result that extends beyond the transition sample, as shown by Korteweg (2010) on the US. Finally, our results are robust to different sample periods.

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Appendix

3.A Estimation of Total Factor Productivity

We estimate the following production function:

$$y_{i,t} = \alpha_k k_{i,t} + \alpha_l l_{i,t} + \alpha_m m_{i,t} + \epsilon_{i,t} \tag{3.A.1}$$

where subscripts i, and t refer to firm i and year t; $y_{i,t}$, $k_{i,t}$, $l_{i,t}$, and $m_{i,t}$ represent the logarithm of a firm's output (sales) and the production inputs: capital (measured as the book value of fixed assets), labour (number of employees) and material costs respectively. We estimate TFP from 3.A.1 and then compute log(TFP). To deflate monetary values we use the consumer price index due to the lack of available industrial price deflators for many of our sample countries.

One of the most common econometric problems with the estimation of TFP is endogeneity. Typically, the regressors will be correlated with the error term because firms change their factor inputs in the anticipation of TFP changes. If that is the case, then profit maximization implies that the realization of the error term is expected to influence the decision on factor inputs. Consequently the OLS estimates could be inconsistent. Therefore, we use the Levinsohn-Petrin correction. Levinsohn and Petrin (2003) extend Olley and Pakes (1996) by using material inputs as a proxy to control for unobservable productivity shocks.

3.B Estimation of a fitted debt ratio

Our approach is based on the existing literature, which identifies a number of firm-specific factors that determine corporate leverage (e.g. Rajan and Zingales, 1995; Flannery and Rangan, 2006; Driffield and Pal, 2010). Following our discussion in Section 3.2, we also include some country specific institutional variables, namely the EBRD index of banking sector reforms (that captures banking sector efficiency) and stock market capitalization as a share of GDP.

Accordingly, we estimate the following leverage equation for firm i in year t (t=1999, ..., 2008)

$$\text{Leverage}_{i,t} = \beta_0 + \beta_1 \text{Ln(assets)}_{i,t-1} + \beta_2 \text{Age}_{i,t-1} + \beta_3 \frac{\text{Intangible Fixed Assets}_{i,t-1}}{\text{Total Assets}_{i,t-1}}$$
$$+ \beta_4 \frac{EBIT_{i,t-1}}{\text{Total Assets}_{i,t-1}} + \beta_5 \text{Inflation}_{i,t-1} + \beta_6 \text{Bank efficiency}_{i,t-1}$$
$$+ \beta_7 \text{Stock market capitalization}_{i,t-1} + \beta_8 \text{Industry Median Leverage}_t + \nu_{i,t} + u_{i,t}$$

where EBIT stands for earnings before interest and taxes, $\nu_{i,t}$ is a firm-specific fixed effect and $u_{i,t}$ is the error term[22]. The firm-specific fixed effects account for various unobserved firm-specific factors that may also influence leverage. We use panel data fixed effects, using both debt and liability ratios as alternative measures of leverage. In order to mitigate a potential simultaneity bias, we follow the general convention (e.g. Driffield and Pal, 2010) and use (one year) lagged explanatory variables. The fixed effects estimates are summarized in Table 3.B.1 below. In general, more profitable firms tend to have lower leverage. Foreign firms and firms in industries with higher median leverage tend to have higher leverage. The bank reform coefficient is positive but remains insignificant. The coefficient on stock market capitalization to GDP is however positive and significant for both measures of leverage, thus highlighting a leverage premium for firms operating in countries with better stock market development.

[22]Note that we do not have data on market-to-book ratios. In alternative specifications, the growth of total assets was included and always found to be insignificant. Fixed assets as a share of total assets are also excluded because there could also be a problem of multicollinearity with the share of intangible fixed assets.

Table 3.B.1: **Determinants of Leverage: Fixed effects estimates of debt and liability ratios, 1999-2008**

VARIABLES	Debt ratio	Liability ratio
Total assets	0.0017	-0.0133
	(0.0036)	(0.0131)
Small/Medium firms	-0.0256***	-0.0105
	(0.0058)	(0.0092)
Young firms	0.00103	-0.000113
	(0.0012)	(0.0024)
Foreign firms	0.0736***	0.107***
	(0.0068)	(0.0178)
Industry median debt ratio	0.257***	
	(0.0593)	
Industry median liability ratio		0.189*
		(0.103)
Intangible assets	0.0501	-0.11
	(0.0339)	(0.0694)
Profitability	-0.0535**	-0.166***
	(0.0228)	(0.0479)
Inflation	-0.000343	-0.00368***
	(0.0002)	(0.0009)
Market capitalization	0.000702***	0.000869*
	(0.0002)	(0.0004)
Banking reforms index	0.00526	0.0217
	(0.0075)	(0.0332)
Constant	0.0129	0.410**
	(0.0747)	(0.176)
Observations	9310	10433
R^2	0.09	0.132
Number of firms	2243	2379

Note: Robust standard errors in parentheses. *** indicates p-value<0.01, ** indicates p-value<0.05, * indicates p-value<0.1. **Initial TFP** is lagged total factor productivity. **TDTA** is the **Debt ratio** defined as total debt to total assets. **TLTA** is the **Liability ratio** defined as total liabilities to total assets. **Small/Medium firms** is a dummy for small and medium firms, defined as firms in the first two quartiles of total assets. **Young firms** is a dummy for young firms established in or after 1995. **Foreign firms** is a dummy indicating whether the firm is foreign-owned. **Industry median debt ratio** is the median debt ratio in the firm's industry. **Industry median liability ratio** is the median liability ratio in the firm's industry. **Intangible assets** is the share of intangible fixed assets in total assets (IFATA). **Profitability** is the firm's ROA (Return on Assets). **Inflation** is the rate of inflation as measured by the Consumer Price Index. **Market capitalization** is stock market capitalization as a share of GDP. **Bank reforms index** is the EBRD index of banking sector reforms.

Chapter 4

The sullying effect of credit sclerosis on productivity[1]

Abstract

This paper explores the impact of depressed credit flows on productivity in a partial equilibrium search and matching model of the banking market. Reputational costs associated with the termination of lending relationships drive a wedge between rates on new and legacy loans. This induces misallocation of capital across borrowers. The phenomenon is one of "credit sclerosis": loan destruction is subdued by the separation cost, hence loan creation must decrease to restore equilibrium. Low-productivity firms are kept alive through subsidised loan rates, while high-productivity entrants face an inefficiently high cost of borrowing and limited supply of new loan facilities. As a consequence, too much credit is allocated to old firms. Aggregate labour productivity and TFP are reduced. The model may shed some light on why a policy tool like the UK's Funding for Lending Scheme might fail to revive productivity in the presence of costly loan termination.

4.1 Introduction

It has long been recognised that credit market frictions are an important determinant of macroeconomic performance. The events since the financial crisis of 2007-2008 suggest that the banking sector is indeed a crucial determinant of business cycle fluctuations. A key channel through

[1]I gratefully acknowledge financial support from the Paul Woolley Centre for the study of capital market dysfunctionality. I am indebted to Alex Clymo for his invaluable advice on using Matlab and Dynare.

which banks affect the economy is the provision of credit to fund corporate investment. A banking sector which promotes creative destruction is one which withdraws credit from poorly performing firms and forces them to either improve their performance or exit the market. In a frictionless world, banks should lend if and only if the borrower has a positive net present value project. Credit would then be reallocated to more productive firms, allowing these firms to enter the market or expand. The present paper proposes a simple framework to study the impact of credit frictions which undermine the ability of the banking sector to foster creative destruction.

Specifically, I develop a partial equilibrium search and matching model of the credit market where heterogenous firms bargain with banks over loan contracts with endogenous loan rates and loan volumes. Banks incur termination costs when ending a lending relationship with an existing borrower. After a shock which raises termination costs, the economy is characterized by what Caballero and Hammour (1998, 2001) call "sclerosis" - the preservation of firms that would not otherwise survive. In the present model, sclerosis is a situation with depressed credit flows. When hit by a shock to termination costs, banks revise the price terms of their legacy contracts downwards and keep lower productivity loans on their books. Since loan destruction is subdued by the separation cost, loan creation must decrease to restore equilibrium. The resulting congestion comes at the expense of entrants looking for funds to start production: they face an inefficiently high cost of borrowing and limited supply of new loan facilities. They are crowded out both in terms of credit volume and price. In other words, credit sclerosis impairs creative destruction - a process by which new firms replace less productive ones (Schumpeter, 1942). Aggregate productivity declines.

The termination costs can be seen as reputational rather than monetary. Bank managers may be concerned about the perception that the market has of their abilities, for example because they worry about keeping their jobs or getting jobs in other firms[2]. This can induce them to actively influence the market's perceptions by manipulating earnings through changes in their credit policies (see e.g. Rajan, 1994). Another possibility is that the bank has to raise new external finance (to meet regulatory requirements) or roll over some of its existing debt obligations. The bank may then attempt to convince the market of the profitability of its loan portfolio. In my model, the termination cost induces banks to extend the duration of legacy loans and this boosts their earnings. The regulator is either unable to observe the termination cost or is willing to close a blind eye. Such behaviour on the part of banks and the regulator is more likely when

[2]Barro and Barro (1990) show that CEO turnover and compensation growth depend on relative performance.

the economy is hit by a bad shock which results in a credit crunch. The regulator may be willing to help banks keep low productivity borrowers afloat to avoid liquidations and massive unemployment, possibly under political pressure (Mishkin, 2000; Brown and Dinç, 2005; Hamao, Kutsuna, and Peek, 2012).

In the model, the termination cost induces banks to lend to negative NPV projects. This is akin to forbearance - also referred to as "zombie lending" or "evergreening" (Peek and Rosengren, 2005; Caballero et al, 2008). Forbearance is a practice whereby banks accommodate bad borrowers struggling to meet their obligations instead of terminating their loans. Forbearance can take various forms, among others providing temporary payment relief. Incentives to forbear may increase in the context of a banking crisis. First, the continuation value of a bad loan may be larger than the value that the lender may be able to recoup in bankruptcy, due for example to the low resale value of collateral and general bankruptcy costs. Second, banking sector regulation may be an important factor (Bertrand, Schoar, and Thesmar, 2007). Banks may not wish to reveal that they have non-performing assets on their books. Foreclosing on weak borrowers forces banks to recognize losses and undermines their capital positions. Forbearance has been a concern of regulators in several European countries since the financial crisis (See Section 4.2.2). To be as general as possible, I call leniency towards low-productivity borrowers "creditor passivity" or "credit sclerosis" independently of the source of the friction. Because it is modelled in a very general way, the cost associated with ending a lending relationship can be seen as resulting from a variety of factors.

This paper is related to the literature on the "credit supply channel" which works through banks' capital constraints. In a recession, low levels of capital may result in a supply-driven credit crunch, exacerbating the impact of the recession on output and productivity[3]. However, the literature on the the credit supply channel has less to say about frictions which affect the *composition* of credit retained by banks on their books, rather than its overall *volume*. Whether banks reduce credit supply or not, the composition of credit itself matters for macroeconomic performance. I try to fill this gap by studying the allocational consequences of creditor passivity. The search and matching framework is an appropriate tool to study the composition of credit flows. In addition to studying the effect of termination costs on the steady state, I show that a shock to termination costs induces a change in credit policies and short-run dynamics -

[3]See e.g. Chodorow-Reich, 2014, for evidence on the US; Albertazzi and Marchetti, 2010, and Gambacorta and Mistrulli, 2011, for Italy; Bentolila et al, 2013 for Spain. Using Spanish data, Garicano and Steinwender (2016) show that a credit crunch can also alter the composition of investment within firms from long term to short term investments.

in the absence of any other macroeconomic shock. The model has heterogenous firms with idiosyncratic productivity shocks but is tractable enough to show how creditor passivity affects production and lending decisions - which firms remain active and how much capital each firm employs. These decisions, in turn, affect the equilibrium levels of output, investment, interest rates, total factor productivity (TFP), and labour productivity. The model may shed light on some of the post-crisis phenomena observed in the UK: low productivity, surprisingly low liquidations, and a decreased correlation between firm-level health and investment behaviour.

Finally, the model is used to illustrate why a policy tool like the UK's Funding for Lending Scheme (FLS) may damage productivity in the presence of costly loan termination. The FLS was launched in July 2012 to incentivise banks to increase their net lending by providing them with cheap funding. The model suggests that non-targeted cheap funding may exacerbate misallocation.

The remainder of the paper is structured as follows. Section 4.2 briefly describes three related strands of literature. Section 4.3 briefly discusses the key phenomena on which the model may shed light, using the UK as a case study. Section 4.4 describes the model economy. Section 4.5 derives the steady state equilibrium and the aggregate variables of interest. Section 4.6 presents the baseline calibration and comparative statics on the steady state. Section 4.7 sheds more light on the mechanisms of misallocation by studying the cyclical dynamics after a shock to termination costs. It illustrates why a policy such as the UK's FLS might have exacerbated misallocation. Section 4.8 concludes.

4.2 Related literature

4.2.1 Creative destruction and banking crises

The paper is related to the literature on the financial impediments to creative destruction. The process of Schumpeterian creative destruction has an impact on long-run growth but also on short-run economic fluctuations. Limitations to this process, whether natural or institutional, can have severe macroeconomic consequences. Empirical work using decomposition methods - which break down aggregate productivity growth into a within effect, a between effect, and the contribution of entry and exit, have provided support for this claim[4].

[4]The within-effect measures the contribution to productivity growth from productivity changes within continuing firms, assuming that market shares are fixed. The between-effect measures the contribution from changes in market shares among continuing firms, assuming productivity levels are fixed. The composition (or reallocation) effect is the

The cyclical features of creative destruction are more controversial. Davis and Haltiwanger (1992) argue that recessions are "cleansing": less productive jobs are destroyed and resources are reallocated to more productive uses. A series of theoretical papers formalize this notion (See e.g. Hall, 1991, 2000; Mortensen and Pissarides, 1994; and Caballero and Hammour, 1994, 1996, 2005). However, subsequent empirical work has contradicted the predictions of those models and found that recessions actually exacerbate the misallocation of resources (See Barlevy, 2002). Whether recessions have a cleansing or a sullying effect is still open for debate.

Recessions associated with banking crises can be particularly damaging for resource allocation. When capital markets are imperfect, the availability of finance becomes an important determinant of a firm's investment[5]. In a credit crunch, those firms that require the least financial resources to survive are not necessarily the most productive ones. Low productivity firms that do not depend on bank finance remain active for longer and maintain market share due to reduced competition from bank dependent firms. These ideas have been explored in papers such as Caballero and Hammour (2005), Barlevy (2003), Khan and Thomas (2013), and Midrigan and Xu (2014). Foster et al. (2014) find that the intensity of reallocation fell rather than rose in the US during the Great Recession. In addition, the reallocation effects were less productivity enhancing than in prior recessions. Misallocation associated with financial crises has important macroeconomic consequences. Oulton and Sebastiá-Barriel (2013) find that financial crises permanently reduce long-run productivity.

4.2.2 Forbearance

Several theoretical contributions examine the causes of forbearance lending. The first stream of literature to study aspects of zombie banking is the one on soft budget constraints (SBC) in the context of transition economies (e.g. Kornai, Maskin, and Roland, 2003). As part of the SBC literature, Berglöf and Roland (1995, 1997) and Dewatripont and Maskin (1995) explain forbearance lending through the fact that banks can improve the recovery value of their bad loans by giving borrowers more time and capital to improve the return on their projects. Another motivation for forbearance lending is to improve the bank's perceived solvency and to gamble for resurrection (e.g. Mitchell, 1993, 1997; Niinimaki, 2007, 2012; Bruche and Llobet, 2011). Peek and Rosengren (2005) show that weakly capitalised banks are more likely to forbear in order to

sum of the between-effects and net entry. See e.g. Foster, Haltiwanger and Krizan, 2001; Bartelsman, Haltwanger and Scarpetta, 2004.

[5] See Bond and Van Reenen (2007) for a survey.

appear solvent to the regulator. Finally, bank managers may have private benefits from staying in power, as suggested by Aghion, Bolton, and Fries (1999) and Mitchell (2001). Termination costs as modelled in the present paper can also lead to excessively liberal credit policies towards weak borrowers in "normal times" (Rajan, 1994). Macroeconomic shocks that induce a credit crunch are "cleansing" in this case. Other theoretical papers study the consequences of forbearance. Kornai, Maskin, and Roland (2003) and Mitchell (2001) highlight the negative impact of forbearance on the borrower's managerial effort to maximise profits. Caballero et al (2008) develop a model of entry and exit to show that the presence of "zombie firms" attenuates the surge in destruction that would arise after a negative macroeconomic shock. These distortions depress productivity.

