BACKGROUND PAPER

PRELIMINARY VERSION

THE AGGREGATE EFFECTS OF CREDIT MARKET FRICTIONS: EVIDENCE FROM FIRM-LEVEL DEFAULT ASSESSMENTS

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The Aggregate Effects of Credit Market Frictions: Evidence from Firm-level Default Assessments*

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Abstract

This paper develops an approach to studying the implications of credit market frictions for aggregate output and productivity. Using a model of credit contracts with moral hazard, we show that a firm's probability of default (PD) is a sufficient statistic for capital allocation. The theoretical framework suggests an aggregate measure of credit market inefficiencies based on firm-level probabilities of default. The most novel feature of the approach is that we can take the theory to the data using estimates of firm-level probabilities of default calculated with Standard and Poor's own algorithmic "PD Model" software. We use the UK as a case study as it was hit particularly hard by the 2008-09 Great Recession. We merge PD estimates with firm-level administrative data on output, employment, and investment and show a strong correlation between PDs and a firm's future survival, employment and investment. Using the theory and data, we find that credit frictions cause a loss of between 3% and 5% of GDP on average per year in 2004-12. These frictions increased during the crisis accounting for between 11% and 18% of the productivity fall in 2008-2009. The frictions also lingered after the Great Recession and account for around one fifth of the gap between actual and trend productivity by the end of 2012.

Key words: productivity, default risk, credit frictions, misallocation

JEL classification: D24, E32, L11, O47

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1 Introduction

The period following the financial crisis heightened awareness of the role of credit frictions in affecting economic efficiency, particularly the potential costs if capital is not allocated to its most productive uses. This paper develops a framework for studying credit frictions and capital allocation which can be applied to firm-level data. The UK, where we apply the model, is an excellent case study for three 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 (e.g. Kay, 2012; Besley and Van Reenen, 2013). Second, the UK's productivity performance has been consistently disappointing since the financial crisis.[1] Third, we have access to firm-level data on output, employment and investment decisions, as well as estimates of firm-level probabilities of default. This rich panel data set allows us to take our theory to the data, creating a unique perspective on the role of credit frictions both at the firm-level and in the aggregate.

Our approach is theoretically grounded and builds on the model of default risk when there is moral hazard from Besley et al (2012). It suggests 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. We then use a large administrative establishment-level panel data set, the Annual Business Inquiry and Annual Business Survey (ABI/ABS), which provide measures of value added, employment, and capital expenditures. The key innovation in the paper is to use an estimate of each firm's probability of default (PD) to take the theory to the data. We do so by using 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. The PD Model uses a combination of financial accounts data, industry, and macroeconomic factors to assess the credit risk of a company. Together with near-population data on private and publicly listed incorporated company accounts (from BvD Orbis) this allows us to construct a firm-specific time-varying financial friction measure which we can use to study company behavior and also to estimate measures of aggregate output loss using the underlying theory as a guide.

To validate the estimates from the PD model, we provide a micro-level analysis relating a firm's probability of default to its performance (e.g. capital investment, employment, value added, and the probability of survival). We then present a theory-based measure of aggregate credit frictions. We show how this can be calculated from firm-level data. The results suggest that credit frictions caused on average a 2.7% to 4.7% 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, helping

[1] The UK's official fiscal watchdog, the Office of Budget Responsibility (2017) recently downgraded its assumptions on underlying productivity growth citing the impact of the financial crisis (see also Pessoa and Van Reenen, 2014).

account for between 11% and 18% of the aggregate productivity fall. Moreover, these factors dragged on throughout the post-crisis period which helps account for the near stagnation of productivity in the recovery. We show that our approach can account for between 13% and 23% of the difference between actual UK productivity and its pre-crisis trend by the end of 2012.

Another feature of our approach is that it enables us to decompose the effect of credit frictions into a "scale effect" and a"TFP (total factor productivity) effect". The scale effect (based on average default rates) reflects how the aggregate capital stock is affected by credit frictions, while the TFP term shows how repayment probabilities vary across firms with differing levels of productivity. Following the ideas of Hsieh and Klenow (2009), the latter reflects "misallocation" of capital. We find that changes over time during and after the credit crisis are driven by scale effects rather than misallocation. We also show that credit frictions play a larger role in depressing output and labor productivity among small and medium sized enterprises (SMEs). This is consistent with SMEs being more dependent on bank financing and facing tighter credit constraints than larger firms. Interestingly, the aggregate deterioration following the financial crisis is driven almost entirely by increasing credit frictions for SMEs. Finally, the use of micro data allows us to look at sectoral heterogeneity. The increase in credit frictions is broad-based but the non-manufacturing sector was slightly more affected.[2] All three of these findings make use of the fact that we use firm-level data to look at the macro-economic picture.

Our approach follows the spirit of the literature on the aggregate consequences of firm-level distortions.[3] This literature shows how firm-specific distortions to output or input prices can lead to sizeable decreases in aggregate output and measured TFP by distorting the allocation of inputs (and hence the size of firms) and the selection of firms producing in the market. These approaches rely on model-based measures of firm-level distortions which can be estimated empirically and guide the empirical evaluation of the impact of those distortions on aggregate productivity. The measured distortions can result from a large number of frictions, including policy-induced frictions, for example labor 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 (2013) where 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

[2] Construction and hotels and restaurants were the worst affected by credit frictions on average. These were also two sectors in which the productivity slowdown was particularly strong.

[3] In addition to Hsieh and Klenow (2009, 2013) see among others Foster, Haltiwanger and Krizan (2002), Restuccia and Rogerson (2008), Bartelsman, Haltiwanger and Scarpetta (2013). Disney et al. (2003) look at UK manufacturing. For a GE treatment in the time series dimension see Baquee and Fahri (2017).

cost of lending to a particular firm.

A large literature focuses on the potentially severe macro-economic effects of financial crises (e.g. Reinhard and Rogoff, 2011). However, many authors remain skeptical about the role of financial mechanisms in explaining persistently low productivity after the Great Recession (e.g. Fernald et al, 2017; Brynjolfsson et al, 2017). Several recent micro-studies examine the role of the Great Recession in depressing productivity. Garcia-Macia (2017), de Ridder (2017), Garicano and Steinwender (2016) and Aghion et al (2010, 2012) stress the role played by the cut-back in productivity-enhancing investments (such as R&D). Some papers analyze the employment and investment effects of credit shocks using firm-level banker-lender relations, such as pre-crisis connections with Lehman Brothers (Chodorow-Reich, 2014).[4] There is also a vast literature examining the role of financial frictions on firm investment (for example, see Bond and Van Reenen, 2007, for a survey).

Our 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). In their framework capital frictions are reflected in the variance of the marginal product of capital as measured by the variance of the value added to capital ratio.[5] Our approach can be embedded in a standard model of firm heterogeneity to study how competition, funding costs, productivity, demand or asset value shocks affect aggregate output and productivity. The impact of these shocks is heterogeneous across firms and is summarized in each firm's equilibrium repayment probability. Other papers which have tried to incorporate financial frictions into equilibrium misallocation models include Midrigan and Xu (2012), Moll (2014) and Asker et al (2014). Our approach has less rich dynamics than these papers, but a much simpler structure which enables transparent analytical calculations of welfare losses.

The remainder of the paper is organized as follows. Section 2 presents a conceptual framework which models capital market imperfections as endogenous repayment probabilities. We show how this induces heterogeneity in the price of capital across firms, establishing a link between a firm's repayment probability and the level of its capital stock. In Section 3, we embed this framework in a model with heterogeneous firms and derive empirical implications at the firm-level and for the aggregate economy. In particular, we construct an aggregate measure of credit market frictions which we decompose into a scale and a TFP component. In Section 4 we combine a panel data set with firm-level data on employment, investment and value-added with an estimate of each firm's repayment probability (obtained using a credit-scoring model from Standard and Poor's). Section 5 presents our core results. First, we validate the use of repayment probabilities by looking at their correlations with a range of firm decisions. We then apply

[4] See also Acharya et al (2015), Amiti and Weinstein (2011), Bentolila et al (2015), Greenstone et al (2014), Huber (2017) and Manaresi and Pierri (2017).