Empirical contributions have tested the predictions of those models and tried to gauge the impact of forbearance on economic activity. The topic has been widely studied in the context of Japan's "Lost Decade". Peek and Rosengren (2005) find that Japanese firms were more likely to be granted additional bank credit if they were in poor financial health. Evergreening was more likely among banks with reported capital ratios close to the regulatory minimum. Caballero et al (2008) show that industries with a high proportion of zombie firms had more depressed job flows (creation and destruction) and lower productivity. The prevalence of zombie firms depressed the investment and employment growth of healthy firms. Forbearance has also been a concern in several European countries since the financial crisis. Banks had inadequately low loan loss provisions pre-crisis and the introduction of Basel II standards in 2008 may have contributed to the increasing difficulties faced by banks to maintain adequate capital. Evidence of forbearance has been found in Italy (Albertazzi and Marchetti, 2010), Portugal (Iyer et al, 2014), and Spain (Bentolila et al, 2013).

Although I use an entirely different modeling framework, the present model produces the same "crowding out" predictions as Caballero et al (2008). It is in line with other papers which predict that by keeping zombie firms alive, the bank has fewer funds for financing new projects and healthy firms are deprived of credit[6]. The contribution of the present paper to the forbearance literature is as follows. First, the search and matching framework has the advantage that it allows me to study exactly how congestion happens through the volume, composition and pricing of credit flows, which in turn determine entry and exit. Existing models explain why unprofitable firms survive, but do not allow for the analysis of which firms receive financing and what the lending conditions are. The present paper focusses on lending conditions, in terms

[6]e.g. Aghion, Bolton, and Fries (1999), Bruche and Llobet (2011), Berglöf and Roland (1997).

of volume and loan interest rates, and the characteristics of firms receiving credit. Second, the model is tractable enough to study the dynamics of a wide range of aggregate variables and perform policy experiments.

4.2.3 Search and matching

Job flows have been extensively used as a proxy for the intensity of creative destruction. In a similar spirit, credit flows are used to study how credit market imperfections impede creative destruction by preventing the allocation of capital to its most productive uses. Most papers are concerned with equilibrium credit market quantities and their impact on output dynamics and equilibrium employment (Den Haan et al., 2003; Wasmer and Weil, 2004). Other papers study equilibrium interest rates (Wasmer and Weil, 2004; Becsi et al, 2005) and their dynamics (Beaubrun-Diant and Tripier, 2015). By contrast, the compositional dynamics of credit (both in terms of volume and prices) and their aggregate consequences have remained underresearched.

The model presented here is a variant of a standard search and matching model with heterogeneous agents and endogenous destruction. The model has specific features which are key to capturing changes in the composition of credit flows. First, lenders incur a termination cost if they decide to end a lending relationship. This creates two distinct categories of loans, new loans (new matches) and legacy loans (old matches). Second, new matches are assumed to be at the frontier of idiosyncratic productivity. This is meant to capture the process of creative destruction. Most importantly, firms choose how much to borrow and invest - instead of having a fixed loan amount for all firms as in Beaubrun-Diant and Tripier (2015). Interest rates on loans and loan volumes are determined simultaneously by the bargaining process and profit maximisation. Variable investment as a function of access to credit is crucial to study the aggregate consequences of credit misallocation and relative behaviour of loan rates on new and legacy lending agreements.

The rollover of low-performing loans has been studied in Chamley and Rochon (2011) in a continuous-time search and matching framework. However, their model is entirely different. They have two types of projects (short term versus long term) whereas the present paper has a continuum of project types characterized by the firms' idiosyncratic productivity draws in each period. In their model, inefficient rollover originates in a search externality, not a termination cost. Their model generates two steady states without or with rollover, while I derive a continuous productivity threshold which pins down the fraction of rolled over loans in every period. The long-term projects in Chamley and Rochon (2011) are low performing but still have a positive NPV. Finally, crises have a cleansing effect in their model (akin to Rajan, 1994) and the model is not tractable enough to perform a dynamic analysis without simplifying assumptions. By contrast, the tractability of the present model allows for simple comparative statics and the study of impulse response functions to a variety of exogenous shocks.

4.3 Case study: Post-crisis UK

Most major countries have experienced a sharp fall in productivity growth since the Great Recession. Falls or slowdowns in GDP per worker are a common feature of recessions, but the persistence of low productivity growth in the recovery period has been an ongoing source of concern (e.g. Gordon, 2016; Summers, 2016). Countries with relatively large financial sectors appear to have been particularly affected, including the UK. There are three key post-crisis phenomena observed in the UK on which the model may help shed some light: the sharp decline in labour productivity, the increase in the practice of forbearance, and surprisingly low rates of liquidations.

Labour productivity in the UK has been unusually weak since the financial crisis. In the fourth quarter of 2015 the gap between trend and actual labour productivity stood at around 16%, up from 12% at then end of 2012 (See Figure 4.A.1 in the Appendix). This picture stands in sharp contrast with the experience in other post-war recessions, when the fall in productivity was less dramatic and the economy recovered more rapidly (See Figure 4.A.2). The shortfall cannot be explained by possible measurement errors and a decline in North Sea oil output, and hence is referred to as the "UK productivity puzzle".

Another striking feature of the Great Recession is the fact that business deaths were relatively muted despite the size of the output loss (See Figure 4.A.3). This points to subdued creative destruction because one would expect a sharp increase in liquidations and job destruction during contractions. A lower rate of business failure and unemployment may have contributed to low aggregate productivity growth.

Several observers have emphasized the similarities between the Japanese "Lost Decade" and the recent financial crisis (e.g., Hoshi and Kashyap, 2008; Kobayashi, 2008). It is therefore natural to ask whether forbearance could be a factor contributing to the UK productivity puzzle. A 2013 investigation by the Bank of England into the extent of loan forbearance[7] showed that around 6% of SMEs were in receipt of some form of forbearance. Forbearance appeared to be most significant in the property-related industrial sectors such as construction and accommodation and food - sectors which have been particularly hit hard in terms of productivity. The most common form of forbearance is the extension of the duration of loan contracts. The Bank of England estimated that productivity was 40% lower in SMEs in receipt of forbearance. The survey suggests that the impact on private sector labour productivity has been around 1%. However, the authors stress that the overall impact is likely to have been greater because forbearance is not limited to the SME sector. In the absence of a credit register it is impossible to obtain a full picture of the extent of forbearance in the UK.

4.4 Model

4.4.1 Credit Market and Matching Process

The model economy is populated by two types of agents: entrepreneurs and lenders. Lenders and entrepreneurs spend time and resources looking for each other on the credit market. Entrepreneurs produce a unique final good. They have no private wealth and use the entrepreneur's own labour and capital as inputs. Capital is entirely provided by the lenders. This implies that an entrepreneur can only produce if he receives external funds. The bank has funds but does not possess the skills to manage production. The credit market is characterised by search frictions. A lender which opens a new credit line must pay a fixed search cost to find an entrepreneur on the market in every period. As long as the value of a vacant credit line is greater than zero, banks open new credit lines. Once a vacant credit line is matched with an entrepreneur, the lender and the borrower agree on a financial contract that determines both the quantity and the price of the funds lent by the bank. Contracting is the result of a Nash bargaining process. Loans are intra-period, so a new loan rate and loan amount is negotiated every period. Production technology is subject to idiosyncratic productivity shocks. If idiosyncratic productivity is sufficiently high, the contract is renewed in every period. If not, both parties agree to end the relationship. These loan creation and destruction decisions generate entrepreneur flows in and out of production. The lender incurs a separation cost when terminating a lending relationship that is no longer profitable.

[7] Bank of England Quarterly Bulletin 2013 Q4.

Entrepreneur and lender matching is viewed as a production process described by the matching function. We assume that all lenders and inactive entrepreneurs search at the same given intensity, so the inputs to the matching function are the number of vacant credit lines and the number of unmatched entrepreneurs. The output of the matching process is the number of new matches. Matched firms do not search while matched. Let $E = 1$ be the fixed population of entrepreneurs and N_t the number of entrepreneurs matched with lenders. Denote with M_t the flow of new matches. C_t is the number of vacant credit lines, i.e. lenders' loan supply waiting to be matched to borrowers. The matching function is $M_t = m(C_t, 1 - N_t) \leqslant min\{C_t, 1 - N_t\}$. As is usual, the matching function is assumed to be increasing in both arguments and concave, i.e. it displays decreasing marginal products to each input. For convenience it is assumed to have constant returns to scale. The assumption of constant returns to scale for the matching function pins down the matching probabilities. The lender's matching probability is $q_t = \frac{M_t}{C_t} = q(\theta_t)$ where $\theta_t = \frac{C_t}{1-N_t}$ is the credit market tightness. An entrepreneur's matching probability is $p_t = \frac{M_t}{1-N_t} = \theta_t q(\theta_t)$. We assume the following Cobb-Douglas matching function $p_t = \overline{m}\theta_t^{\chi}$, with $\overline{m} > 0$ a scale parameter and $0 < \chi < 1$ the elasticity parameter. Credit market tightness can be interpreted as a measure of credit market liquidity. When θ increases the credit market is more liquid: it becomes easier for projects to find financing. Given those definitions, $\frac{1}{p_t}$ is the mean duration of inactivity for an entrepreneur looking for financing, and $\frac{1}{q_t}$ is the mean duration of a vacant credit line.

4.4.2 Idiosyncratic Productivity Shocks, Reservation Productivity, and Separation Cost

Entrepreneurs produce Y_t units of a final good according to the CRS technology $Y_t = z_t \epsilon_t K_t^{1-\alpha}$. The inputs to production are capital K_t and the labour input of the entrepreneur which is normalised to 1. The price of the good is normalised to 1. Unlike Beaudrun-Diant and Tripier (2015), we do not normalize the amount of loan to unity for all firms. Allowing firms to freely choose how much to borrow and invest is central to studying the aggregate consequences of misallocation. z_t is the aggregate productivity level and ϵ_t is the entrepreneur's idiosyncratic productivity level. During each period, $t = 0, 1, 2, ...$, the flow into inactivity results from shocks to the idiosyncratic productivity of active firms. Idiosyncratic productivity is assumed to be uniformly distributed on the interval $[\underline{\epsilon}, \overline{\epsilon}]$. When a new match occurs, the project has the highest possible productivity, i.e. $\epsilon_t = \bar{\epsilon}$ and the project is financed with certainty. This assumption is used in Mortensen and Pissarides (1994). It is meant to capture the idea that new entrants are more productive as is usual in models of creative destruction (e.g. Caballero et al 2008). Entrants are assumed to choose the product or service that delivers the highest expected future profit. Therefore, they undertake projects at the highest level of idiosyncratic productivity. In each subsequent period, projects are hit by idiosyncratic productivity shocks and the entrepreneur picks a new value for ϵ_t from the uniform distribution $G(\epsilon_t)$ on $[\underline{\epsilon}, \bar{\epsilon}]$. The sequence of shocks is i.i.d. and ϵ_t is assumed to be perfectly observed by firms and lenders. After observing the new level of idiosyncratic productivity, the lender can decide to either continue the lending relationship or terminate it. The match is dissolved when a sufficiently low level of productivity is realized and thus expected profits and incomes from the match fall below what the bank and the firm can get from terminating the loan. The level of productivity below which the lender terminates the loan is the reservation productivity $\tilde{\epsilon}_t$. It is the level of idiosyncratic productivity of the borrower at which the lending relationship delivers a net surplus of zero to the lender (and the firm). Given $\tilde{\epsilon}_t$, the endogenous separation rate is

$$s_t = G(\tilde{\epsilon}_t) = \frac{\tilde{\epsilon}_t - \underline{\epsilon}}{\bar{\epsilon} - \underline{\epsilon}} \tag{4.4.1}$$

The law of motion for the number of matched entrepreneurs, N_{t+1}, is

$$N_{t+1} = O_{t+1} + M_{t+1} \tag{4.4.2}$$

where M_{t+1} is the number of new matches at $t+1$

$$M_{t+1} = (1 - N_t(1 - s_{t+1}))\, \theta_{t+1} q_{t+1} \tag{4.4.3}$$

and O_{t+1} is the number of old (continued) matches at $t+1$

$$O_{t+1} = N_t(1 - s_{t+1}) \tag{4.4.4}$$

New matches are the product of the mass of inactive entrepreneurs and the entrepreneur's matching probability. Old matches are those that survive destruction as they remain above reservation productivity. When endogenous separation takes place, the bank incurs a termination cost τ. This is a reduced-form way of modelling creditor passivity without specifying why it occurs. Rajan (1994) and Berglöf and Roland (1997) make a similar modelling assumption.

Denote with $L_t^O(\epsilon_t)$ the value function of a matched lender with a legacy loan (old loan). Let V_t be the value function of a lender with a vacant credit line, i.e. a loan waiting to be matched. The reservation productivity is defined as $\tilde{\epsilon}_t$ such that $L_t^O(\tilde{\epsilon}_t) = V_t - \tau$. In other words, the separation cost reduces the value of the lending relationship that the lender is willing to keep alive. Costly separation creates a hold-up problem where the borrower holds up the lender.

4.4.3 Value Functions

Banks Let V_t, L_t^N, and $L_t^O(\epsilon_t)$ denote the present-discounted value of the expected income of a vacant credit line, a new loan, and a continued loan, respectively. As all new loans start at idiosyncratic productivity level $\bar{\epsilon}$, I omit to index N-variables with productivity. In other words, $K_t^N = K_t^N(\bar{\epsilon}), R_t^N = R_t^N(\bar{\epsilon})$ etc. The value function of a lender with a vacant credit line is

$$V_t = -c + \beta E_t \left(q_t L_{t+1}^N + (1 - q_t) V_{t+1} \right)$$

where β is the discount rate. This equation states that a vacant credit line has a flow cost c and becomes filled with probability q_t with a return of L_{t+1}^N and with probability $(1 - q_t)$ with a return V_{t+1}. Once a loan contract has been signed, the present-discounted value of a new match to the bank, L_t^N, is

$$L_t^N = (R_t^N - \rho)K_t^N + \beta E_t \left[-G(\tilde{\epsilon}_{t+1})\tau + \int_{\tilde{\epsilon}_{t+1}}^{\bar{\epsilon}} L_{t+1}^O(\epsilon_{t+1}) dG(\epsilon_{t+1}) \right]$$

where $(R_t^N - \rho)K_t^N$ is the revenue generated by the loan net of funding costs. ρ is the exogenous bank funding rate and R_t^N is the endogenous repayment (1 + interest rate) made by the borrower for a new loan. Similarly, the value function of a lender with a legacy loan is

$$L_t^O(\epsilon_t) = (R_t^O(\epsilon_t) - \rho)K_t^O(\epsilon_t) + \beta E_t \left[-G(\tilde{\epsilon}_{t+1})\tau + \int_{\tilde{\epsilon}_{t+1}}^{\bar{\epsilon}} L_{t+1}^O(\epsilon_{t+1}) dG(\epsilon_{t+1}) \right]$$

where $R_t^O(\epsilon_t)$ is the endogenous interest rate paid by the borrower for a continuing loan on a project with idiosyncratic productivity ϵ_t. Both equations above state that a match generates interest revenue net of funding costs and a net expected present-discounted value if the match is not destroyed. The expected future value of the loan is net of termination costs. Should the bank decide to terminate the loan, it incurs the penalty τ.

Entrepreneurs Let U_t, W_t^N, and $W_t^O(\epsilon_t)$ denote the present-discounted value of the expected income of an inactive, newly funded, and refinanced entrepreneur, respectively. The inactive entrepreneur enjoys a return f while inactive. This represents e.g. the value of his free time. He expects to find a loan and move into production with probability p_t. Hence, the value function of an inactive entrepreneur is

$$U_t = f + \beta E_t \left[p_t W_{t+1}^N + (1 - p_t) U_{t+1} \right]$$

where β is the same discount rate as for lenders. Being matched with a lender ensures that the entrepreneur is granted funds for his project and enters the market. This equation states that the value of inactivity is made up of the yield f and the present-discounted value of the expected capital gain resulting from the change of state.