[5] Gopinath et al (2017) exploit this idea in explaining declining TFP in Southern Europe which they link to the low interest rates following monetary union.

the theory to measure the effects of credit frictions on aggregate output, and decompose these effects into a scale and an allocation component. Section 6 discusses several additional results. First, we find significant differences between SMEs and large firms, both in the magnitude and time pattern of credit frictions. Second, we enhance the model with labor market frictions and show that the results are robust. Finally, we compare our approach to the measurement of credit frictions with a more conventional measure from the misallocation literature. Section 7 applies the framework to the UK productivity slowdown and Section 8 concludes. Online Appendix A gives further details on the data and Appendix B on the application of the theory.

2 Conceptual Framework

The model is based on Besley et al (2012) and gives a tractable way to motivate why the repayment probability is an important sufficient statistic for credit market frictions. Banks offer credit to firms which are heterogeneous in their productivity levels and balance sheets, the latter affecting their access to collateral.

2.1 Basics

Firms Firms produce using labor and capital and vary in their productivity, θ. Let

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

be a firm's conditional profit function when the wage is w and K is capital. We assume that $\Pi(\theta, w, K)$ is increasing in θ, decreasing in w, 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 variable θ could capture productivity in the conventional way but we can also think of firm-specific demand shocks being captured by variation in θ.

Below, we will work below with the specific functional form with a Lucas (1978) "span of control" model with production function:

$$Y = \theta \left(L^{1-\alpha} K^{\alpha}\right)^{\eta} \tag{1}$$

with $0 < \eta < 1$.[6] In this case, the conditional profit function has the following closed form:

$$\Pi(\theta, w, K) = [1-(1-\alpha)\eta]\, \theta^{\left(\frac{1}{1-(1-\alpha)\eta}\right)} \left[\frac{w}{(1-\alpha)\eta}\right]^{\frac{-(1-\alpha)\eta}{1-(1-\alpha)\eta}} K^{\left(\frac{\alpha\eta}{1-(1-\alpha)\eta}\right)}. \tag{2}$$

Firms also have assets A which can be pledged as collateral as well as being used productively.

Let $\phi \in [0,1]$ denote whether the firm produces successful and hence is able to repay any loan which has been made to it. We assume that this probability depends on managerial effort which costs $c(\phi)$, an increasing and convex function. Capital is committed up front and labor is hired once the default outcome has been realized. If the firm defaults, we suppose that it forfeits its assets A which serve as collateral.

Banks Banks offer loans to a firm tailored to its productivity and assets. However, we assume that ϕ is not observed so that there is a potential moral hazard problem. A credit contract is a pair $\{B, R\}$ comprising the amount borrowed, B, and an amount to repay, R. Hence $(R-B)/B$ is the interest rate. Since assets can also be used productively, a firm's capital stock is $A+B$.

Lenders can access funds, from depositors or the interbank market at rate $\rho > 1$. A bank's expected profit if lends to a firm with assets A and repayment probability ϕ is:

$$\phi R + (1-\phi) A - \rho B.$$

Hence with probability ϕ, the bank is repaid and receives R while with probability $(1-\phi)$ the bank seizes the firm's collateral.[7]

2.2 Lending Contracts

Each firm faces an outside option $U(\theta, A)$ which reflects what is available to the firm in the market place. Many lending relationships are relationship specific and hence there could be a premium from staying with an existing lender which could be modeled like a switching cost. We will suppose that initially each firm is "assigned" to a lender who offers terms relative to a fixed outside option. Below, we discuss how the outside option can be made endogenous. The timing is as follows:

[6] 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. See Hsieh and Klenow (2009, Appendix) for the close relationship between Lucas span of control models and monopolistic competition.

[7] 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.

1. Nature assigns each firm to a bank.

2. Banks offer credit contracts $\{B, R\}$ with given an outside option $U(\theta, A)$

3. The firm chooses ϕ.

4. Default occurs with probability $1 - \phi$ in which case the firm loses A.

5. If there is no default, then firms make labor hiring decisions and produce, repaying their loan.

We solve the model backwards. For simplicity, we focus on the case where the outside option of the firm always binds.[8]

Optimal ϕ (stage 3) The optimal effort (repayment probability) maximizes the expected profits of the firm given any credit contract $\{R, B\}$ that they are offered, i.e.

$$\phi \left[\Pi(\theta, w, A + B) - R\right] - (1 - \phi) A - c(\phi). \tag{3}$$

It is useful to define $f(z)$ from $z = c'(f(z))$. Then the first order condition for the optimal effort implies:

$$\phi = f(\Pi(\theta, w, A + B) - R + A) \tag{4}$$

which is increasing in profit and assets but decreasing in the interest payment. Throughout we will assume interior solutions.

Optimal Contracts (stage 2) The optimal credit contract solves

$$Max_{\{B,R\}} \left[\phi R + (1 - \phi) A - \rho B\right]$$

subject to

$$\phi \Pi(\theta, w, A + B) - R - (1 - \phi) A - c(\phi)$$

and (4). To solve this, note that with the outside option binding and (4), the interest payment solves

$$f(\Pi(\theta, w, B) - R^* + A) \left[\Pi(\theta, w, A + B) - R^* + A\right] - A = U(A, \theta).$$

Inverting this allows us to write the repayment as

$$R^* = g(U(A, \theta) + A) + \Pi(\theta, w, A + B) + A \tag{5}$$

[8]See Besley et al (2012) for an exploration of the case where this is not true.

with $\phi^*(A,\theta) = f(g(U(A,\theta)+A))$, i.e. the repayment probability is now pinned down by the asset level of the firm and its outside option. Thus, the model captures the reasons why we would have expected the repayment rate to fall in the financial crisis: (i) there could be factors which act directly on the function $f(\cdot)$ due to more challenging business conditions; (ii) a firm's balance sheets could deteriorate if asset values are marked down, i.e. a fall in A; and (iii) opportunities to switch to competing lenders are diminished e.g. due to higher switching costs as lenders are less keen for new business which would show up in a lower value of $U(A,\theta)$.

Plugging (5) into the bank's profit function gives an expression which depends only on B, the amount borrow:

$$f(g(U(A,\theta)+A))[g(U(A,\theta)+A)+\Pi(\theta,w,A+B)]+A-\rho B. \tag{6}$$

Maximizing 6) with respect to B yields the following key equation for the optimal allocation of capital:

$$\Pi_K(\theta,w,A+B^*(A,\theta)) = \frac{\rho}{\phi^*(A,\theta)}. \tag{7}$$

This says that the firm's marginal product of capital is set equal to the bank's risk-adjusted cost of funds.[9] Higher repayment means more capital, all else equal. Another way to think of this, following Gilchrist, Sim, and Zakrajsek (2013), is as an endogenously-determined firm-specific credit spread $\rho[(1-\phi^*(A,\theta))/\phi^*(A,\theta)] > 0$ if $\phi^*(A,\theta) < 1$ and which is decreasing in the repayment rate. It is the core equation for the allocation of capital that we use throughout the paper and provides a direct link between estimates of firm-level repayment probabilities and factor allocations.

The Outside Option Closing the model requires us to determine the outside option $U(A,\theta)$ endogenously. To do this, we adopt a simple approach which permits us to think how market conditions can matter. Specifically, we postulate a switching cost, κ, incurred of a firm moves to an alternative bank. So if $\kappa = 0$, switching is costless. To explore the implications of this, let

$$\pi^*(A,\theta:U) = \max_{B\geq 0}(f(g(U+A))[g(U+A)+\Pi(\theta,w,A+B)]+A-\rho B)$$

be the maximized profit of a lender facing an outside option U.

Now define $\tilde{U}(A,\theta)$ from $\pi^*\left(A,\theta:\tilde{U}(A,\theta)\right) = 0$,i.e. the outside option which generates zero profits for an alternative bank. This effectively defines the best possible terms that another bank would be willing to offer in order to attract a firm. We then suppose that the equilibrium outside option will be:

$$U(\theta,A) = \tilde{U}(A,\theta) - \kappa,$$

[9]Here we are implicitly assuming that $B^* > 0$, i.e. firms have insufficient assets to finance their own investment.

the firm earns a discount on its best outside option equal to the switching cost. If there is greater reluctance by lenders to take on new clients, modeled as the switching cost increasing, it will reduce $U(A,\theta)$. This lowers the firm's profit. However, it also has a "real" effect in our second best model since worsening the outside option reduces the repayment probability and hence reduces the amount of capital that any firm who borrows is allocated.

3 Empirical Implementation

The model highlights the role played by the endogenously determined repayment probability in affecting the allocation of capital. We now embed this idea in a model with heterogeneous firms and derive the implications of firm-specific credit frictions for firm behavior and aggregate output.

3.1 Firm-Level Implications

Let N_t be the population of firms active at date t with characteristics $\{\theta_{nt}, A_{nt}\}_{n=1}^{N_t}$. The production function of firm n at time t is:

$$Y_{nt} = \theta_{nt} \left(L_{nt}^{1-\alpha} K_{nt}^{\alpha}\right)^{\eta} \tag{8}$$

Although we only model credit market distortions endogenously, the empirical framework can allow for further distortions in allocation. Write the firm's profit function as:

$$\Pi_{nt} = Y_{nt} - \frac{w_t L_{nt}}{\tau_{nt}^{L}} - \frac{\rho_t K_{nt}}{\tau_{nt}^{K}}$$

where w_t is the wage and ρ_t is the cost of capital, both of which are common to all firms. Our theoretical model above derives credit market distortions endogenously. However, in principle, we can allow for arbitrary distortions $\left\{\tau_{nt}^{L}, \tau_{nt}^{K}\right\}$ in factor markets where $\tau_{nt}^{K} = \phi^{*}\left(A_{nt}, \theta_{nt}\right)$ in our model as detailed above. Lower values of τ_{nt}^{L} or τ_{nt}^{K} characterize more distorted factor markets. Output prices remain normalized to 1. Allowing a more general set of distortions in this way will allow us to test the robustness of our findings and to compare the results to the earlier literature on misallocation.

The first-order conditions for profit maximization deliver the following factor demands at price vector $\{w_t, \rho_t\}$

$$L_{nt} = \frac{(1-\alpha)\eta\tau_{nt}^{L}}{w_t} Y_{nt} \tag{9}$$

and

$$K_{nt} = \frac{\alpha\eta\tau_{nt}^K}{\rho_t} Y_{nt} \tag{10}$$

Substituting (9) and (10) into (8) and solving for Y_{nt}, we obtain

$$Y_{nt} = \theta_{nt}^{\frac{1}{1-\eta}} \psi(w_t, \rho_t) \tau_{nt} \tag{11}$$

where

$$\tau_{nt} \equiv \left(\tau_{nt}^L\right)^{\frac{(1-\alpha)\eta}{1-\eta}} \left(\tau_{nt}^K\right)^{\frac{\alpha\eta}{1-\eta}} \tag{12}$$

summarizes the impact of firm-specific distortions on firm-level output. As we shall see below, firm-specific distortions will also translate into a distorted aggregate wage level w_t. This macro-economic distortion will be reflected in $\psi(w_t, \rho_t)$:

$$\psi(w_t, \rho_t) \equiv \left(\frac{(1-\alpha)\eta}{w_t}\right)^{\frac{(1-\alpha)\eta}{1-\eta}} \left(\frac{\alpha\eta}{\rho_t}\right)^{\frac{\alpha\eta}{1-\eta}} \tag{13}$$

In a frictionless world, where $\tau_{nt}^L = \tau_{nt}^K = 1$ for all firms $n = 1, ..., N$, the output of a firm is solely determined by its fundamental productivity θ_{nt}, the technological parameters α and η, and the frictionless factor prices.

3.2 Aggregate Implications

Summing output across all firms in the economy yields:

$$Y_t = \sum_{n=1}^{N} Y_{nt} = \psi(w_t, \rho_t) \hat{\theta}_t^{\frac{1}{1-\eta}} \Theta_t$$

where $\hat{\theta}_t = \left(\sum_{n=1}^N \theta_{nt}^{\frac{1}{1-\eta}}\right)^{1-\eta}$ and $\omega_{nt} = \left(\frac{\theta_{nt}}{\hat{\theta}_t}\right)^{\frac{1}{1-\eta}}$ are relative productivity weights that add up to one at each point in time, i.e. $\sum_{n=1}^N \omega_{nt} = 1$ and

$$\Theta_t = \sum_{n=1}^{N} \omega_{nt} \tau_{nt}. \tag{14}$$

The quantity Θ_t represents factor market distortions and is the key theoretical concept that we want to measure in the data. It is equal to one only when there are no credit or labor market distortions. In our set-up, the absence of credit market frictions means that all firms repay their loans with probability one.

Finally, suppose that ρ_t is determined in global capital markets. With exogenously fixed labor supply L, the equilibrium real wage solves

$$w_t = \frac{(1-\alpha)\eta\psi(w_t,\rho_t)\hat{\theta}_t^{t\,\frac{1}{1-\eta}}\Theta_t}{L}. \tag{15}$$

Thus, our measure of aggregate distortions also has implications for the equilibrium wage.

Having a theoretical framework in which output and wages are determined endogenously will allow us to derive a counter-factual level of output associated with any reference level of distortions $\left\{\hat{\tau}^K, \hat{\tau}^L\right\}$ and an associated "reference efficiency level" $\hat{\Theta}_t$. A special reference point is an undistorted economy where $\tau_{nt} = 1$ for all firms at each t, and hence $\hat{\Theta}_t = \hat{\Theta} = 1$. This would be the case when there are no credit frictions (in our set-up there is no default in credit markets) and labor markets work perfectly so as to equalize the marginal product of labor across firms.

Associated with a reference level of distortions will be a counter-factual level of output, $\hat{Y}_t$. It is straightforward to show that the deviation of actual output from its reference level is then given by:

$$\frac{\hat{Y}_t - Y_t}{\hat{Y}_t} = 1 - \left[\frac{\Theta_t}{\hat{\Theta}_t}\right]^{\frac{1-\eta}{1-\alpha\eta}}. \tag{16}$$

Thus $\frac{\Theta_t}{\hat{\Theta}_t}$ is a sufficient statistic for the aggregate output loss in the economy due to factor market imperfections.

The aggregate effect of factor market distortions can usefully be decomposed into two parts. The first is an aggregate "scale effect" which reflects the impact of credit frictions on the aggregate capital stock. In the case of the financial crisis this would reflect how perceptions of default in the economy affect all firms and lenders. Reducing aggregate distortions induces capital deepening and therefore higher output. The second term reflects how factor market distortions covary with the productivity levels of firms. In our theoretical model this is determined by how repayment probabilities vary with firm-level productivity. We call this a "TFP effect" since, in an accounting sense, it determines how a given stock of aggregate capital and labor are utilized. This parallels precisely the concerns in the recent literature on misallocation as in Hsieh and Klenow (2009).