The funded entrepreneur produces according to the production function described above. He may lose his bank funding in the next period with probability $G(\tilde{\epsilon}_{t+1})$. Due to the presence of termination costs, the interest rate charged to newly funded entrepreneurs is different from that charged on legacy loans at the same level of productivity $\overline{\epsilon}$, i.e. $R_t^N \neq R_t^O(\overline{\epsilon})$. Hence, the present-discounted values of a new match and of a continued match are not the same at $\overline{\epsilon}$, i.e. $W_t^N \neq W_t^O(\overline{\epsilon})$. The value function of an entrepreneur with a newly funded project is

$$W_t^N = z_t \overline{\epsilon} (K_t^N)^{1-\alpha} - R_t^N K_t^N + \beta E_t \left[G(\tilde{\epsilon}_{t+1}) U_{t+1} + \int_{\tilde{\epsilon}_{t+1}}^{\overline{\epsilon}} W_{t+1}^O(\epsilon_{t+1}) dG(\epsilon_{t+1}) \right]$$

where $z_t \overline{\epsilon} (K_t^N)^{1-\alpha} - R_t^N K_t^N$ is the value of production net of the borrowing costs. R_t^N is the credit interest rate. Similarly, the value function of an entrepreneur with a legacy project is

$$W_t^O(\epsilon_t) = z_t \epsilon_t (K_t^O(\epsilon_t))^{1-\alpha} - R_t^O(\epsilon_t) K_t^O(\epsilon_t) + \beta E_t \left[G(\tilde{\epsilon}_{t+1}) U_{t+1} + \int_{\tilde{\epsilon}_{t+1}}^{\overline{\epsilon}} W_{t+1}^O(\epsilon_{t+1}) dG(\epsilon_{t+1}) \right]$$

Both equations above state that the value of a loan for the entrepreneur is equal to the value of production net of borrowing costs plus the present-discounted value of the entrepreneur.

4.4.4 Loan Contracts

The assumptions of the model ensure that a new match yields some positive economic surplus. The surplus from a relationship is the value of expected profits to the bank, plus the value of expected incomes to the firm, minus the value of what both parties would get if they chose to terminate the match. The split of this surplus between the entrepreneur and the lender is determined by the loan interest rate. Loans are intra-period and the rates are bargained every period. Hence they always depend on the current level of productivity. The loan contracts determine the loan interest rates, R_t^N and $R_t^O(\epsilon_t)$, at every point in time. Interest rates are the result of a Nash bargaining process where $0 < \eta < 1$ is the bargaining power of the entrepreneur. The Nash bargaining solution delivers the traditional sharing rules[8]. Given the notation introduced above, the interest rate on a new loan, R_t^N, is such that

$$R_t^N = argmax\left\{[W_t^N - U_t]^\eta [S_t^N - (W_t^N - U_t)]^{1-\eta}\right\}$$

where S_t^N is the surplus from a new lending relationship, namely

$$S_t^N = W_t^N - U_t + L_t^N - V_t$$

$\left(W_t^N - U_t\right)$ is the net surplus of being matched from the perspective of an entrepreneur with a new loan. $L_t^N - V_t$ is the net surplus of being matched from the lender's perspective. Analogously, the loan rate on a continued loan, $R_t^O(\epsilon_t)$, satisfies

$$R_t^O(\epsilon_t) = argmax\{[W_t^O(\epsilon_t) - U_t]^\eta [S_t^O(\epsilon_t) - (W_t^O(\epsilon_t) - U_t)]^{1-\eta}\}$$

where S_t^N is the surplus from a continuing lending relationship, namely

$$S_t^O(\epsilon_t) = W_t^O(\epsilon_t) - U_t + L_t^O(\epsilon_t) - V_t + \tau$$

$\left(W_t^O(\epsilon_t) - U_t\right)$ is the net surplus of being matched from the perspective of an entrepreneur with a legacy loan. $(L_t^O(\epsilon_t) - V_t + \tau)$ is the net surplus of being matched from the lender's perspective. The latter is clearly distorted by τ.

[8]See Pissarides (2000) for a description of the Nash bargaining solution in the context of wage bargaining in a search and matching model of the labour market.

The difference between the rate on new loans and that on renegotiated legacy loans arises because termination costs are not incurred if no initial match is formed but are paid if an existing loan is terminated. The loan rate on a new match is negotiated to split the surplus *before* the termination penalty becomes effective. In other words, the separation cost τ is part of the surplus only for legacy loans, not for new matches. The solutions to the optimization problems above satisfy the following first-order conditions

$$\eta(L_t^N - V_t) = (1-\eta)(W_t^N - U_t) \tag{4.4.5}$$

and

$$\eta(L_t^O(\epsilon_t) - V_t + \tau) = (1-\eta)(W_t^O(\epsilon_t) - U_t) \tag{4.4.6}$$

Since continuing loans are subject to termination costs, the interest rate bargaining rule for continuing matches, as shown in Equation (4.4.6), internalizes termination costs τ. On the other hand, termination costs do not appear in Equation (4.4.5). The termination cost τ is not part of the new firm's "threat point" in the bargaining process as it is not incurred by the lender if a new match is not formed.

4.5 Equilibrium

4.5.1 Equilibrium conditions

Free entry condition The endogenous entry of lenders determines credit market tightness. As long as the value of a vacant credit line is greater than zero, banks open new credit lines. As the number of vacant credit lines increases, the probability that any open credit line will find a project to finance decreases, thereby reducing the profitability of new credit lines. In equilibrium free entry ensures that the present value of a vacant credit line equals zero. In other words, free entry ensures that $V_t = E_t[V_{t+1}] = 0$. The value function of a vacant credit line V_t can be re-written as

$$\beta E_t(L_{t+1}^N) = \frac{c}{q_t} \tag{4.5.1}$$

It states that the expected value of a new match in the next period equals the current average cost of a match, $\frac{c}{q_t}$.

In steady state, a loan is therefore terminated when $L_t^O(\tilde{\epsilon}_t) = -\tau$, i.e. when the value of a continuing loan for the lender is equal to minus the cost of separation. The separation cost creates "forbearance" in the sense that lenders keep loans alive which have a negative expected net present value. In the absence of a separation cost, a loan would be terminate when $L_t^O(\tilde{\epsilon}_t) = 0$. With $\tau > 0$, some loans are inefficiently continued. The credit policy deviates from one that lends if and only if borrowers have positive net present value projects.

Interest rates Interest rates are pinned down by the sharing rules 4.4.6 and 4.4.5, the value functions, and the free entry condition (4.5.1). The equilibrium loan rate on new loans satisfies

$$R_t^N K_t^N = (1-\eta) z_t \bar{\epsilon} (K_t^N)^{1-\alpha} + \eta \rho K_t^N - (1-\eta) f - \eta c \theta_t + \beta \eta \tau \tag{4.5.2}$$

$R_t^N K_t^N$ is the gross revenue of the lender. The first term, $(1-\eta) z_t \bar{\epsilon} (K_t^N)^{1-\alpha}$, is the fraction of the value of production appropriated by the lender. The second term, $\eta \rho K_t^N$, accounts for a fraction of the lender's funding costs passed on to the borrower. The third term, $-(1-\eta) f$, accounts for the borrower's outside opportunity, i.e. the value of free time. As a better outside opportunity improves the borrower's threatpoint, the revenue of the lender decreases in f. The fourth term, $-\eta c \theta_t$, is a reward to the borrower for the savings on vacancy costs. An increase in credit market tightness θ_t improves the bargaining position of entrepreneurs and diminishes the lender's revenue. The final term, $\beta \eta \tau$, is the part of the expected future separation cost which is passed on to new borrowers. Despite the fact that new loans are never terminated, as their idiosyncratic productivity is always above the reservation threshold, newly funded projects may be terminated in the future, so the interest rate for newly funded projects internalizes future expected firing costs. As can be seen, the interest rate on new loans *increases* in the separation cost for a given loan amount K_N.

Similarly, the equilibrium loan rate on continuing loans satisfies

$$R_t^O(\epsilon_t) K_t^O(\epsilon_t) = (1-\eta) z_t \epsilon_t (K_t^O(\epsilon_t))^{1-\alpha} + \eta \rho K_t^O(\epsilon_t) - (1-\eta) f - \eta c \theta_t + \beta \eta \tau - \eta \tau \tag{4.5.3}$$

The expression is very similar to that for $R_t^N K_t^N$ except for the last term. Borrowers with rolled-over loans are compensated for the avoidance of the termination cost today. Once a lending relationship is established, the termination cost is the lenders' liability if the match is destroyed.

This strengthens the borrower's threat point in bargaining and so pushes the negotiated loan rate down. Since $\beta\eta\tau - \eta\tau = -(1-\beta)\eta\tau$, the interest rate on continued loans *decreases* in the separation cost for a given loan amount K_O. The termination cost introduces a distortionary wedge in the difference between the interest rate on new and old matches: given the same level of productivity $\bar{\epsilon}$, a legacy loan is cheaper than a new one.

The interest rates are determined simultaneously with the loan amounts $K_t^O(\epsilon_t)$ and K_t^N using the first-order conditions for profit maximisation below. In equilibrium, every borrower has a contract with the bank which is a pair $\{K_t^i(\epsilon_t), R_t^i(\epsilon_t)\}$ pinning down the amount and price of the loan.

Capital allocation Each firm chooses how much to borrow to maximize profits

$$\max_{K_t^i} z_t\epsilon_t(K_t^i(\epsilon_t))^{1-\alpha} - R_t^i(\epsilon_t)K_t^i(\epsilon_t)$$

where $i \in [O, N]$. The first order condition for optimal borrowing for old loans is

$$R_t^O(\epsilon_t) = \frac{(1-\alpha)z_t\epsilon_t}{K_t^O(\epsilon_t)^\alpha} \tag{4.5.4}$$

The first order condition for optimal borrowing for new loans is

$$R_t^N = \frac{(1-\alpha)z_t\bar{\epsilon}}{(K_t^N)^\alpha} \tag{4.5.5}$$

Loan termination condition The Nash rate-setting rule, together with the fact that the surplus from a continuing match $S_t^O(\epsilon_t)$ is monotonically increasing in ϵ_t, implies that separation takes place if and only if idiosyncratic productivity falls below a threshold level, i.e. reservation productivity $\tilde{\epsilon}_t$[9]. Hence, loans are terminated when $S_t^O(\tilde{\epsilon}_t) = L_t^O(\tilde{\epsilon}_t) - V_t + W_t^O(\tilde{\epsilon}_t) - U_t + \tau = 0$. Substituting for the value functions, applying the sharing rule (4.4.6), and the free-entry condition (4.5.1), and recognising the fact that $S_t^O(\epsilon_t) = \pi_t^O(\epsilon_t) - \pi_t^O(\tilde{\epsilon}_t)$ where $\pi_t^O(\epsilon_t) =$

[9] $S_t^O(\epsilon_t)$ is monotonically increasing in ϵ_t. In addition, by the rate-setting rule, $(W_t^O(\epsilon_t) - U_t)$ and $(L_t^O(\epsilon_t) - V_t + \tau)$ are proportional to $S_t^O(\epsilon_t)$. Since $(V_t - \tau)$ and U_t are invariant in ϵ_t, $L_t^O(\epsilon_t)$ and $W_t^O(\epsilon_t)$ are increasing in ϵ_t. Hence separation decisions by both firms and banks satisfy the reservation property. Furthermore, if the net surplus of the lender is negative, the net surplus of the borrower is also negative. In other words, lenders and borrowers agree on the reservation productivity. Indeed, reservation productivity $\tilde{\epsilon}_t$ satisfies

$$(W_t^O(\tilde{\epsilon}_t) - U_t) = \frac{\eta}{1-\eta}(L_t^O(\tilde{\epsilon}_t) - V_t + \tau) = 0$$

$z_t\epsilon_t(K_t^O(\epsilon_t))^{1-\alpha} - \rho K_t^O(\epsilon_t)$ is the value of production of an old project net of the bank's funding costs, we obtain the loan termination condition:

$$\pi_t^O(\tilde{\epsilon}_t) + \beta E_t \int_{\tilde{\epsilon}_{t+1}}^{\overline{\epsilon}} [\pi_{t+1}^O(\epsilon_{t+1}) - \pi_{t+1}^O(\tilde{\epsilon}_{t+1})] dG(\epsilon_{t+1}) + (1-\beta)\tau = f + \frac{\eta}{1-\eta}\theta_t c \tag{4.5.6}$$

The condition states that termination occurs when the surplus from continuing the loan equals the opportunity cost of doing so. The surplus from continuing the loan is equal to the reservation value of production net of the bank's funding costs, plus the option value of continuing the loan, plus the avoided termination cost if the loan is rolled-over, minus the future expected termination cost. The right hand side is the flow value of separation to the entrepreneur, i.e. his outside option[10]. Higher market tightness θ_t increases reservation productivity because the entrepreneur's outside option improves with θ_t. Note that the reservation value of production net of the bank's funding costs is lower than the entrepreneur's outside option as there is a positive option value in existing lending relationships. This is the equivalent of 'labour hoarding' in the labour-market literature.

Credit creation condition The surplus from a new loan is $S_t^N = L_t^N - V_t + W_t^N - U_t$. Substituting for the value functions, applying the sharing rule (4.4.5), and the free-entry condition (4.5.1), and recognising the fact that $S_t^N = \pi_t^N - \pi_t^O(\tilde{\epsilon}_t) - \tau$ where π_t^N is the value of production of a new project net of the bank's funding costs, we obtain the credit creation condition:

$$\frac{c}{q_t} = \beta E_t(1-\eta)[\pi_{t+1}^N - \pi_{t+1}^O(\tilde{\epsilon}_{t+1}) - \tau] \tag{4.5.7}$$

Since $\frac{1}{q_t}$ is the average duration of a vacant credit line, the left hand side is the expected cost of posting a vacancy and finding a match. The right-hand side of the equation is the lender's share of the expected net surplus from a new match.

4.5.2 Aggregate variables

Capital stock The aggregate capital stock in the economy is derived by aggregating across active production units in equilibrium. The average capital stock of a firm with a legacy loan is

[10] It can be shown that the RHS is equal to U_t. Remember that the flow value of a vacant credit line to the bank is zero by the free-entry condition - so this does not enter the flow value of separation.

$$\overline{K}_t^O = \int_{\tilde{\epsilon}}^{\overline{\epsilon}} K_t^O(\epsilon_t) f(\epsilon_t|\epsilon_t > \tilde{\epsilon}_t) d(\epsilon_t) \tag{4.5.8}$$

The aggregate capital stock in the economy is given by

$$\overline{K}_t = O_t \overline{K}_t^O + M_t K_t^N \tag{4.5.9}$$

The first term is the total amount lent to continuing firms and the second the total amount lent to new firms.

Output Aggregate output is derived by aggregating across active production units in equilibrium.

$$\overline{Y}_t = O_t \int_{\tilde{\epsilon}}^{\overline{\epsilon}} z_t \epsilon_t (K_t^O(\epsilon_t))^{1-\alpha} f(\epsilon_t|\epsilon_t > \tilde{\epsilon}_t) d(\epsilon_t) + M_t z_t \overline{\epsilon} (K_t^N)^{1-\alpha} \tag{4.5.10}$$

Interest rates on loans The average loan rate on legacy loans is

$$\overline{R}_t^O = \int_{\tilde{\epsilon}}^{\overline{\epsilon}} R_t^O(\epsilon_t) f(\epsilon_t|\epsilon_t > \tilde{\epsilon}_t) d(\epsilon_t) \tag{4.5.11}$$

The average loan rate in the economy is

$$\overline{R}_t = \omega_t R_t^N + (1 - \omega_t) \overline{R}_t^O \tag{4.5.12}$$

where $\omega_t = \frac{M_t}{N_t}$ and $(1 - \omega_t) = \frac{O_t}{N_t}$. An important variable of interest is the wedge between the interest rate charged on new and continued loans. Define $\triangle R_t(\overline{\epsilon}) = R_t^N - R_t^O(\overline{\epsilon})$ as the distortionary interest rate wedge introduced by the separation cost for the most productive firms. If $\tau = 0$, $\triangle R_t(\overline{\epsilon}) = 0$. If $\tau > 0$, $\triangle R_t(\overline{\epsilon}) > 0$.

Total factor productivity Average TFP in the economy is defined as

$$TFP_t = \frac{\overline{Y}_t}{N_t^\alpha \overline{K}_t^{1-\alpha}} \tag{4.5.13}$$

Labour productivity Aggregate labour productivity is defined as aggregate output divided by the mass of active entrepreneurs:

$$LP_t = \frac{\overline{Y}_t}{N_t} \tag{4.5.14}$$

Forbearance The number of loans in forbearance can be computed as the difference between the number of legacy loans if $\tau > 0$ and their number if $\tau = 0$, i.e. $O_t^F = O_{t,|\tau>0} - O_{t,|\tau=0}$. The amount of forborne credit is measured by the difference between the amount of credit on legacy loans if $\tau > 0$ and if $\tau = 0$, namely $\overline{K}_{F,t}^O = (O_t\overline{K_t}^O)_{|\tau>0} - (O_t\overline{K_t}^O)_{|\tau=0}$.