To state this decomposition more precisely, write:

$$Y_t = TFP_t \times SCALE_t \tag{17}$$

where

$$
\begin{aligned}
TFP_t &= \hat{\theta}_t \left[\frac{\sum_{n=1}^{N} \omega_{nt}\tau_{nt}}{\left(\sum_{n=1}^{N} \omega_{nt}\tau_{nt}\tau_{nt}^{L}\right)^{(1-\alpha)\eta} \left(\sum_{n=1}^{N} \omega_{nt}\tau_{nt}\tau_{nt}^{K}\right)^{\alpha\eta}} \right] \equiv \hat{\theta}_t \Theta_t^T & (18) \\
SCALE_t &= \hat{\theta}_t^{\frac{\eta}{1-\eta}} \psi(w_t, \rho_t) \left(\sum_{n=1}^{N} \omega_{nt}\tau_{nt}\tau_{nt}^{L} \right)^{(1-\alpha)\eta} \left(\sum_{n=1}^{N} \omega_{nt}\tau_{nt}\tau_{nt}^{K} \right)^{\alpha\eta} \equiv \hat{\theta}_t^{\frac{\eta}{1-\eta}} \psi(w_t, \rho_t) \Theta_t^S & (19)
\end{aligned}
$$

Then the overall distortion in output above can be written as $\Theta_t = \Theta_t^S \Theta_t^T$. Below, we will estimate both of these terms and examine how they have changed over time.

4 Data and Measurement

In this section, we describe our data sources and show how the magnitudes suggested by the model can be measured empirically.

Firm Productivity and Size Our main sources of micro data are the Annual Business Inquiry and the Annual Business Survey (ABI/ABS). These are establishment-level business surveys conducted by the UK Census Bureau (the Office for National Statistics or ONS) that are used in the construction of various national account aggregates for the UK.[10] The sampling frame is the Inter-Departmental Business Register (IDBR) which is a business register of all UK establishments. An "establishment" or "firm" is defined as the business unit to which survey questionnaires are sent (called the "reporting unit"). In most cases, the reporting unit is the same as an "enterprise", defined by the ONS as "the smallest combination of legal units, which have a certain degree of autonomy within an enterprise group"[11].

The ABI/ABS surveys are a census of larger businesses and a stratified (by industry, region and employment size) random sample of businesses with fewer than 250 employees (SMEs). The surveys comprehensively cover the entire private sector from 2002 onwards and some sectors, such as manufacturing, back to 1979. We focus on what is often called the non-financial "market sector" - i.e. dropping agriculture, mining and quarrying and utilities as well as sectors where output is particularly hard to measure - education, health care, financial services, real estate and non-profit organizations. Sampling weights are applied to ensure that our results are representative of aggregate productivity developments (see Appendix A.1 for more details on

[10] See Barnett et al (2014) and Riley et al (2015) for useful discussions of these datasets 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.

[11] A small number of large enterprises with a more complex structure have several reporting units. The surveys also contain data for "local units", which are sub-units of a reporting unit. These local units correspond to what is usually understood as "plants".

the sampling frame and weights). Table 1 shows the number of employees in the market sector. We cover on average 15.6 million employees per year, roughly split in half between SMEs and larger firms. Tables A1 and A2 give more details about this population of firms.

We measure labor productivity as real gross value added (GVA) per employee using industry producer price deflators. Survey data are subject to measurement error and we therefore take two steps to ensure that our results are not driven by extreme values. First, we drop the top and bottom 1% of the labor productivity distribution in the ABI/ABS market sector sample (as in Riley et al, 2015). Second, we work with winsorized data (top and bottom 1% of each variable). We construct capital stock estimates 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 A.2 for details).

Financial Statements and Default Probabilities A unique feature of our study is that we use data on estimates of firms' repayment probabilities ϕ_{nt}. In order to estimate ϕ_{nt}, we use financial statement data from Bureau Van Dijk's (BvD) Orbis database in combination with S&P's "PD Model". The PD (Probability of Default) Model is a 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 publicly firms. Financial inputs include *inter alia* total assets, cash on the balance sheet, pre-tax profits (EBIT), and total liabilities (See Appendix A.3). The model 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 primary output is the one-year probability of default estimated using data on actual defaults provided by various regulators. The one-year probability of default is the probability that a firm will default on its credit obligations within one year. The actual default rates used in the calculations are averages by risk category which incorporate a long history of observed defaults up to the present. This is potentially problematic as it means that the estimation of probabilities of default in, say, 2007 will incorporate observed default rates post-2007. Since 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 do not want to incorporate data on observed defaults after the year of each observation. In order to compute historical probabilities of default, we make use of risk scores and historical default data. PD Model maps the one-year default probabilities into risk scores (called "implied credit worthiness") using forward-looking expectations.[12] The credit worthiness is expressed using S&P's traditional rating symbols, ('triple A' = aaa, 'triple B' = bbb, etc.). We map these scores into "historical

[12] These are derived from S&P's publications "Corporate default studies".

PDs" using backward-looking CreditPro data. The historical default data incorporate observed default rates by risk category in the entire universe of firms rated by S&P up to each year in our sample, i.e. from 1980 up to 2005 for 2005 perceived PDs, from 1980 up to 2006 for 2006 perceived PDs, etc.[13]. We work with repayment probabilities in percentages which are simply equal to 100 minus default probabilities. The financial data and the default probabilities were linked to our ABI/ABS data set by the UK Data Service (see Appendix A.3 and Table A3).

Figure 1 shows the evolution of the 'aggregate probability of default' of UK firms according to our data. It is a weighted average of industry-level aggregate probabilities of default where the weights are industry employment shares. The industry-level aggregate probability of default is itself a weighted average of firm-level probabilities of default in the industry using sampling weight adjustments. The data show that default probabilities are systematically higher for SMEs - consistent with the idea that lenders regard SMEs as riskier.[14] Second, the time series pattern suggests that there is a tendency for default probabilities to increase among SMEs throughout the period 2004-2012 and 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 followed by a recovery. Figure 2 presents an alternative look at the data. We regress probabilities of default on year dummies (with 2004 as our base year) controlling for three-digit industries. This shows that there is an increase in default probabilities estimated from the PD model for all firms after 2007, which is statistically significant. It is also largely driven by SMEs which motivates looking at differences between large firms and SMEs in the analysis of the data below.

The increase in default probabilities in our sample reflects the deterioration of credit conditions faced by UK firms during and after the financial crisis. All of the effects suggested by the model are likely to have been at work. First, banks' funding conditions deteriorated, represented by a increase in ρ, due to stress in inter-bank markets. The average annual CDS premium for the 6 major UK banks stood at 21.34 basis points in 2007 and peaked at 211.28 basis points in 2012.[15] The true cost of granting new loans is likely to have been even higher due to the need to repair balance sheets and adhering to stricter capital requirements. Second, the valuation of commercial real estate saw a sharp decline during the crisis, which can be thought

[13]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.

[14]This is implied by our model as they have a lower value of θ_{nt} and are also likely to have weaker balance sheets, low A_{nt}.

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

of as a fall in A. According to Benford and Burrows (2013), by the end of 2007 commercial real estate loans accounted for more than a third of the stock of lending to UK private non-financial companies by UK-resident banks.[16] Third, competition in the UK banking sector was negatively affected during the crisis. Concerns about the effectiveness of competition in the retail lending market are long-standing and the financial crisis exacerbated this through mergers and exits from the market.[17] In 2010, concentration was higher than before the crisis in many retail banking sub-markets, including SME banking (Independent Commission on Banking, 2011). [18]

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 and a repayment probability for each firm.[19] We have on average 24 thousand establishments per year. Large establishments (250 employees or more) make up on average around 18% of the sample and 89% of employment. While the core sample covers on average 66% of firms in the ABI/ABS market sector, it covers 97% of total employment. Since our sample is a census of large firms but a stratified random sample of SMEs, we correct for the over-representation of large establishments using sampling weights. The ABI and ABS surveys contain grossing weights which reflect the survey design (See Appendix A.1 for more details). We use those weights and adjust them further for the extra selection created by our data requirements.