4.6 Steady state and comparative statics

The steady state equilibrium is defined by the endogenous variables $\{R_t^N, K_t^N, \theta, \tilde{\epsilon}_t\}$ and vectors $R_t^O(\epsilon_t)$ and $K_t^O(\epsilon_t)$ that satisfy the conditions (4.5.2), (4.5.3), (4.5.4), (4.5.5), (4.5.6), and (4.5.7).

The number of matched entrepreneurs, i.e. the total number of loans and active firms in steady state is derived from Equations 4.4.2 and 4.4.3 as:

$$N = \frac{p}{p + s(1-p)}. \tag{4.6.1}$$

Normalizing $E = 1$, the number of unmatched entrepreneurs is $1 - N$. The number of vacant credit lines is $C = \theta(1 - N)$ by the definition of credit market tightness. The number of continued loans is $O = N(1 - s)$ and the number of new loans is $M = (1 - O)\theta q$.

The unit of time is taken to be one quarter. The annual interest rate on lender resources is assumed to be 50 basis points - the level of the Bank Rate since March 2009, so the quarterly interest rate is $\rho = 1.005^{1/4}$. The parameters $\overline{m}$, f, and c are calibrated to achieve $p = 0.5$ (it takes two quarters to find a lender), $q = 0.75$, and $s = 1/15$ (the average loan relationship lasts roughly seven years). Using data from Bureau Van Dijk's FAME database on outstanding loan charges registered at Companies House, Franklin et al (2015) show that banking relationships in the UK appear to be very sticky. By 2011 around 90% of companies in their sample still had an outstanding charge with the same institution as they did in 2007, 5 years earlier. The UK SME banking sector has long been characterised by very low switching rates (OFT, 2006, 2010). The elasticity parameter of the matching function is set as $\chi = 0.5$. The lower and upper bounds of the productivity distribution are set as $\underline{\epsilon} = 0.95$ and $\overline{\epsilon} = 1$. Aggregate productivity is $z = 4$. The discount rate is set to $\beta = 0.95^{1/4}$. The labour share is set as $\alpha = 0.6$. Finally, the bargaining power of firms is set to $\eta = 0.8$. There are no estimates of η in the literature on credit markets, so the choice of bargaining power is rather discretionary. However, my choice is guided by the fact that $\eta > \alpha$ is a necessary condition for a firm's capital input choice to increase in its level of idiosyncratic productivity - a fact that is supported by UK data. This means that the

Hosios condition cannot be satisfied in equilibrium. Table 4.6.1 below summarizes the parameter values.

Table 4.6.1: **Calibration in the absence of termination costs ($\tau = 0$)**

z	ρ	$\overline{\epsilon}$	$\underline{\epsilon}$	χ	β	α	η	$\overline{m}$	f	c	τ
4	1.00125	1	0.95	0.5	0.99	0.6	0.80	0.61	3.05	0.04	0

Note that while the chosen and calibrated parameter values are "reasonable" and lead to plausible interest rates in equilibrium, I cannot claim that the steady state is an accurate representation of the UK economy. A rigorous calibration exercise would necessitate data on credit flows, e.g. from a central credit register, which the UK does not have. Hence, the analysis is to be taken as an illustration of the mechanisms at work rather than as a quantification exercise.

Table 4.6.2 below presents the comparative statics for three economies that only differ in terms of termination costs, using the parameters in Table 4.6.1. The economy without termination costs ($\tau = 0$) is the benchmark. The first scenario assumes $\tau = 0.009$. This figure is chosen to achieve a fraction of borrowers in receipt of forbearance close to that found in the Bank of England survey (i.e. 6%). When $\tau = 0.018$, this fraction is roughly doubled. To put those numbers in perspective, $\tau = 0.009$ ($\tau = 0.018$) represents approximately 18% (36%) of the bank profits made on a representative new loan in the benchmark economy with no termination costs.

Table 4.6.2: **Comparative statics based on the calibration in Table 4.6**

	τ=0	τ=0.009	% dev.	τ=0.018	% dev.
Matching process					
Separation rate	0.067	0.034	-48.75	0.000	-99.71
Mean duration of inactivity	2.000	2.004	0.21	2.006	0.29
Credit market tightness	0.667	0.664	-0.43	0.663	-0.58
Reservation productivity	0.953	0.952	-0.17	0.950	-0.35
Firm composition					
Active firms	0.938	0.967	3.13	1.000	6.65
Vacant credit lines	0.042	0.022	-47.15	0.000	-99.69
Incumbents	0.875	0.934	6.72	1.000	14.24
Entrants (new matches)	0.063	0.033	-47.15	0.000	-99.69
Fraction of entrants	0.067	0.034	-48.75	0.000	-99.71
Firms receiving forbearance		0.059		0.125	
In % of active firms		6.08		12.46	
Lending rates					
Economy mean lending rate	1.003	1.002	-0.07	1.001	-0.17
Mean lending rate on old loans	1.002	1.002	-0.04	1.001	-0.09
Lending rate on new loans	1.014	1.017	0.34	1.021	0.68
Loan rate wedge		0.003		0.007	
In % of new loan rate when $\tau = 0$		0.339		0.682	
Investment					
Economy wide capital stock	1.968	2.027	2.97	2.094	6.36
Capital stock of an entrant	2.139	2.127	-0.56	2.115	-1.12
Capital stock of incumbents	1.835	1.957	6.65	2.093	14.09
Forborne credit		0.122		0.258	
In % of total credit		6.02		12.34	
Output					
Economy wide output	4.936	5.079	2.90	5.241	6.18
Output of an entrant	5.422	5.409	-0.23	5.397	-0.45
Output of incumbents	4.597	4.900	6.60	5.240	13.99
Productivity					
TFP	3.913	3.907	-0.16	3.900	-0.33
Labour productivity	5.265	5.253	-0.22	5.242	-0.44

Note: Comparative statics using the parameters in Table 4.6.1. The economy without termination costs ($\tau = 0$) is the benchmark. The first scenario assumes $\tau = 0.009$. This figure is chosen to achieve a fraction of borrowers in receipt of forbearance close to that found in the Bank of England survey (i.e. 6%). The second scenario assumes $\tau = 0.018$. **% dev.** is the percentage deviation of the economy with respect to the benchmark with $\tau = 0$.

In the benchmark economy without termination costs, the separation rate is $\frac{1}{15}$, i.e. lending relationships last approximately seven years. The mean duration of inactivity is two quarters.

Credit market tightness is 0.667 and reservation productivity is 0.953. Roughly 94% of firms are active, of which 87.5% have legacy lending relationships with a bank. Roughly 6.7% of all active firms in each period are entrants. Forbearance is non-existent. Using the quarterly lending rates in Table 4.6.2, the steady state equilibrium average annual lending rate is about 1.2%. The average lending rate on old loans is about 0.8% and the rate on a representative new loan is about 5.7%. There is no wedge between rates on old and legacy loans.

In both economies with positive termination costs ($\tau = 0.009$ and $\tau = 0.018$), these costs generate a downwards shift in the loan separation condition and a leftwards shift in the credit creation schedule. They make banks more tolerant of low productivity borrowers and lending relationships last longer. The equilibrium reservation productivity unambiguously declines and so does the loan termination rate. The supply of new credit lines declines. Credit market tightness decreases, which increases inactivity duration. Because of the negative effects on both destruction and creation, the qualitative effect on equilibrium activity is indeterminate. In our calibration, the lower rate of destruction dominates the increase in inactivity duration, and the overall rate of activity is higher. The composition of active firms differs between the two economies and the benchmark. In the presence of termination costs, the fraction of entrants is smaller (e.g. 3.4% when $\tau = 0.009$ against 6.7% when $\tau = 0$). They are crowded out by incumbents which are now in receipt of forbearance. When $\tau = 0.009$ ($\tau = 0.018$), roughly 6% (12.5%) of active firms receive forbearance.

Termination costs also distort prices. The distortion brought about by termination costs is reflected in the positive loan rate wedge. This wedge is absent when $\tau = 0$. A positive wedge means that at the same level of productivity, entrants pay more than incumbent firms for the same loan amount. For example, when $\tau = 0.009$ the wedge amounts to around 0.34% of the rate on new loans in the absence of termination costs. In other words, legacy borrowers are being partially "subsidized" by entrants. The average lending rate on continued loans falls whereas the rate on new loans increases. The economy wide average lending rate decreases due to the fact that the rate on continued loans falls, the proportion of continued loans increases, and most loans in the economy are legacy loans. Entrants find it more difficult to find a loan. When $\tau = 0.009$, the steady state equilibrium average annual lending rate is about 0.9%. The average lending rate on old loans is about 0.7% and the rate on a representative new loan is about 7.1%. When $\tau = 0.018$, the steady state equilibrium average annual lending rate is about 0.5%. The average lending rate on old loans is about 0.5% and the rate on a representative new loan rises to about 8.6%.

The assumption that new projects start with a productivity level above the reservation threshold does not significantly affect the results because the proportion of new loans is small compared to that of continued loans. The steady state values of investment, output, and productivity are mainly driven by the number and idiosyncratic productivity of legacy loans. Investment by incumbents is higher in the steady state with termination costs - capital is stuck in the "wrong" projects. The capital stock of a representative entrant decreases. The impact on the aggregate capital stock is a priori indeterminate. In this calibration, it increases. The same applies to output. However, the composition of firms investing is clearly quite different - with negative repercussions for productivity. TFP and labour productivity are permanently depressed. When $\tau = 0.009$, TFP and labour productivity are permanently 0.16% and 0.22% lower respectively every quarter. When $\tau = 0.018$, the impact is roughly doubled. Since this comparison does not assume any fundamental deterioration in the economy, the overall impact of forbearance would be larger if, for example, the average idiosyncratic productivity of the pool of incumbent firms should decrease.

4.7 Stochastic analysis: shock to termination costs

In this section, I simulate shocks to the termination cost τ under different "policy scenarios".

4.7.1 Shock processes

Assume that the economy experiences a positive shock to the loan termination cost, according to the process

$$\tau_t = (1 - \rho_\tau)\tau_{SS} + \rho_\tau \tau_{t-1} + \sigma_\tau e \tag{4.7.1}$$

τ_{SS} is the steady state, i.e. $\tau_{SS} = 0$. The persistence of the shock, ρ_τ, is set at 0.9. As the positive shock hits, τ increases from its steady state value ($\tau_{SS} = 0$) to σ_τ and then slowly reverts to steady state. I set the standard deviation $\sigma_\tau = 0.009$ so that roughly 6% of borrowers receive forbearance when the shock hits.

I present three policy scenarios. In the first scenario, new and old matches are subject to the same *constant* funding cost ρ as assumed throughout Section 4.4. In the second scenario, the policy maker intervenes to decrease the cost of funds for banks (ρ). I assume that ρ evolves according to the following process:

$$\rho_t = (1 - \rho_\rho)\rho_{SS} + \rho_\rho \rho_{t-1} - \sigma_\rho e \tag{4.7.2}$$

This can be loosely interpreted as a policy function where the central bank responds to a shock to τ by *decreasing* bank funding costs. Using the calibration in Table 4.6.1, ρ_{SS} is equal to 50 basis points per annum. I set the standard deviation σ_ρ such that ρ decreases from its steady state of 50 basis points per annum to 25 basis points per annum at the same time the τ shock hits the banking sector. ρ_ρ is chosen to be the same persistence as the shock to separation costs, i.e. $\rho_\rho = \rho_\tau = 0.9$. Note that I do not model the central bank and hence the process above does not describe an optimal policy rule which responds to τ. This is a very simple way of capturing a policy which aims at incentivising banks to lend across the board, such as the UK's Funding for Lending Scheme (FLS).

This policy experiment only captures the key idea of the FLS, i.e. provide cheap funding to banks to incentivise lending. Beyond an initial entitlement of discounted funding available to all banks, banks can borrow additional funding equal to their net lending *if* the latter is positive during a given reference period. The price of funding provided is also linked to the banks' net lending performance. The fee is 25 basis points per year for banks that expand their net lending. Banks that contract their net lending stock pay more. A potential issue with the FLS is that it does not formally discriminate between loans to *new* borrowers and rolled-over/new loans to *existing* borrowers. Hence, Scenario 2 assumes that the central bank decreases funding costs ρ on all loans.

In the third scenario, each type of loan is subject to a different funding cost. In particular, the central bank is able to target subsidised funding to new borrowers only - while excluding legacy loans from the scheme. The bank funding cost on new loans is ρ_N and that on legacy loans is ρ_O, with $\rho_N \neq \rho_O$. ρ_O is kept constant throughout the analysis and its value is that of ρ in Table 4.6.1. I investigate how a policy shock to ρ_N can counteract the misallocation generated by the shock to termination costs. I assume that ρ_N evolves according to the following process:

$$\rho_{N,t} = (1 - \rho_{\rho_N})\rho_{N,SS} + \rho_{\rho_N} \rho_{N,t-1} - \sigma_{\rho_N} e \tag{4.7.3}$$

Again, this can be loosely interpreted as a policy function where the central bank responds to a shock to τ by *decreasing* bank funding costs on *new loans only*. As the τ shock hits, ρ_N

immediately decreases from its steady state of 50 basis points per annum to 25 basis points per annum (change captured by σ_{ρ_N}) and then gradually reverts to steady state. Again ρ_{ρ_N} is chosen to be the same persistence as the shock to separation costs ($\rho_{\rho_N} = 0.9$). This is a very simple way of capturing a policy which aims at incentivising banks to extend new loans. Banks pay 25 basis points on funding for loans to new borrowers when the policy shock hits, but continue to pay 50 basis points for legacy lending relationships. The policy is phased out as $\rho_{N,t}$ returns to equilibrium.

In the model, the policy in Equation (4.7.3) stimulates credit supply to new borrowers through the credit creation condition. The credit creation condition with a single funding cost ρ is given by Equation (4.5.7):

$$\frac{c}{q_t} = \beta E_t(1-\eta)[\pi^N_{t+1} - \pi^O_{t+1}(\tilde{\epsilon}_{t+1}) - \tau]$$

where

$$\begin{aligned}\pi^N_{t+1} - \pi^O_{t+1}(\tilde{\epsilon}_{t+1}) = z_{t+1}\left(\bar{\epsilon}(K^N_{t+1})^{1-\alpha} - \tilde{\epsilon}_{t+1}(K^O_{t+1}(\tilde{\epsilon}_{t+1})^{1-\alpha}\right) \\ -\rho\left(K^N_{t+1} - K^O_{t+1}(\tilde{\epsilon}_{t+1})\right)\end{aligned}$$

With $\rho_N \neq \rho_O$, the credit creation condition becomes:

$$\begin{aligned}\pi^N_{t+1} - \pi^O_{t+1}(\tilde{\epsilon}_{t+1}) = z_{t+1}\left(\bar{\epsilon}(K^N_{t+1})^{1-\alpha} - \tilde{\epsilon}_{t+1}(K^O_{t+1}(\tilde{\epsilon}_{t+1})^{1-\alpha}\right) \\ -\rho_O\left(K^N_{t+1} - K^O_{t+1}(\tilde{\epsilon}_{t+1})\right) + \triangle\rho K^N_{t+1}\end{aligned}$$

where $\triangle\rho = \rho_O - \rho_N$. Hence $\rho_O > \rho_N$ will stimulate credit creation. In the presence of termination costs, $\triangle\rho K^N_{t+1}$ can partially offset the negative effect of termination costs ($-\tau$ in Equation (4.5.7)) on the creation of new credit lines.

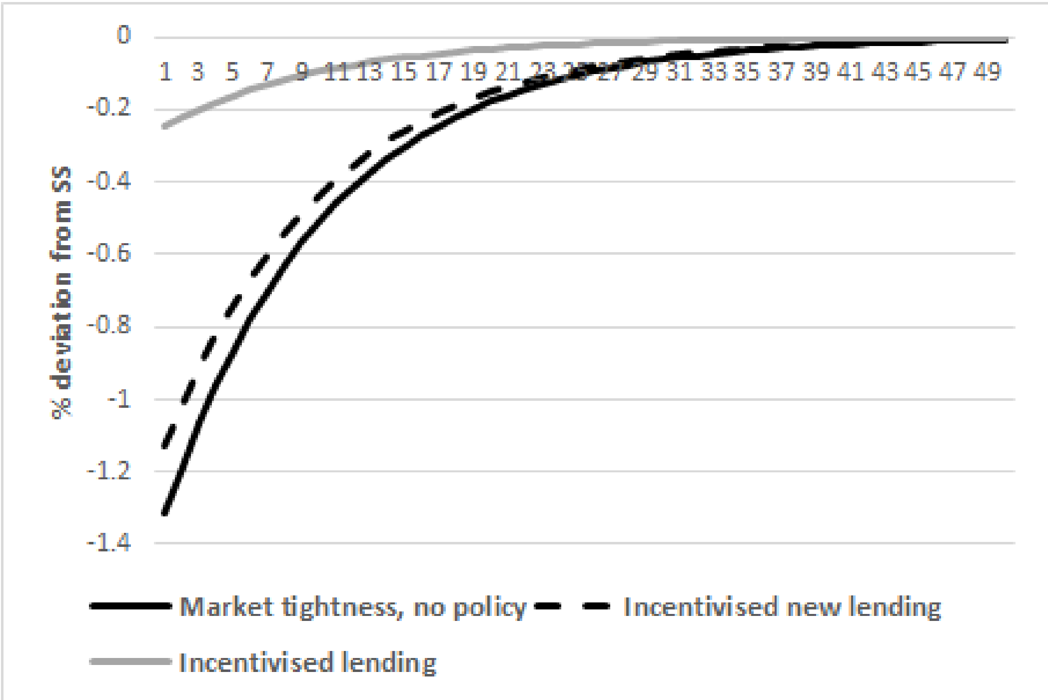
4.7.2 Impulse response analysis

In this section, I simulate the three scenarios above:

- Scenario 1: Positive shock to termination cost, no policy.
- Scenario 2: Positive shock to termination cost, "incentivised lending" across the board (non-targeted policy).
- Scenario 3: Positive shock to termination cost, "incentivised new lending" (targeted policy).

The figures below show the impulse response functions of aggregate variables as percentage deviations from their steady state values following a positive shock to termination costs. In each figure there are three time series. The first one (no policy) assumes that the funding cost stays constant. The second one (incentivised lending) corresponds to the scenario where the central bank decreases the bank funding costs for all types of loans (Equation (4.7.2)). The final one (incentivised new lending) corresponds to the scenario where the central bank decreases the bank funding costs for new loans only (Equation (4.7.3)).

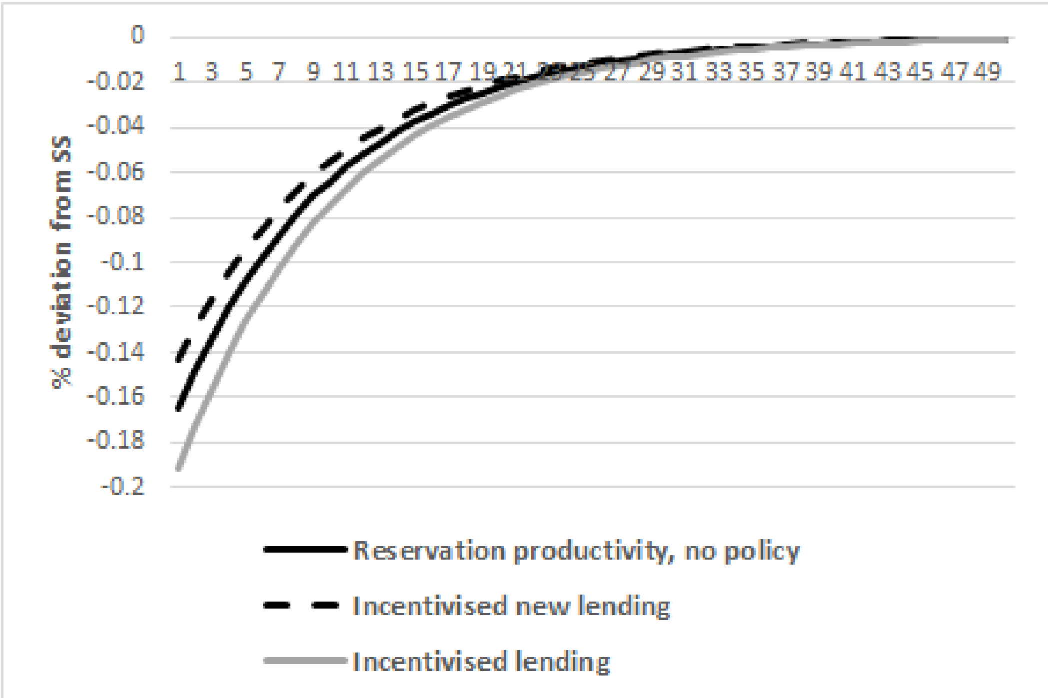
Figure 4.7.1: **Market tightness: Shock to τ with** $\sigma_\tau = 0.009$



Note: IRFs of market tightness to a shock to the termination cost τ with $\sigma_\tau = 0.009$ under three policy scenarios. % deviations from steady state. Unit of time is one quarter. IRFs over 50 quarters.

Figures 4.7.1 and 4.7.2 show the impact of the shock to termination costs on the outcomes of the matching process. Termination costs generate a downwards shift in the loan separation condition and a leftwards shift in the credit creation schedule. Termination costs affect the inter-temporal credit supply decisions of the lenders: Banks put less effort in supplying credit in the expectation that the created loans will result in a costly termination penalty at some point in the future. This leads to lower destruction and lower creation, i.e. depressed credit flows. Credit market tightness decreases (Figure 4.7.1), which increases the duration of the search for external finance for new entrepreneurs (inactivity duration). The equilibrium reservation productivity unambiguously declines (Figure 4.7.2) and so does the loan termination rate. The non-targeted policy substantially reduces the impact of the shock on market tightness as it increases credit supply across the board. By contrast, the targeted policy has little impact on market tightness. This is because the proportion of new loans is small compared to that of continued loans. The non-targeted policy worsens the impact of the termination cost on reservation productivity. In other words, it makes banks even more tolerant of low-productivity projects. By contrast, the policy targeted at new loans mitigates the fall in the reservation productivity.

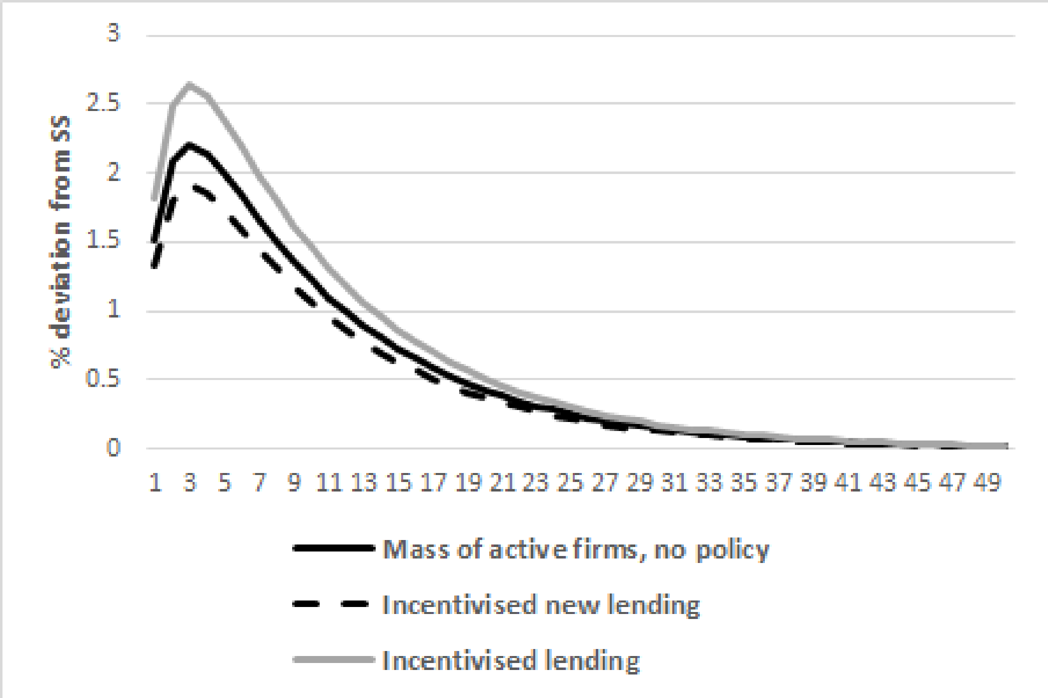
Figure 4.7.2: **Reservation productivity: Shock to τ with** $\sigma_\tau = 0.009$



Note: IRFs of reservation productivity to a shock to the termination cost τ with $\sigma_\tau = 0.009$ under three policy scenarios. % deviations from steady state. Unit of time is one quarter. IRFs over 50 quarters.

Because of the negative effects on both destruction and creation, the qualitative effect on equilibrium activity is indeterminate. In this calibration, the lower rate of destruction dominates the increase in inactivity duration, and the overall rate of activity increases (Figure 4.7.3). The non-targeted policy increases the positive impact of the shock on the rate of activity, while the targeted policy decreases it slightly compared to the benchmark without policy.

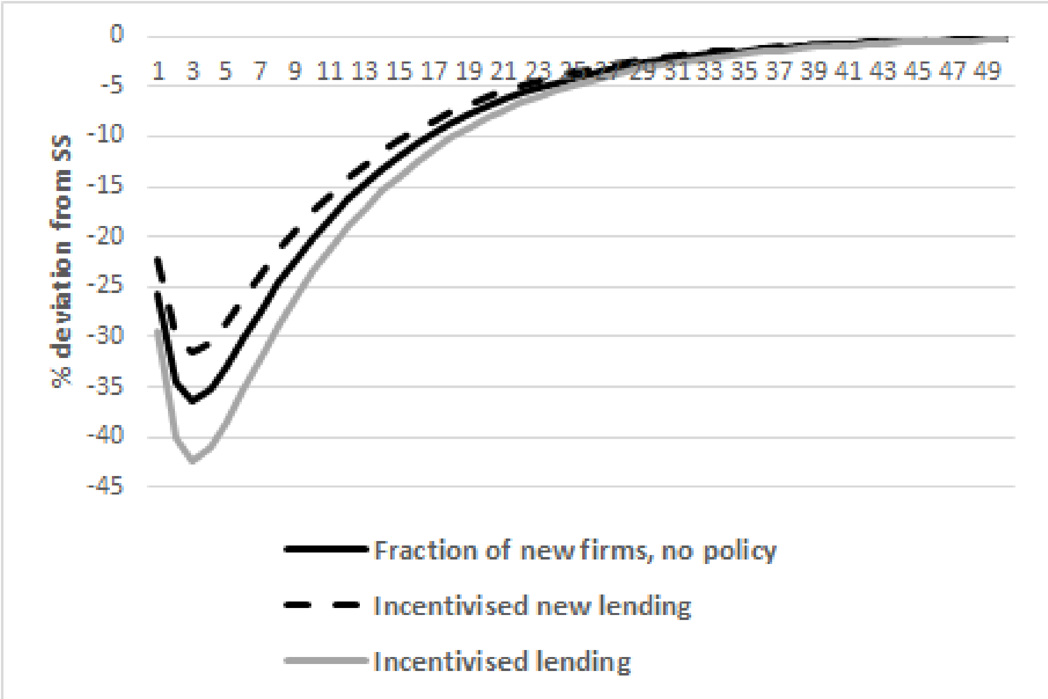
Figure 4.7.3: **Active firms: Shock to τ with** $\sigma_\tau = 0.009$



Note: IRFs of mass of active firms to a shock to the termination cost τ with $\sigma_\tau = 0.009$ under three policy scenarios. % deviations from steady state. Unit of time is one quarter. IRFs over 50 quarters.

The composition of active firms changes. The fraction of entrants decreases as the latter are crowded out by incumbents which start to be in receipt of forbearance (Figure 4.7.4). The provision of new credit must slow to reequilibrate the credit market. Credit flows are depressed. The dynamics following the shock are therefore characterized by sclerosis (Caballero and Hammour, 2001) - the preservation of firms that would not be saved without the banks' subsidized loan rates. Crowding out is exacerbated by the non-targeted policy, while the targeted policy reduces the distortion generated by the termination cost. In that sense, it is possible that the FLS may have facilitated forbearance towards legacy borrowers, undermining the scheme's ability to channel funds to the most productive firms.

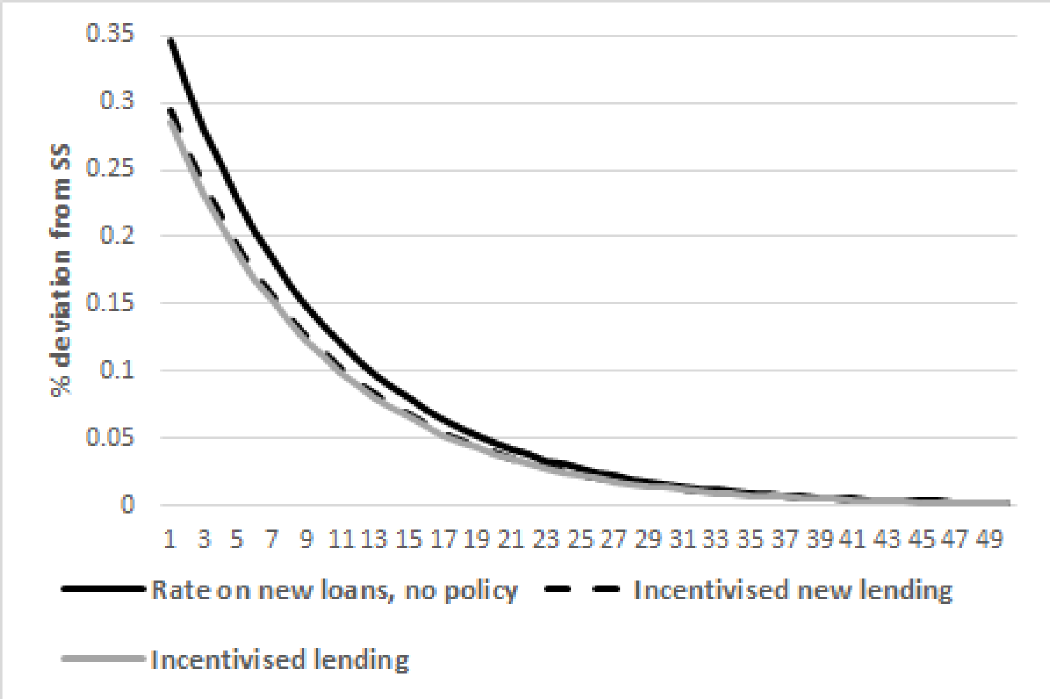
Figure 4.7.4: **Fraction of new firms: Shock to τ with σ_τ = 0.009**



Note: Note: IRFs of the fraction of entrants to a shock to the termination cost τ with $\sigma_\tau = 0.009$ under three policy scenarios. % deviations from steady state. Unit of time is one quarter. IRFs over 50 quarters.

Termination costs distort prices (Figures 4.7.5, 4.7.6, and 4.7.7). Because banks anticipate future termination costs, they charge higher loan rates on new loans. By contrast, the bargaining position of legacy borrowers improves and the average lending rate on continued loans falls. In other words, there is excessive credit tightening for high TFP firms and too lax lending for low TFP firms at the same time. Berglöf and Roland (1997) show for transition economies that credit supply restriction and soft budget constraints can co-exist. This is such a situation.

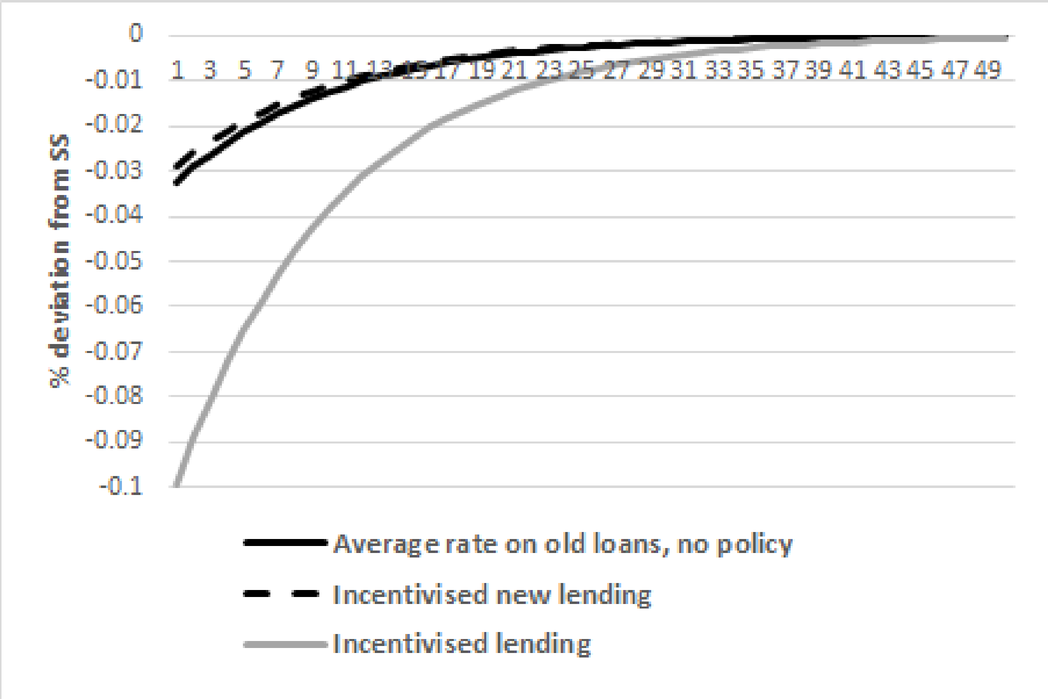
Figure 4.7.5: **Rate on new loans: Shock to τ with $\sigma_\tau = 0.009$**



Note: IRFs of the rate on new loans to a shock to the termination cost τ with $\sigma_\tau = 0.009$ under three policy scenarios. % deviations from steady state. Unit of time is one quarter. IRFs over 50 quarters.