Estimating Aggregate Distortions Θ_t How can we estimate aggregate distortions from equation (14)? In our core results, we will ignore the possibility of labor market distortions, i.e. set $\tau^L_{nt} = 1$ and focus on credit market distortions as measured by our PD Model estimates (we then consider allowing labor market distortions in the extensions). We first disaggregate across industries (which we index by j) to calculate industry-specific distortions Θ_{jt}. We then compute industry size-weighted aggregates Θ_t to obtain macro-economic effects.

The repayment probabilities are obtained using the method detailed in the previous subsection. In addition, we need to measure relative productivity (ω_{nt}) at the firm level. We can

[16] That the availability of pledgeable assets plays a role in affecting corporate investment is also argued, for example, in Gan (2007) and Chaney, Sraer and Thesmar (2012).

[17] 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). During the crisis, the mergers of Lloyds TSB with HBOS and Santander with Alliance & Leicester eliminated the strongest challengers identified by the OFT before the crisis.

[18] As we discuss further below, falls in θ may also reflect reductions in demand which affect the relative price of the firm's goods.

[19] The requirements on capital stock estimates mean that we lose 88,269 observations from the entire ABI/ABS market sector over the entire sample period 2004-2012. In addition, about 22% of valid ABI/ABS establishments are not directly matched with a repayment probability, so these are imputed (see Data Appendix for details). The results are robust to not imputing any data on repayment probabilities.

do so with two different approaches. First, we can compute Solow residuals using data on value added, the wage bill, and our capital stock estimates. However, using Solow residuals might not be appropriate as this would deliver a measure of revenue productivity ("TFPR") rather than quantity-based productivity ("TFPQ"). In addition, there are many measurement issues with firm-level data, particularly as regards calculating the capital stock (e.g. De Loecker and Collard-Wexler, 2016). The second approach only relies on employment data, which are more accurately measured than capital stocks. It is the one we use in our baseline results. This approach uses the theoretical structure of the model to obtain an estimate of underlying TFP without using information on the wage bill, capital or value added. Specifically, using Equations (9), (11), and (15), we can write a firm's employment share in total industry employment as

$$\gamma_{njt} = \frac{L_{njt}}{\sum_{n=1}^{N_{jt}} L_{njt}} \tag{20}$$

where L_{njt} denotes the employment of firm n in industry j at time t. Using our model, it is easy to show that with $\tau_{nt}^{L} = 1$, this is equivalent to

$$\gamma_{njt} = \frac{\omega_{njt}\phi_{njt}^{\frac{\alpha\eta}{1-\eta}}}{\Theta_{jt}}. \tag{21}$$

Hence, we can estimate relative firm-level productivity using the following equation:

$$\omega_{njt} = \frac{\gamma_{njt}\Theta_{jt}}{\phi_{njt}^{\frac{\alpha\eta}{1-\eta}}} \tag{22}$$

In other words, relative productivities can be teased out from the data by adjusting the observed employment shares for firm-specific frictions and the aggregate impact of firm-specific frictions. In our analysis, we will work with firms' average employment.

The final issue we need to deal with concerns sampling adjustments. Putting it all together, we proceed as follows. Denote the sampling weight of firm n in year t with ξ_{nt} [20]. Let $\tilde{\gamma}_{njt}$ be the employment share of firm n in industry j at date t in total employment, adjusted for the firm's sampling weight ξ_{nt}, defined as

$$\tilde{\gamma}_{njt} = \frac{\xi_{nt}\bar{L}_{nj}}{\sum_{n=1}^{N_{jt}} \xi_{nt}\bar{L}_{nj}} \tag{23}$$

where $\bar{L}_{nj}$ denotes the average employment of firm n in industry j over the entire sample period. With $\tau_{nt}^{L} = 1$, then

[20] A firm's sampling weight represents the inverse of its sampling probability.

$$\tilde{\gamma}_{njt} = \frac{\omega_{njt}\phi_{njt}^{\frac{\alpha\eta}{1-\eta}}}{\Theta_{jt}}. \tag{24}$$

Given our estimates $\hat{\phi}_{nt}$ from the PD model, we can estimate firm-level productivity using the following equation:

$$\hat{\omega}_{njt} = \frac{\tilde{\gamma}_{njt}\hat{\Theta}_{jt}}{\hat{\phi}_{njt}^{\frac{\alpha\eta}{1-\eta}}} \tag{25}$$

Since $\sum_{n=1}^{N} \hat{\omega}_{njt} = 1$, we can write $\hat{\Theta}_{jt}$ entirely in terms of observables as

$$\hat{\Theta}_{jt} = \left[\sum_{n=1}^{N_{jt}} \left(\frac{\tilde{\gamma}_{njt}}{\hat{\phi}_{njt}^{\frac{\alpha\eta}{1-\eta}}}\right)\right]^{-1}.$$

Finally, we use industry employment shares to obtain an estimate of $\hat{\Theta}_t$. Specifically, we write $\hat{\Theta}_t = \sum_{j=1}^{J} \chi_{jt}\hat{\Theta}_{jt}$, where χ_{jt} is industry j's share of aggregate market sector employment at time t.

We also have to calibrate some parameters. For the degree of returns to scale we assume $\eta = \frac{3}{4}$ (Bloom, 2009 and Garicano et al, 2016 use this as their baseline value for example). For the output-capital elasticity we use $\alpha = 1/3$ in all industries as is standard, but we also examine the sensitivity of our resuts to industry-specific factor shares estimated from our data.

5 Core Results

We look at the evidence in two steps. We begin by looking at the firm-level implications of credit market frictions. Specifically, we investigate how the repayment probabilities correlate with firm-level behavior. We then use the data to examine the aggregate effects of credit frictions.

Firm-level Outcomes Looking at firm-level outcomes will serve to validate the use of the PD model in explaining firm behavior and underline its relevance as a measure of firm-level access to credit. We look at several firm-level variables including employment, value-added, the capital stock, investment (as measured by net capital expenditure), total assets, fixed assets and empirical survival rates. We estimate the following empirical model for firm n in industry j at date t:

$$\ln(y_{njt}) = \beta\phi_{njt}(x_{nj,t-1}) + a_n + \tau_t + \varepsilon_{njt}. \tag{26}$$

where y_{njt} is the performance outcome, ϕ_{njt} is the firm's predicted repayment probability at t using the PD model parameters and information on the firm available at $t-1$ ($x_{nj,t-1}$), a_n are either industry fixed effects or firm fixed-effects, τ_t are year dummies and ε_{njt} is an error term that we allow 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.

We begin by estimating equation (26) using only industry dummies in Panel A of Table 2. In Panel B, we include firm fixed-effects, which means that we identify the correlation with the repayment probably solely from how ϕ_{njt} changes within firms over time.[21] This specification effectively controls for all sources of persistent heterogeneity at the firm level and hence is quite demanding. We use a consistent sample of firms for which all the regressors are available. Across both panels, there is a consistently positive correlation between the expected repayment probability and the various performance variables. With the exception of column (7) in Panel B, all of the correlations are highly significant. Hence, a higher repayment probability is associated with higher employment, greater investment and a larger capital stock.

Across eight of the nine outcomes the coefficient on the repayment probability is larger in Panel A than in Panel B of Table 2, which is consistent with the fact that ϕ_{njt} is correlated with unobserved productivity differences. The coefficients are non-trivial in an economic as well as a statistical sense. For example, a ten percentage point increase in the repayment probability is associated with a 9.6% (1 - exp(0.913)) increase in investment (column (4) Panel B) and a 6.3% increase in value added (column (2)).