Both the non-targeted and the targeted policies reduce the loan rate on new lending contracts compared to the no-policy scenario. The improvement is only marginally larger under the selectively subsidized bank funding cost. This is because there are two effects at work. While the targeted policy reduces the loan rate on new lending contracts for a given loan amount, each entrant will also enter the market with a higher capital stock as new firms take advantage of lower rates. Since the loan rate increases in the loan amount, these two effects offset each other partially. One cannot understand what happens to new loan rates without looking at what happens to new loan volumes (Figure 4.7.9). By contrast, the picture differs substantially when it comes to the rates charged on legacy loans (Figure 4.7.6). The shock to termination costs reduces the average lending rate on continued loans *and* the volume of legacy loans increases (Figure 4.7.10). The subsidy to legacy borrowers is significantly exacerbated when the policy maker subsidizes bank funding in a non-targeted manner. The targeted policy only sightly counteracts the effect of termination costs. Again, this is because the proportion of new loans is small compared to that of continued loans.

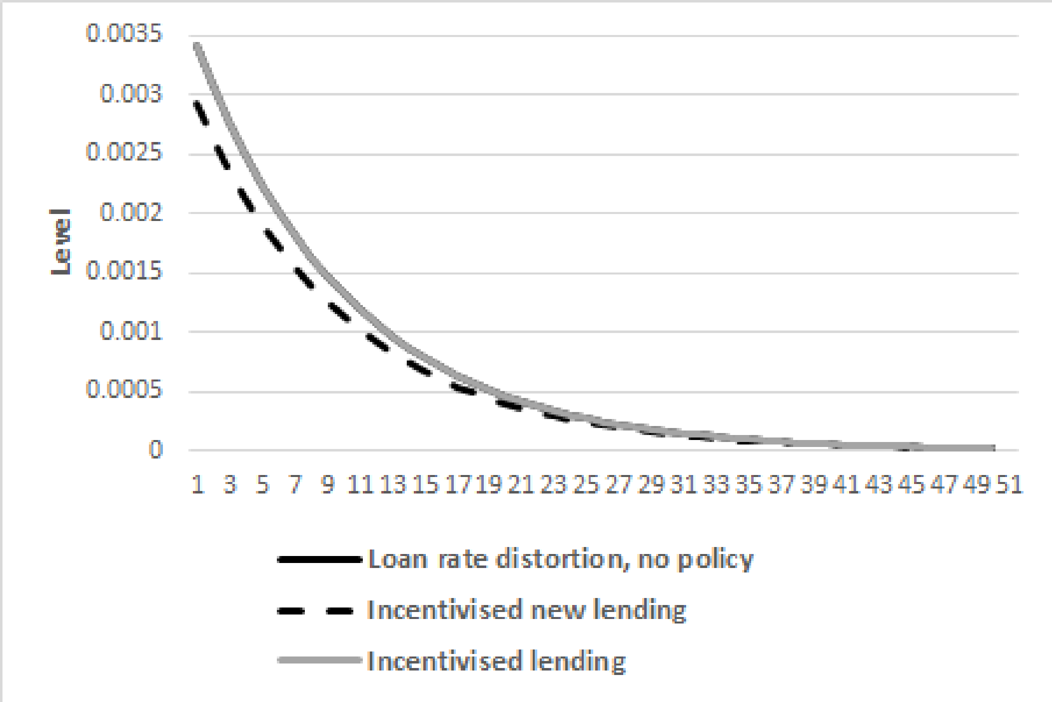
Figure 4.7.6: **Rate on legacy loans: Shock to τ with** $\sigma_\tau = 0.009$



Note: IRFs of the rate on legacy loans to a shock to the termination cost τ with $\sigma_\tau = 0.009$ under three policy scenarios. % deviations from steady state. Unit of time is one quarter. IRFs over 50 quarters.

The price distortions are reflected in the distortionary wedge between the loan rates on new and legacy loans at productivity level $\bar{\epsilon}$. The wedge becomes positive when the τ shock hits and then slowly reverts to its steady state value of zero. A positive wedge means that at the same level of productivity, entrants pay a higher interest rate than incumbent firms. While a scheme which incentivises new lending reduces distortions, a non-targeted scheme does not have any impact on the wedge.

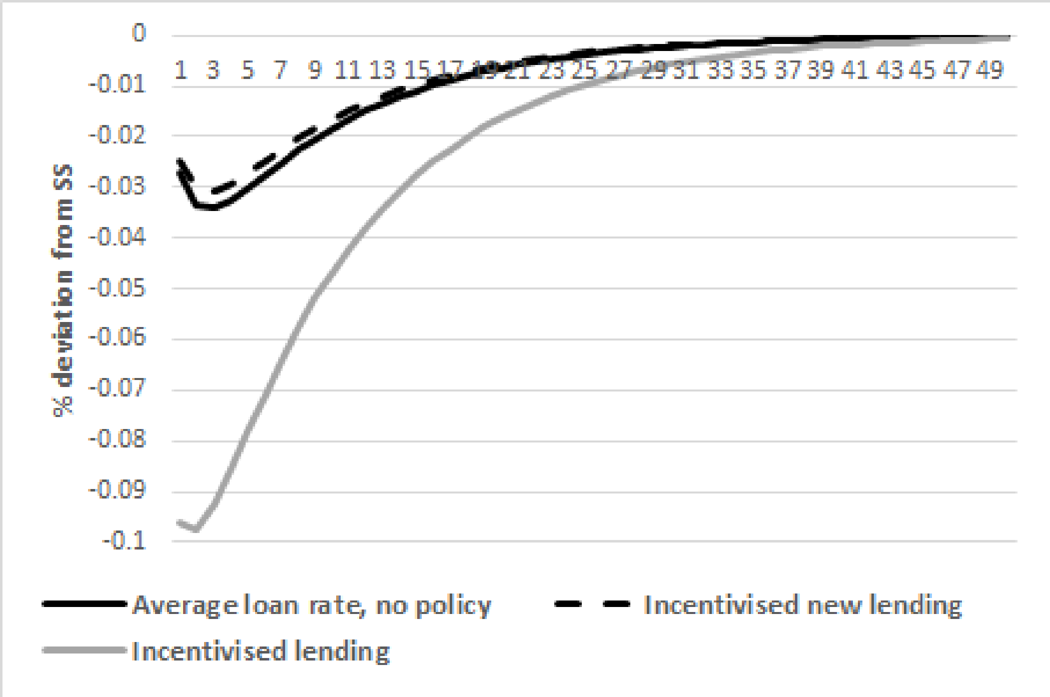
Figure 4.7.7: **Loan rate distortion: Shock to τ with** $\sigma_\tau = 0.009$



Note: IRFs of the interest rate wedge (level) to a shock to the termination cost τ with $\sigma_\tau = 0.009$ under three policy scenarios. Unit of time is one quarter. IRFs over 50 quarters.

Finally, the economy wide average lending rate decreases due to the fact that the rate on continued loans falls and the proportion of continued loans increases. The reduction is substantially larger under the non-targeted policy.

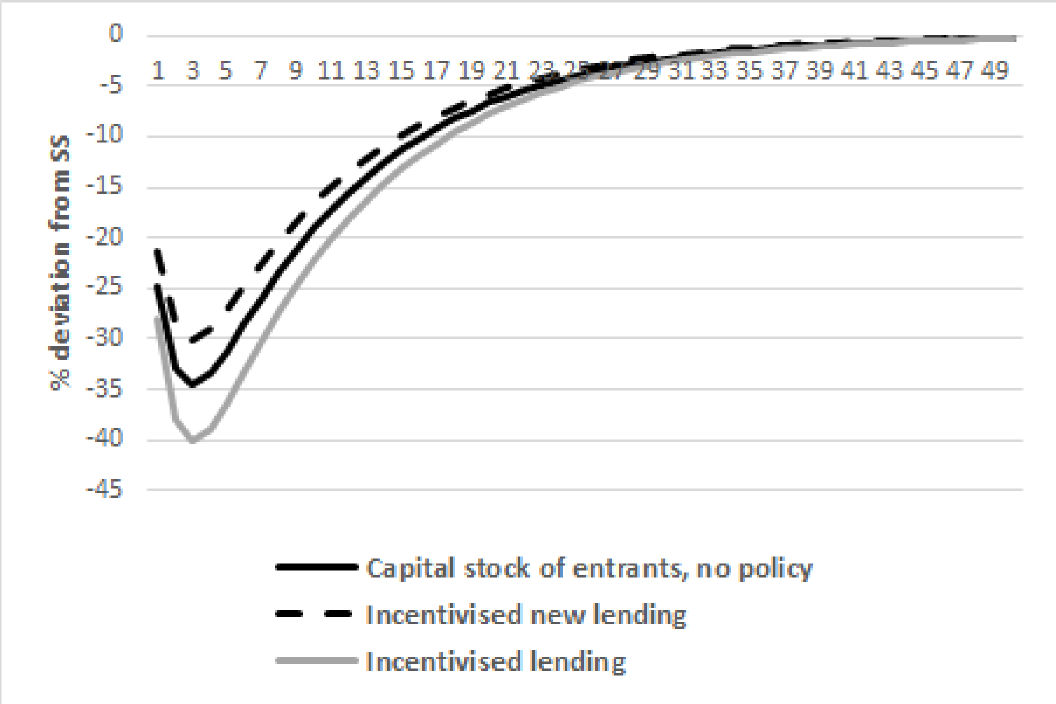
Figure 4.7.8: **Average loan rate: Shock to τ with** $\sigma_\tau = 0.009$



Note: IRFs of the average loan rate to a shock to the termination cost τ with $\sigma_\tau = 0.009$ under three policy scenarios. % deviations from steady state. Unit of time is one quarter. IRFs over 50 quarters.

As a result of the distortions above, the capital stock of entrants decreases (Figure 4.7.9). By contrast, incumbents invest more (Figure 4.7.10). In our calibration, this is sufficient to offset lower investment by entrants and aggregate investment increases (Figure 4.7.11). Since all the capital is fronted up by banks, the aggregate capital stock in the economy is equal to aggregate credit supply. Since the proportion of new loans is small compared to that of continued loans, the overall dynamics are mainly driven by the number and idiosyncratic productivity of continuing loans.

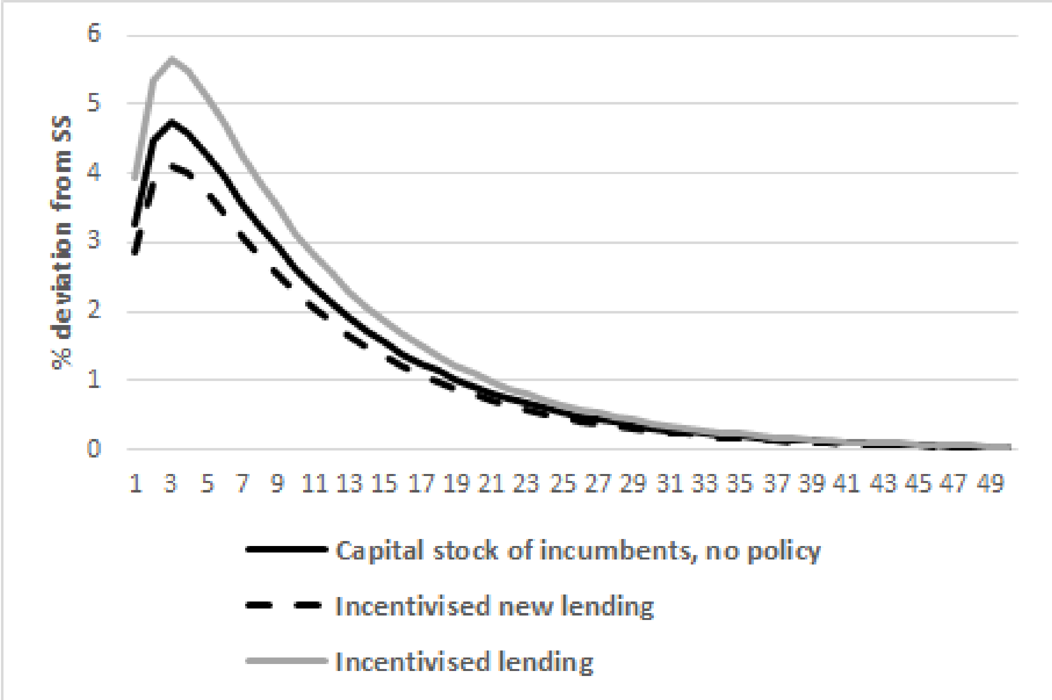
Figure 4.7.9: **Capital stock of entrants: Shock to τ with** $\sigma_\tau = 0.009$



Note: IRFs of the capital stock of entrants to a shock to the termination cost τ with $\sigma_\tau = 0.009$ under three policy scenarios. % deviations from steady state. Unit of time is one quarter. IRFs over 50 quarters.

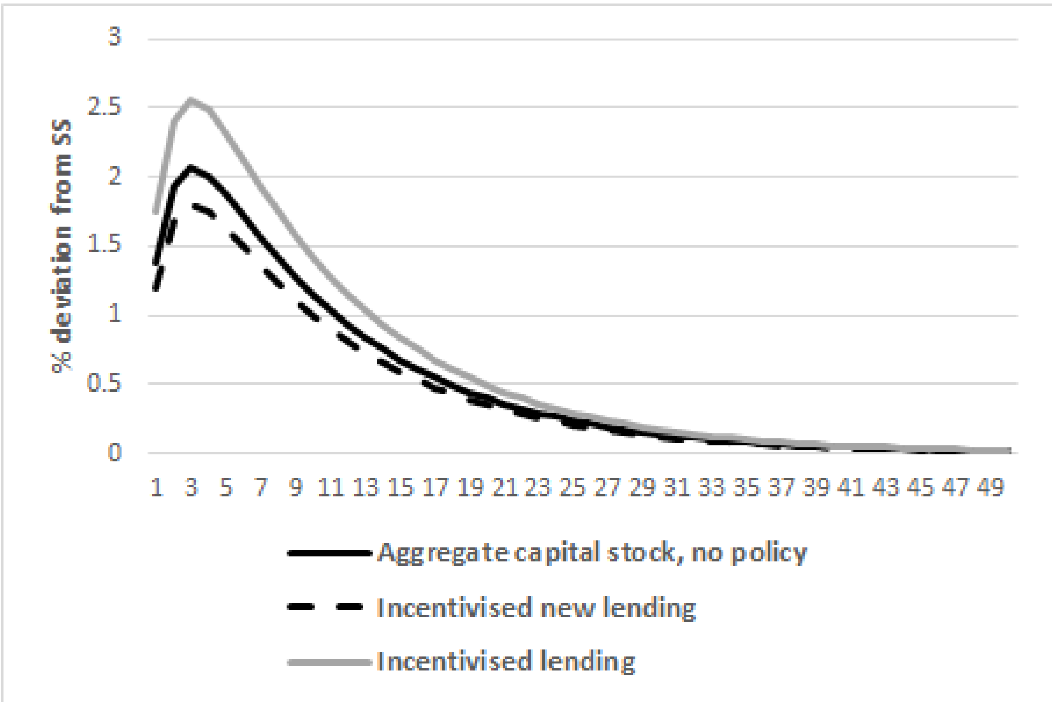
In conclusion, the allocational efficiency of the banking sector has fallen. Creditor passivity undermines the correlation between access to credit and firm-level productivity, resulting in the misallocation of capital inputs. Capital inputs differ systematically across firms for reasons other than their productivity. The direct compositional inefficiency (composition of the population of active firms) created by the reputational cost is reinforced by the borrower's choice of capital stock in reaction to the interest rate distortion. While the aggregate credit volume increases, new credit supply decreases as entrants are crowded out. There is more investment, but it is less productive. A policy which subsidises new loans dampens misallocation. It does not have a significant impact on the aggregate stock of lending (See Figure 4.7.11), but rather on where capital is channelled. Output follows a similar pattern to investment. The output of entrants decreases whereas that of incumbents increases. Economy wide output increases in my calibration (Figures 4.A.4, 4.A.5, and 4.A.6 in the Appendix).

Figure 4.7.10: **Capital stock of incumbents: Shock to τ with $\sigma_\tau = 0.009$**



Note: IRFs of the capital stock of incumbents to a shock to the termination cost τ with $\sigma_\tau = 0.009$ under three policy scenarios. % deviations from steady state. Unit of time is one quarter. IRFs over 50 quarters.

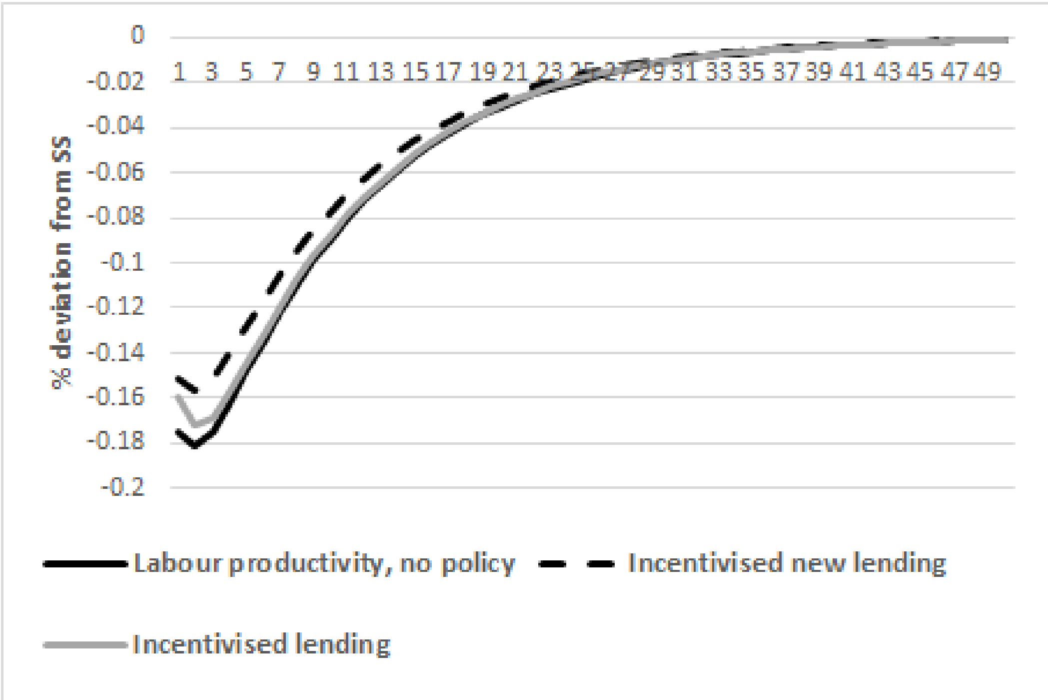
Figure 4.7.11: **Aggregate capital stock: Shock to τ with $\sigma_\tau = 0.009$**



Note: IRFs of the aggregate capital stock to a shock to the termination cost τ with $\sigma_\tau = 0.009$ under three policy scenarios. % deviations from steady state. Unit of time is one quarter. IRFs over 50 quarters.

While the evolution of aggregate investment and output depends on the calibration (e.g. the productivity distribution of incumbents), TFP and labour productivity unambiguously decline when there is a shock to termination costs (Figures 4.7.12 and 4.7.13). The composition of credit, rather than its volume, is what drives the distortionary effects of termination costs on productivity. The fact that banks are more lenient towards continuing firms mitigates the costs of the credit crunch for them, but the size of this effect is small relative to the loss associated with decreased mobility of loanable funds. Despite the fact that the aggregate capital stock increases, capital is mainly channelled into lower productivity projects.

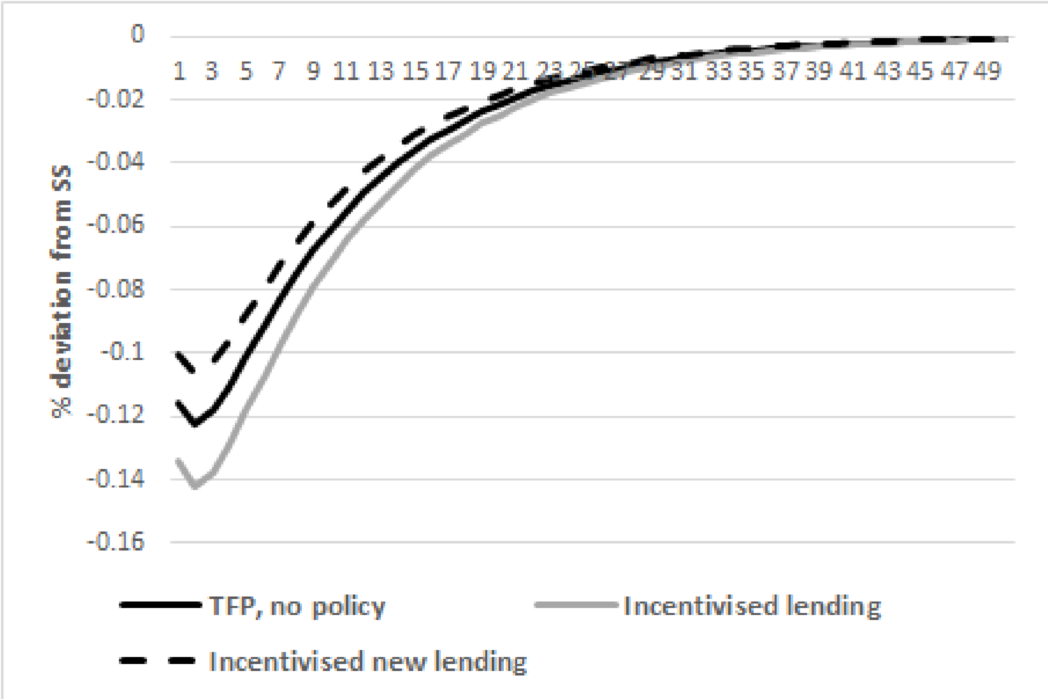
Figure 4.7.12: **Labour productivity: Shock to τ with** $\sigma_\tau = 0.009$



IRFs of labour productivity to a shock to the termination cost τ with $\sigma_\tau = 0.009$ under three policy scenarios. % deviations from steady state. Unit of time is one quarter. IRFs over 50 quarters.

The direct sullying effect of the termination cost, which manifests itself through the composition effects, is magnified by the distortion in investment decisions (rates, quantities) which endogenously affects the productivity of new and surviving relationships. Allowing firms to freely choose capital is key to capturing this sullying effect. The total amount of credit in the economy is not an appropriate measure of how "efficient" credit provision to the economy actually is during a banking crisis. While a targeted policy mitigates these misallocation effects, a non-targeted policy exacerbates them.

Figure 4.7.13: **Total factor productivity: Shock to τ with** $\sigma_\tau = 0.009$



Note: IRFs of TFP to a shock to the termination cost τ with $\sigma_\tau = 0.009$ under three policy scenarios. % deviations from steady state. Unit of time is one quarter. IRFs over 50 quarters.

In conclusion, the FLS might have exacerbated the misallocation of resources resulting from banks' distorted incentives. It might have had a role to play in the lack of creative destruction during the crisis. Decomposition techniques to distinguish contributions to aggregate productivity of restructuring and of productivity growth within firms can be used to gauge the extent of reallocation during the crisis. Both Barnett et al (2014) and Riley et al (2015) provide some evidence of reallocation being subdued during the crisis. Barnett et al. (2014) find that the contribution from reallocation declined in 2008-2009 and became negligible between 2010 and 2012, instead of increasing significantly as one would expect as a result of higher insolvencies. They estimate that less efficient reallocation and a slowdown in creative destruction account for around one third of the fall in average annual productivity growth between 2002-2007 and 2008-2011. Similarly, Riley et al. (2015) find that the growth contribution of both between-firm effects (changes in market share among continuing firms) and net entry were more subdued between 2007 and 2013 than between 1998 and 2007. Those two papers also provide some evidence of a weakening correlation between firms' health and their investment and employment behaviour. Barnett et al (2014) find that the positive correlation between profitability and investment weakened significantly after the crisis. Riley et al (2015) find that during the downturn of 2008-2009 the positive correlation between employment growth and firms' relative productivity positions weakened among surviving firms.

4.7.3 Aggregate productivity shocks

In my calibration the effects of forbearance on productivity do not appear to be sizeable. In line with previous research on the UK (Barnett et al, 2014, and Riley et al, 2015), this suggests that a common factor, rather than misallocation, may be driving the productivity puzzle. Suppose that the economy experiences a negative shock to aggregate productivity z_t at the same time it experiences a positive shock to termination costs. Take as an example the following aggregate shock process for z_t, common to all firms:

$$z_t = (1 - \rho_z) z_{SS} + \rho_z z_{t-1} - \sigma_z e \tag{4.7.4}$$

The persistence of the shock, ρ_z, is set at 0.9. As the negative shock hits, z decreases from its steady state value ($z_{SS} = 4$) by σ_z and then slowly reverts to steady state. I set $\sigma_z = 0.02$ so that output deceases by roughly 6%. Compared to a scenario with just an aggregate productivity shock, the concomitant τ shock will lead to[11]

- A larger decrease in: Market tightness, labour productivity, and TFP.
- A smaller decrease in: The mass of active firms, the capital stock and output of incumbents, the economy-wide capital stock and output.
- A smaller increase in: Reservation productivity, the fraction of new firms, the average loan rate on old loans and the average economy-wide loan rate, and the capital stock and output of entrants.
- An increase (rather than a decrease) in the rate on new loans, and hence the creation of a loan distortion which would otherwise be absent.

In other words, the τ shock counteracts the "cleansing" effects of recession. Note that when both types of firms, entrants and incumbents, experience the same aggregate productivity shock (as assumed above), the effects of both shocks will simply be cumulative. More interesting dynamics may come into play when entrants and incumbents face different productivity shocks.

[11] Impulse response functions available upon request.

Very few positive aspects of forbearance lending have been identified in the literature. In this model, forbearance has a "healing" effect on output and the rate of economic activity[12]. However, it depresses productivity further. In other words, it undermines the process of creative destruction that is set in motion by the negative aggregate productivity shock. The fact that depressed credit flows bolster output and employment may provide a reason for the regulator to close a blind eye to forbearance.

4.7.4 Surplus and efficiency considerations

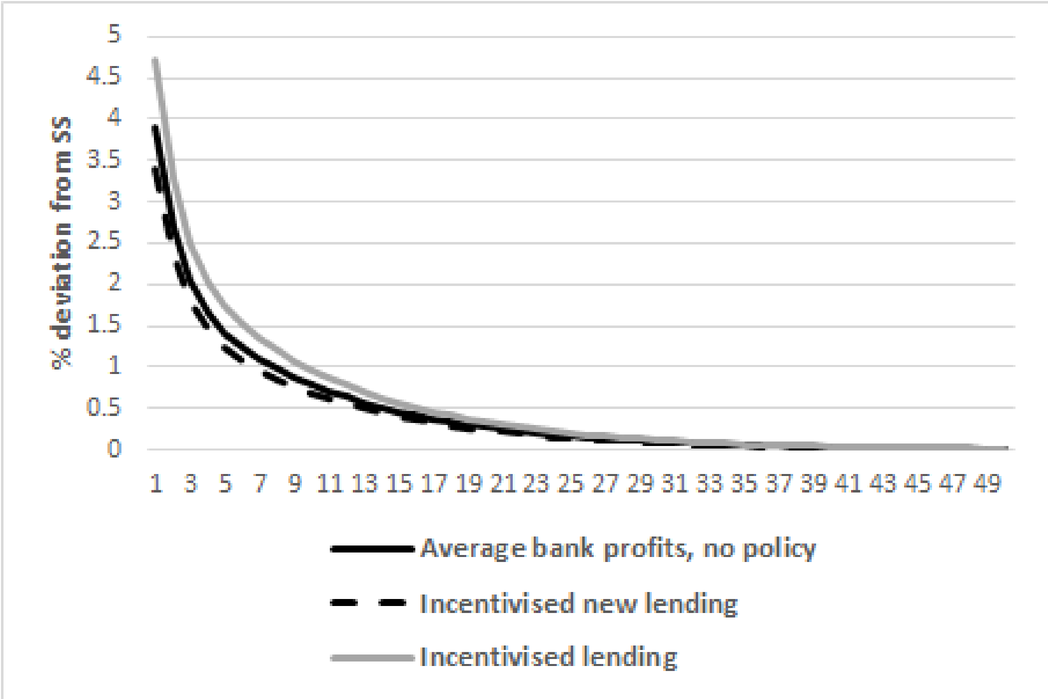
This paper has abstracted entirely from welfare (surplus) and efficiency considerations. These topics are left for future analysis. In the calibration above, the aggregate surplus increases following a shock to termination costs[13]. This is due to the fact that aggregate output and the mass of active firms increase. This also means that the average profits of banks increase (Figure 4.7.14).

My calibration delivers the following qualitative results. In the absence of any policy shock (Scenario 1), the surplus on old loans increases and that on new ones decreases. Aggregate surplus rises because the proportion of new loans is small compared to that of continued loans. In Scenario 2 (non-targeted policy), both the surplus on old and new loans increases. When policy is targeted (Scenario 3) the surplus on old loans increases and that on new ones decreases as in Scenario 1 but the effects are less pronounced.

[12] Another contribution highlighting a potential positive aspect of forbearance is Mitchell (2001). The author argues that banks posses private information about their borrowers, and that terminating loans takes away this information.

[13] Impulse response functions are available upon request.

Figure 4.7.14: **Average profits: Shock to τ with** $\sigma_\tau = 0.009$



Note: IRFs of average profits to a shock to the termination cost τ with $\sigma_\tau = 0.009$ under three policy scenarios. % deviations from steady state. Unit of time is one quarter. IRFs over 50 quarters.

The question of equilibrium efficiency arises in search and matching models because matching frictions introduce externalities. While an increase in search exerts a positive externality on the other side of the market, it creates a negative externality on the same side of the market. In other words, matching alters the meeting opportunities of other agents. In the labour literature, an additional worker (firm) makes it easier (harder) for vacancies to be filled but harder (easier) for workers to be matched with jobs. In the Mortensen-Pissarides search and matching model where agents are ex-ante identical, the Hosios (1990) condition ensures optimal search behavior by agents on both sides of the market. The condition states that firm entry is socially efficient when the surplus-sharing parameter η is equal to the elasticity parameter of the matching function, χ. When this condition is satisfied, unemployment is "optimal" in the sense that it maximise the social planner's objective function, when the planner's goal is to maximize the present discounted value of output net of vacancy costs (surplus).

In my model, agents are ex-ante identical but ex-post heterogenous (such as in Mortensen and Pissarides, 1994, and Smith, 1995). Ex-post heterogeneity does not affect the efficiency conditions of the search model when the matching function has constant returns to scale. So the Hosios condition would require $\eta = \chi$. I deviate from this because $\eta > \alpha$ is a *necessary* (but not sufficient) condition for a firm's capital input choice to increase in its level of idiosyncratic productivity. UK data supports the fact that more productive firms grow larger and invest more. An economy where less productive firms invest more would contradict a simple empirical fact. Hence, since the Hosios condition is violated, the equilibrium is not efficient in the sense that externalities do not cancel out. If that is the case, the rate of inactivity is "too high" in the decentralized equilibrium described above. Since termination costs are found to boost economic activity, they might move the economy towards a more efficient equilibrium.

In addition, a number of intricate parameter restrictions need to be satisfied to ensure the existence and stability of the steady state equilibrium[14]. No inferences about equilibrium (in)efficiency can be made without further examination of the existence and stability conditions and the derivation of the planner's solution which satisfies those conditions. This is left for future research.

4.8 Conclusion

In the aftermath of the financial crisis, commentators and academics alike have been drawing parallels between Europe and Japan's "Lost Decade". Evidence of forbearance has been found in some European countries, namely Italy, Spain and Portugal. In the UK, a Bank of England Survey suggests that the practice of forbearance has increased. In 2013 6% of SMEs were estimated to be in receipt of some form of forbearance. The most common form of forbearance is the extension of the duration of loan contracts.