The findings in Table 2 are robust to a large number of alternative ways of looking at the data. In Table A4, we allow for the sample size to vary across dependent variables to maximize the number of observations. Finally, Table A5 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 magnitude of the correlation coefficient). In a fully dynamic model, it is possible that firms can reschedule their debts rather than disappearing completely.

Taken together, these results are consistent with the role of the default probability in affecting firm-level behavior as suggested by the theory. Firms with high default probabilities will tend to have less access to capital and therefore be smaller, 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 most of the firm outcomes are drawn (ABI/ABS).

[21] 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.

Aggregate Outcomes We now turn to the analysis of the macroeconomic effects of credit frictions by estimating $\hat{\Theta}_t$ based on the PD estimates. This is the key determinant of the output losses due to credit market distortions. It therefore gives an insight into how important default assessments are in affecting output, both through their impact on the aggregate capital stock in the economy and on the allocation of capital across firms.

Our baseline estimates of $\hat{\Theta}_t$ are in Table 3 which gives an estimate for each year in our sample. These estimates use a calibrated labor share of two thirds and our estimates of relative firm-level productivity using data on employment. Column (1) is the core estimate of $\hat{\Theta}_t$ using Equation (14) while Column (2) gives our estimates of the associated output losses according to Equation (16). The results show that credit frictions due to default risk weigh significantly on aggregate output, with Column (2) suggesting that aggregate UK output would have been between 3% and 5% higher in every year over our sample period in the absence of default risk. Table 3 also gives some insight into how aggregate credit frictions as captured by our estimate of $\hat{\Theta}_t$ vary over time. The striking finding in Column (1) is that credit frictions have worsened, particularly following the onset of the financial crisis in 2007. This makes sense given what we saw in the time path of default assessments from the PD model. Overall, we estimate that in 2012 output was 5.3% lower than it would have been in the absence of these frictions compared to 3.2% in 2004. Had default risks remained at their 2007 level, output would have been close to 2% higher in 2012, amounting to roughly 18% of the gap between actual and trend output by the end of 2012.

We also use Equation (17) to decompose the aggregate credit frictions into SCALE and TFP effects. The results from this decomposition are displayed in Columns (3) to (6) of Table 3. The SCALE effect in Columns (3) and (4) reflects how the aggregate capital stock in the economy has, according to the model, been affected by default risk while the TFP effect displayed in Columns (5) and (6) reflects how default risk varies with firm-level productivity. The results show that the SCALE effect is driving most of the aggregate effects of credit frictions in the UK. In other words, it is the aggregate probability of default rather than the way in which default probabilities are distributed across firms of different productivity levels which drives the output loss from credit market distortions. Moreover, it is also striking that changes in the TFP term over time are responsible for very little of the worsening in credit frictions following the financial crisis. This suggests that misallocation of credit is not particularly important in the UK and that most of the action is in "capital shallowing". This makes sense since our theory predicts that more productive firms will all else equal be privileged in their access to capital (except to the extent that there are highly productive firms with weak access to collateral). However, the financial crisis was associated with increased concerns about default risk at all productivity levels.

Although the exact magnitude of the output losses depends on the estimation method, the range of results and their time series patterns are robust. In Appendix Table A6, we use empirical industry-specific wage bill shares to measure α_j instead of assuming a constant α common to all industries (see Appendix B.1). The magnitude of the output losses is on average lower (2.7% on average).[22] Table A6 continues to make use of the employment data to retrieve firm-specific productivity as in Equation (25). In Table A7, by contrast, we use simple Solow residuals (see Appendix B.1) to retrieve relative firm-level productivity (and use the common capital share, α across industries as in the baseline). In this case, the magnitude of the output losses is on average larger than our baseline estimates in Table 3 (4.7% on average). This gives us a range of between 2.7% and 4.7% losses on average per year. The time series patterns of credit market frictions, as well as the relative importance of the scale and TFP components, are robust across estimation methods.

6 Further Results

In this section, we present some further results, both to provide further insights into the patterns observed in the data and to assess the robustness of the results against other ways of measuring credit market frictions.

SMEs versus Large Firms Since the estimates are computed from micro-data, we can disaggregate them in a variety of ways. One particularly interesting distinction is between small and larger firms. We would expect small firms to face a much more challenging environment in accessing credit, as reflected in their higher default assessments by lenders. We have already seen from Figure 1 that there are substantial differences in the default probabilities of large and small firms, including how they have evolved since the financial crisis.

To explore this empirically, Table 4 reports results which disaggregate Θ_t into two sub-groups reflecting firm size (See Appendix B.2 for more details on the decomposition). Table 4 reports the baseline results assuming that $\alpha = 1/3$. The left hand panel contains estimates for SMEs while the right hand panel is for large firms. The results show that, as we would expect from Figure 1, the output losses due to credit frictions among SMEs are much greater than for large firms, being almost twice the size for SMEs (4.9% compared to 2.7% for large firms).

Moreover, worsening credit frictions appear to be mainly due to increased default risk for SMEs. In 2004 the effect of such frictions was a 3.6% output loss for SMEs and 2.3% for large firms, but by 2012 the size of the effect had risen to 6.3% and 3.2% respectively. In both cases, output losses remain larger in 2012 than they were pre-crisis, but the deterioration is clearly more severe for SMEs. This is consistent with evidence from Armstrong et al (2013) that SMEs

[22] This is primarily because the average empirical capital share is around 0.25, lower than our (standard) assumption of $\alpha = 1/3$, rather than being due to cross-industry heterogeneity.

faced severe credit constraints during the crisis and the fact that large firms are typically less credit constrained. Although the exact magnitude of the results vary, these conclusions are robust to alternative estimation methods (using empirical labor shares in each sector instead of a common value of α and using Solow residuals to estimate firm-level productivity).

Adding Labor Market Distortions We have so far focused on the case where the only factor market distortion is due to perceived default risk in credit markets. We now add the possibility of labor market distortions in order to see whether this changes the estimates of the output losses attributed to credit frictions. Although there are good reasons to expect labor markets to be imperfect (e.g. adjustment costs and search frictions), we do not have direct measures of these frictions. Instead, we infer them from the data by using the fact that, from the firms' first-order conditions, the firm-level distortion is given by

$$\tau_{nt}^{L} = \frac{w_t L_{nt}}{(1-\alpha)\eta Y_{nt}} \tag{27}$$

This estimation method parallels the traditional approach that has been taken in the literature on misallocation. A convenient feature of (27) is that it can be estimated from firm-level data on the wage bill and value-added. Since we do not have a direct measure of τ_{nt}^{L}, our measure is sensitive to measurement error in L_{nt}/Y_{nt}. We combine firm-level estimates from Equation (27) with our measure of credit market distortions (default risk) to construct a measure of total distortions τ_{nt} faced by each firm as in Equation (12).