It has been suggested that these credit policies may have contributed to the dramatic productivity decline in the UK since 2009. In the fourth quarter of 2015 the gap between trend and actual labour productivity stood at around 16%. The Bank of England found that forbearance appeared to be most significant in sectors which have been particularly hit hard in terms of productivity. In addition, productivity is lower in SMEs in receipt of forbearance. It is therefore natural to ask whether forbearance could be a factor contributing to the UK productivity puzzle. Other features of the Great Recession point to subdued creative destruction, in particular the fact that business deaths were relatively low despite the size of the output loss.

I develop a partial equilibrium search and matching framework of the credit market to shed light on some of these phenomena. I examine how depressed credit flows can induce misallo-

[14] Conditions available upon request.

cation of capital across firms. I model incentives to forbear with a reduced-form termination cost, which banks have to incur when ending a lending relationship with a borrower. I look at the steady state and dynamic consequences of termination costs in terms of interest rates, investment, output, and economic activity. A positive shock to termination costs generates a situation of "credit sclerosis": loan destruction is subdued by the separation cost, hence loan creation must decrease to restore equilibrium. High-productivity entrants looking for a loan face a credit crunch both in terms of credit supply and the price of credit. Termination costs create a wedge between the cost of finance for new and old firms, and banks lend to their existing borrowers at a "subsidized" interest rate. As a consequence, too much credit is allocated to old firms. Aggregate labour productivity and TFP are reduced. By contrast, total investment, economic activity and output increase. In combination with a negative aggregate productivity shock, a shock to termination costs could help explain the low rate of business closures and the strength of employment in the UK.

Finally, I perform some policy experiments to examine how a policy tool like the UK's Funding for Lending Scheme might exacerbate incentives to forbear and the misallocation of capital. The main problem is that a policy of cheap funding provision which does not discriminate between new and legacy borrowers will end up favouring legacy borrowers at the expense of high-productivity entrants. While the FLS may have helped to keep businesses alive, it may have suppressed productivity even further.

There are three avenues for further work. First, the present exercise is almost purely qualitative. The model could be calibrated rigorously to an economy for which detailed data on credit flows are available (e.g. Italy, Spain, Portugal, and Japan). Second, the model could be integrated in a general equilibrium framework which would further help with the quantification of the aggregate consequences of forbearance. One could also endogenize the termination cost faced by banks and explore a concrete mechanism behind those costs. Finally, efficiency considerations, touched upon in Section 4.7.4, deserve further examination.

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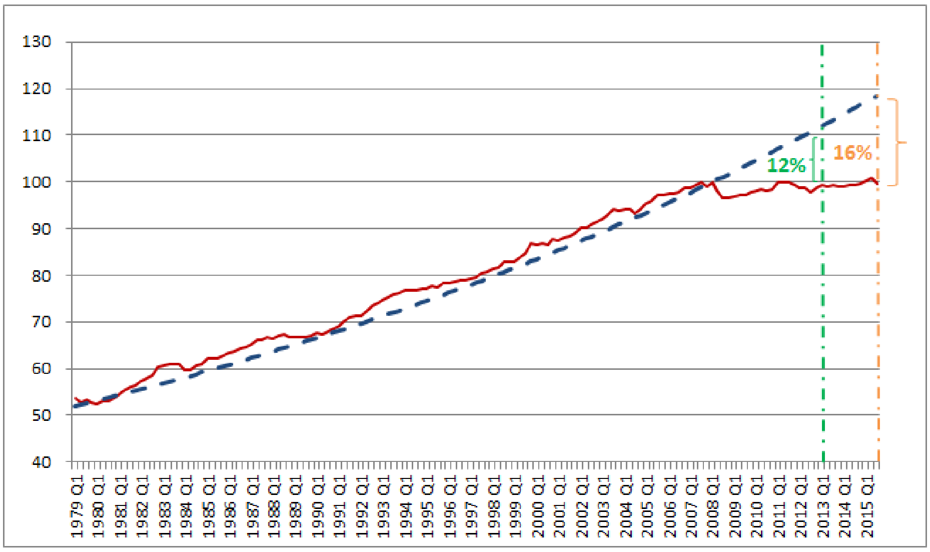
Appendix

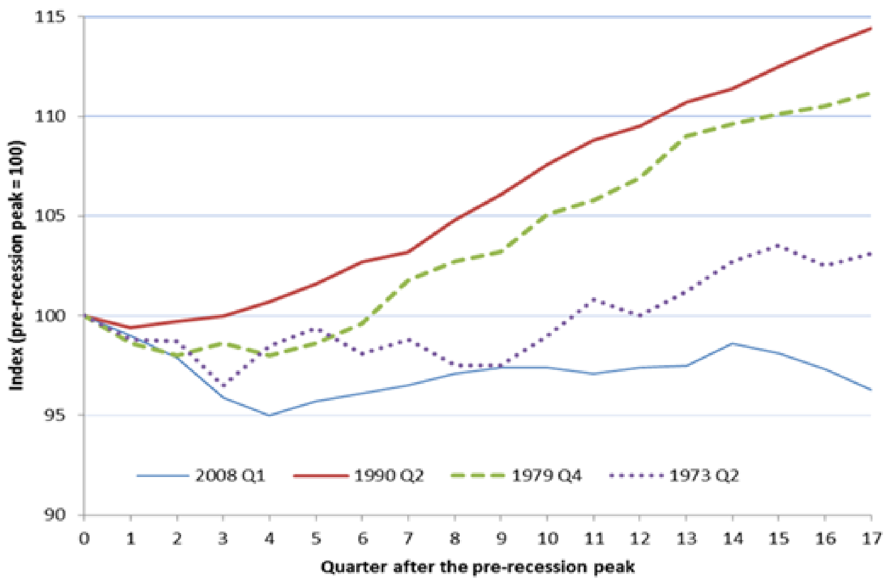
4.A Additional figures

Figure 4.A.1: **Whole Economy GDP per hour - Q2 2008=100**



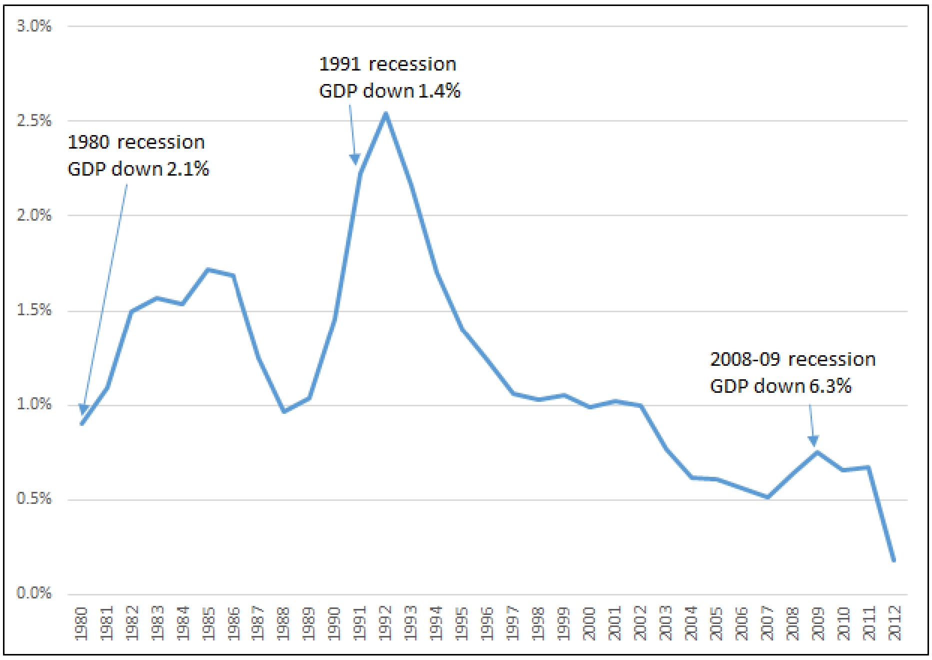
Source: Whole Economy GDP per hour, seasonally adjusted (Q2 2008 =100). ONS Statistical Bulletin, Labour Productivity, Q3 2014, downloaded 6th February 2015. Note: The predicted value after Q2 2008 is the dashed line and assumes a historical average growth rate of 2.3% per annum (the average over the period Q1-1979 to Q2-2008).

Figure 4.A.2: **UK labour productivity in post-war recessions**



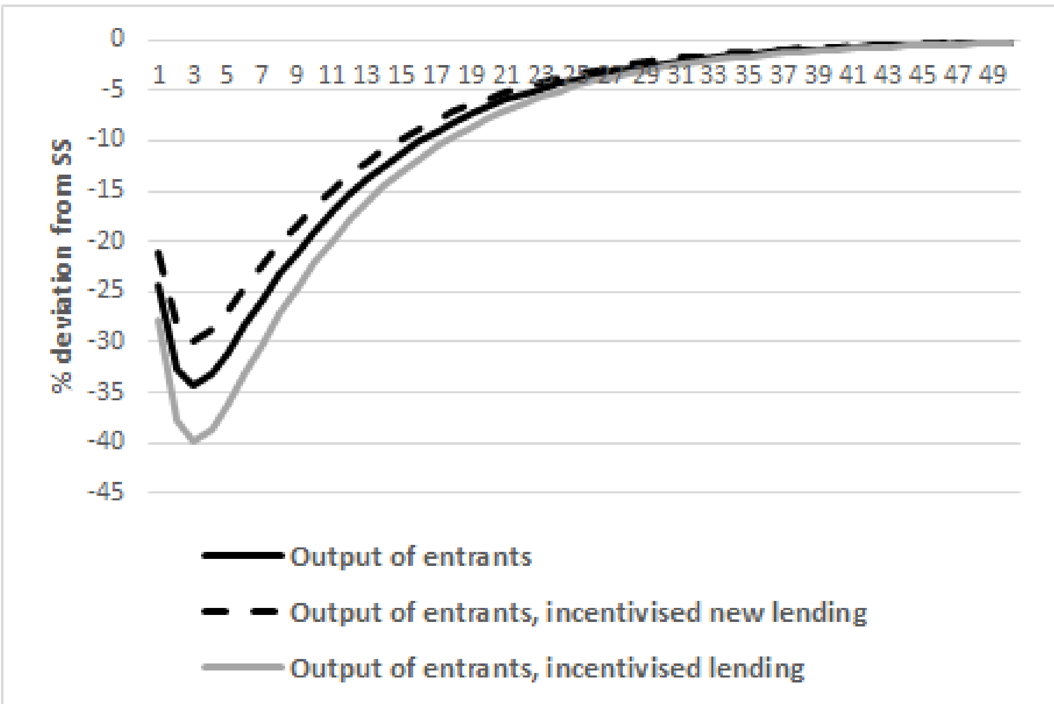
Source: ONS. Cumulative change in labor productivity over 17 quarters from the start of the downturn in major UK post-war recessions. UK productivity levels, output per worker, seasonally adjusted.

Figure 4.A.3: **Liquidations in England and Wales**



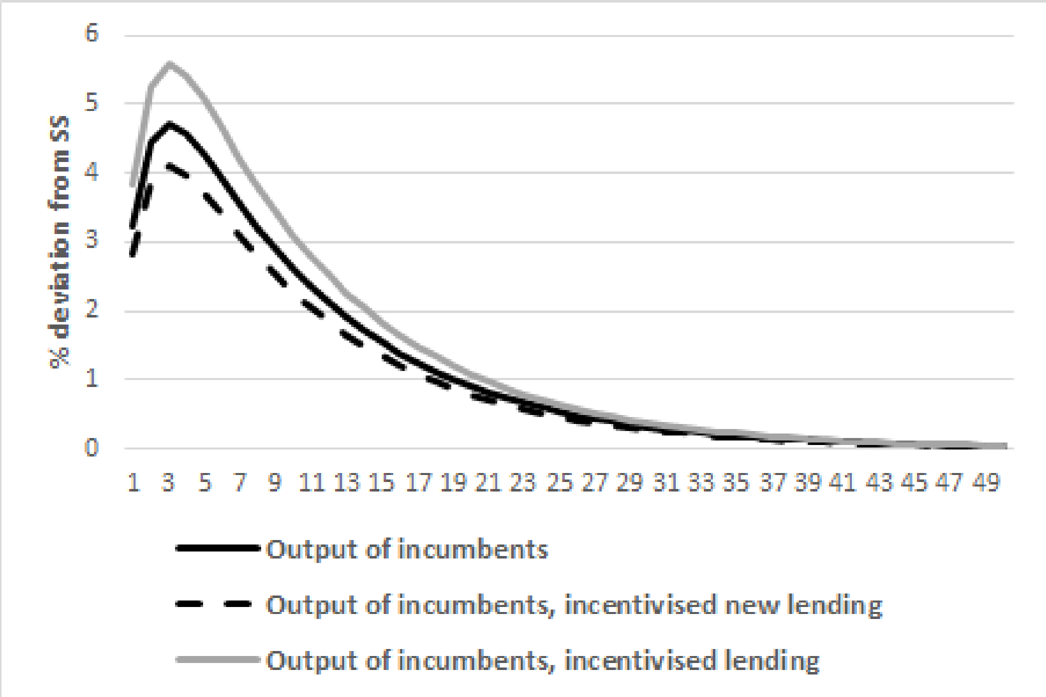
Source: Liquidations in England and Wales - % of active businesses, BIS, ONS, and Companies House.

Figure 4.A.4: **Output of entrants: Shock to** τ **with** $\sigma_\tau = 0.009$



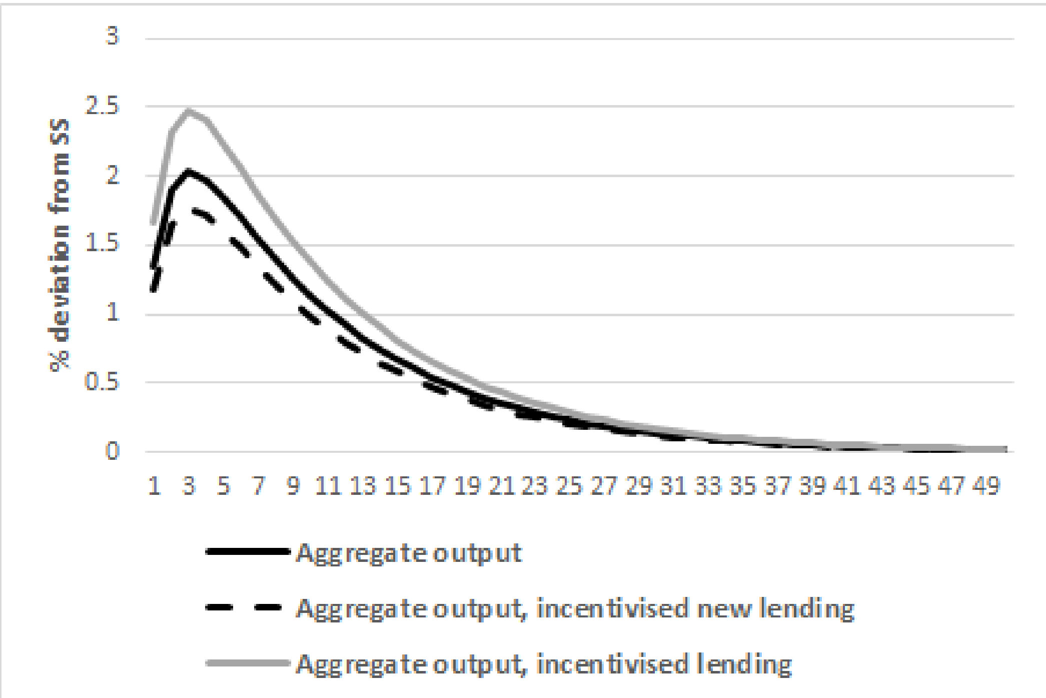
Note: IRFs of the output of entrants to a shock to the termination cost τ with $\sigma_\tau = 0.009$ under three policy scenarios. % deviations from steady state. Unit of time is one quarter. IRFs over 50 quarters.

Figure 4.A.5: **Output of incumbents: Shock to τ with $\sigma_\tau = 0.009$**



Note: IRFs of the output of incumbents to a shock to the termination cost τ with $\sigma_\tau = 0.009$ under three policy scenarios. % deviations from steady state. Unit of time is one quarter. IRFs over 50 quarters.

Figure 4.A.6: **Aggregate output: Shock to τ with $\sigma_\tau = 0.009$**



Note: IRFs of aggregate output to a shock to the termination cost τ with $\sigma_\tau = 0.009$ under three policy scenarios. % deviations from steady state. Unit of time is one quarter. IRFs over 50 quarters.