Our main interest is not to measure the importance of labor market distortions *per se* but to see whether adding this possiblity affects our core results on the importance of credit market distortions. Hence, this is a robustness check on the core findings. The thought experiment that we undertake is to set $\tau_{n}^{K} = 1$, i.e. eliminate credit market distortions, while keeping labor market distortions in place. It is important to bear in mind that the impact of allowing for labor market frictions on our estimates of output losses due to credit market frictions is not clear *a priori* and will depend in part on how the estimates of labor and credit market distortions are correlated in the data.[23]

The results from this exercise are in Table 5 which parallels the core results in Table 3. It shows that, while labor market distortions do (as expected) increase the magnitude of the overall efficiency loss considerably (Columns (1), (3), and (5)), the effect of credit distortions on

[23] To be consistent with the theory, Tables 5 and 6 use revised estimates of firm-level productivity from the data on employment shares. Given, any estimates of $\{\tau_{nt}^{L}, \tau_{nt}^{K}\}$, Equation (24) generalizes to

$$\tilde{\gamma}_{njt} = \frac{\omega_{njt}}{\Theta_{jt}} \tau_n \tau_{nt}^{L}$$

which, as above, can be used to back out Θ_{jt} and ω_{njt} using the condition $\sum_{n=1} \omega_{njt} = 1$.

output is not materially different from the core results (Columns (2), (4), and (6)). Thus, our assessment of the importance of credit frictions due to default risk is not materially different if we assume that labor markets are not perfect. The conclusions in Table 5 are also robust to alternative estimation methods (i.e. using empirical labor shares in each sector instead of a common value of α and using Solow residuals to estimate firm-level productivity).

An Alternative Measure of Capital Market Distortions A virtue of our approach is that we study a specific aspect of credit market frictions, which we can measure directly. However, it would be reasonable to argue that there could be a lot more to capital market imperfections than what our measure of default risk captures. It is therefore interesting to compare the magnitude of credit frictions as measured here to estimates obtained using the approach adopted in the misallocation literature. This approach begins from the observation that the first-order condition for the optimal capital stock yields the following equation for the capital market distortion:

$$\tau_{nt}^{K} = \frac{\rho_t K_{nt}}{\alpha \eta Y_{nt}}. \tag{28}$$

With a suitable estimate of the capital stock and firm-level value added, this equation can be used to estimate of τ_{nt}^{K} (see Appendix A.2). Measuring capital market frictions this way provides a point of comparison with the approach taken in, for example, Hsieh and Klenow (2009). We focus on the manufacturing firms in our sample for this comparison exercise. The misallocation literature has traditionally focused exclusively on manufacturing. In part this is because capital stocks and value added are likely to be better measured in manufacturing than in other sectors (although they remain far from perfect). This alternative approach has pros and cons compared to ours. One the positive side, it can (in principle) capture a wider range of factors which influence capital market distortions, such as adjustment costs, and policy-induced distortions, such as idiosyncratic capital taxes and subsidies. Moreover, there can be error in our measure of ϕ_{nt} since it is only an estimate of the firm's default risk and lenders could use other information which we do not observe. On the negative side, all of the measurement error in Y_{nt} and K_{nt} is now attributed to factor market distortions.[24] But, at the very least, it provides an important point of comparison for our results.

As a first point of comparison, we compute τ_{n}^{K} based on Equation (28) for manufacturing firms and compare it to our estimates of ϕ_{nt}. The magnitudes are very different with the

[24] This is a major issue. White, Reiter and Petrin (2017) show that even in the high-quality US Census of Manufacturing, around three quarters of firms have some aspect of the elements underlying TFPR calculations imputed - which severely reduces the true level of productivity dispersion. Rotemberg and White (2017) show that trimming outliers lowers measured misallocation in Indian data compared to the US - and therefore argue that the conclusions in Hsieh and Klenow (2009) are very sensitive to standard data cleaning procedures. Finally, Bils, Klenow and Ruane (2017) argue that there has been a huge increase in measurement error in the plant-level US TFPR numbers over time.

quantity-based approach yielding an average τ_n^K which is around 0.14 compared to an average repayment probability of 0.89. Another way to think of this is that default risk is only about 16% of total distortions. In other words, the quantity-based approach suggests that capital market frictions are much larger than suggested by default risk. This is not unexpected as the quantity-based measure will encapsulate a range of frictions beyond default risk. However, the difference will also be driven by measurement error. There is also a much larger dispersion in the quantity-based measures of firm-level frictions. These results suggest that we should find much larger losses when we measure distortions using capital stock data. If we regress the quantity based measure on the repayment rate, it is reassuring to find that they are positively correlated although the R^2 is low (0.06). The coefficient is 3.32 and the (robust) standard error is 0.29. The correlation is significant at the 1% level.

Appendix Table A8 repeats the analysis of Table 3 for manufacturing only. The results are largely in line with our earlier findings although the overall size of distortions is smaller (and the estimates of the TFP effect are even smaller still). Table 6 presents estimates of Θ_t and the associated output losses in manufacturing relying exclusively on quantity-based measures for labor and capital market distortions. Table 6 is compared to Table A8. The magnitudes of the distortions due to factor market frictions in Table 6 are now very large, as expected. They imply that if capital market distortions could be removed completely, then output in manufacturing would be 43% to 45% higher. In line with the core results in Tables 3 and A8, the numbers are generally much higher for the scale term compared to the TFP term. However, both are quite substantial. As with our earlier analysis, capital distortions appear to be getting worse over time in Table 6: over 2 percentage points more output are lost at the end of the period than at the beginning of the period. However, the impact of the financial crisis is much less visible here than in our analysis where credit market frictions are measured by default risk.[25]

These findings are in line with Gilchrist, Sim, and Zakrajsek (2013) who use data on credit spreads in a sample of US manufacturing firms to create a firm-specific price of capital. They too find much lower TFP losses using this approach compared to the one based on quantities, relying on measures of the capital stock. Given that we focus on a specific dimension of capital markets – that due to assessed default risk, we should perhaps not be too surprised. As we have already noted, our approach does seem to assign a role to financial factors in shaping the time series pattern of distortions and output losses.

[25] The conclusions of the comparison excercise remain valid if we use the whole sample rather than the manufacturing subsample.

7 Implications for the Productivity Slowdown

It is useful to discuss what our results imply for debates about the impact of the financial crisis on productivity. We have already seen above that our key measure of aggregate credit frictions changed markedly over time. 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 to 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 3 shows that in the UK GDP per hour was around 16% below its pre-crisis trend by the end of 2015.

The productivity fall observed in aggregate statistics in Figure 3 is also apparent in the ABI/ABS surveys. Table 7 reports estimates of the evolution of aggregate labor 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 (iii) the numbers from official publications.[26] Across all series we observe that productivity fell sharply in 2009 and recovered very slowly thereafter. The core sample that we use for our estimates (Column (2)) appears representative of the economy as a whole. Appendix Figure A1 shows this clearly. At Q4 2012 (the end of our sample period), labor productivity was 11% lower than it would have been had it continued on its post-1970 trend.[27] 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 A2). There are many factors that could explain the decline in investment such as weak demand, pessimism over future productivity growth and uncertainty. But the financial crisis also led to restrictions in bank lending to non-financial corporations. Bank lending to the corporate sector in the UK continued to contract long after the acute phase of the credit 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.[28] This echoes the heterogeneity we find between large and small firms. Table 8 reports

[26] "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).

[27] Trend assuming a historical average growth of 2.3% per annum (the average over the period Q1 1979 Q1 to Q2 2008).

[28] 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.

productivity changes by firm size and for manufacturing versus non-manufacturing industries. There is evidence of heterogeneity across sectors, with manufacturing experiencing a smaller decline in labor productivity in 2009, echoing our results in Table A8.

In the case of the UK, a range of explanations have been put forward to explain weak productivity but work on the role of credit supply remains sparse. 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 labor 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 (2014a, 2014b) and Riley et al (2015) find that the within-firm component accounts for the vast majority of the fall in UK productivity. Failure to allocate capital to the most productive firms can reduce the contribution to aggregate productivity of within-firm growth - e.g. directly for small credit constrained firms which forgo profitable investment opportunities, and indirectly for less bank dependent firms that face less competition (Aghion et al, 2009). These papers also provide some evidence of reallocation being subdued during the crisis. Barnett et al (2014a) 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 a slowdown in creative destruction account for around one third of the fall in average annual productivity growth between 2002-7 and 2008-11. 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 behavior.

Financial Frictions and Productivity Changes To estimate the impact of credit frictions on productivity, we use Equation (15). The change in labor productivity, i.e. real wage, that can be explained by changes in credit market frictions is given by:

$$\Delta \log w_t = \frac{1-\eta}{1-\alpha\eta}\left[\ln \hat{\Theta}_t - \ln \hat{\Theta}_{t-1}\right]. \tag{29}$$

We can estimate Equation (29) using our annual estimates of $\hat{\Theta}_t$. Comparing these estimates to the actual labor productivity changes will give us a sense of what fraction of the observed labor productivity change is due to credit frictions. The baseline results based on the estimates of Table 3 are presented in Table 9. On average credit market frictions depressed annual productivity growth by 0.3 percentage points over the period 2004-2012. Smaller firms are on average more affected by credit frictions, with credit market frictions depressing annual productivity growth by 0.35 percentage points compared to 0.11 for large firms. Moreover, credit frictions were particularly acute at the height of the financial crisis in 2008 and 2009, helping account for approximately 16.5% of the aggregate productivity fall. Moreover, these factors also dragged on throughout the post-crisis period which helps account for the near stagnation of productivity in the recovery. An interesting feature of the model-based approach is that it suggests that financial frictions continued to worsen after 2009 in a manner that is consistent with the aggregate pattern of productivity shown in Figure 3 and Table 7. In 2010 productivity rose, only to fall back again in the following two years.

Another way to think about the results is that labor productivity would have been roughly 2% higher in 2012 had financial frictions remained at their 2007 level. Data suggest that UK productivity would have been 11% higher in 2012 if growth had remained on its pre-crisis trend after 2007 (See Figure A1). This means that credit frictions can account for approximately 18% of the difference between actual UK productivity and its pre-crisis trend by the end of 2012. The results are robust to alternative estimation methods but their magnitude varies. Credit frictions account for 13% of the gap when we use empirical employment shares and 23% when we use Solow residuals.

Demand Side Weakness? Although we explain some of the productivity slowdown, our approach 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). Table 4 has shown that credit frictions appear to matter relatively more in accounting for the poor productivity performance of SMEs compared to larger firms. This leaves a larger fraction of the productivity slowdown among large firms unexplained since the productivity performance of larger firms also appears to have been poor since the financial crisis. We now consider the possibility that demand-side weakness can help explain some of the additional productivity fall which is not explained by credit frictions. We surmise that demand-side weakness might have affected SMEs and large firms to different extents. It is plausible that demand conditions weighed more heavily on larger firms which are more exposed to international trade and hence the weakness of the world economy.

To explore this possibility, we estimate firm-level productivity for all firms in our data by computing Solow residuals.[29] Figure 4 plots aggregate TFP trends disaggregated by firm size in two different ways. First we aggregate the time-invariant firm-specific TFP estimates $\hat{\theta}_n$ (the solid line). Changes in this over time are driven purely by changes in the size of firms with different (fixed) productivity levels. Second, we aggregate the time-varying firm-specific TFP estimates $\hat{\theta}_{nt}$ (the dotted line). The time invariant measure is intended to capture the

[29] We use Solow residuals since using employment data only allows us to retrieve *relative* TFP (as opposed to TFP levels) and we are interested in looking at aggregate changes over time.

"fundamental" underlying TFP, whereas the time varying measure will also be contaminated 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 the latter focuses exclusively on supply-side factors. TFP is normalized to 100 in 2007. In the right-hand Panel of Figure 4 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 $\Delta \ln(w_t)$ and create a negative effect on labor productivity. 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 actually less severe for such firms during and after the financial crisis. Indeed, the two time series track each other more closely post-crisis than is the case for large firms.

8 Conclusion

This paper has developed an approach to studying the role of credit frictions both at the firm-level and for aggregate economic performance. 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 where we use the "PD model" of Standard and Poor's to estimate a time-varying default probability for each firm in the sample. Such credit-scoring tools are used by lenders prior to making loans. We merge our PD estimates with data on employment, investment and value added for a representative sample of UK firms. This provides a unique window on the role of credit market frictions. We show that the default probability from the PD model predicts firm-level decisions, even when we include firm fixed-effects.

We show that credit frictions are important in the aggregate but weigh more heavily on SMEs rather than large firms. In our baseline estimates, SMEs suffer output losses of around 5% from credit frictions, around twice the losses suffered by 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 5.3% from around 3.2% prior to the crisis. Moreover, this accounts for between 11% and 18% of the loss in labor productivity experienced in the UK in 2008-09. 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. Finally, we show that most of the impact of credit frictions comes from the average assessment of expected default (scale effect or capital shallowing) rather than the way in which it is distributed across firms with different levels of productivity (TFP effect or misallocation).

The approach taken here is useful in showing how the automated tools for assessing firm-level credit risk can usefully be used as barometers of credit conditions. Moreover, we open up the "black box" of credit frictions in a specific way which is linked to an underlying theory and is likely to be relevant in a variety of contexts.

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A Data Appendix

A.1 ABI/ABS data

A.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 A1 and A2).

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.

A.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

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

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 7). 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.

A.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 mismeasurement 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 values of the capital stock after this procedure, for which we cannot calculate a valid TFP number. Overall we lose 88,269 observations over the entire sample period 2004-2012.

B Data on default probabilities

We use Bureau Van Dijk’s Orbis database to obtain data for the inputs required by Standard and Poor’s PD Model, namely: net Income, total revenue, EBIT, operating income, net property plant and equipment, total assets, total cash and short-term investments, total current liabilities, total equity, total liabilities, number of employees, income tax expense, interest expense, cash from operations, retained earnings, total debt, the industry in which the firm operates, and whether it is a private or a public firm. The model takes into account a corporate industry risk score and a country risk score, as well as macroeconomic data such as CPI growth.

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

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. First, for some records the ONS relied on name matching, which can be problematic if different names or spellings are used. Second, because the CRN and IDBR system are maintained independently, the same business is sometimes represented differently in either register. The IDBR identifies business units according to functional units, which are relevant for the computing of government statistics. 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 approximately 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 A3 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.

C Further Technical details

C.1 Empirical factor shares and Solow residuals

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:

$$\ln(\theta_{nt}) = \ln(Y_{nt}) - \eta\,(1-\alpha)\ln(w_t L_{nt}) - \eta\alpha\ln(K_{nt}) \tag{30}$$

where Y_{nt} is real gross value added, $w_t L_{nt}$ is the wage bill (real labor costs instead of headcount) and K_{nt} is the real capital stock estimated using the perpetual inventory method. In all our 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 our empirical estimates of factor shares, we use the actual levels of labor costs divided by value added from the ABI/ABS. Abstracting from frictions in labor markets, the first order condition for employment generates that the labor share is:

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

We use the share of labor 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.

C.2 Decomposing credit frictions by size

Credit market frictions in industry j at time t are given by

$$\Theta_{jt} = \sum_{n=1}^{N_{jt}} \omega_{njt}\tau_{njt}$$

This can be re-written as the weighted sum of an SME component Θ_{jtS} and a large-firm component Θ_{jtL} as follows

$$\begin{aligned}
\Theta_{jt} &= \lambda_{jtS}\Theta_{jtS} + \lambda_{jtL}\Theta_{jtL} \\
&= \left(\frac{\hat{\theta}_{jtS}}{\hat{\theta}_{jt}}\right)^{\frac{1}{1-\eta}} \sum_{n=1}^{N_{jtS}} \omega_{njtS}\tau_{njt} + \left(\frac{\hat{\theta}_{jtL}}{\hat{\theta}_{jt}}\right)^{\frac{1}{1-\eta}} \sum_{n=1}^{N_{jtL}} \omega_{njtL}\tau_{njt}
\end{aligned}$$

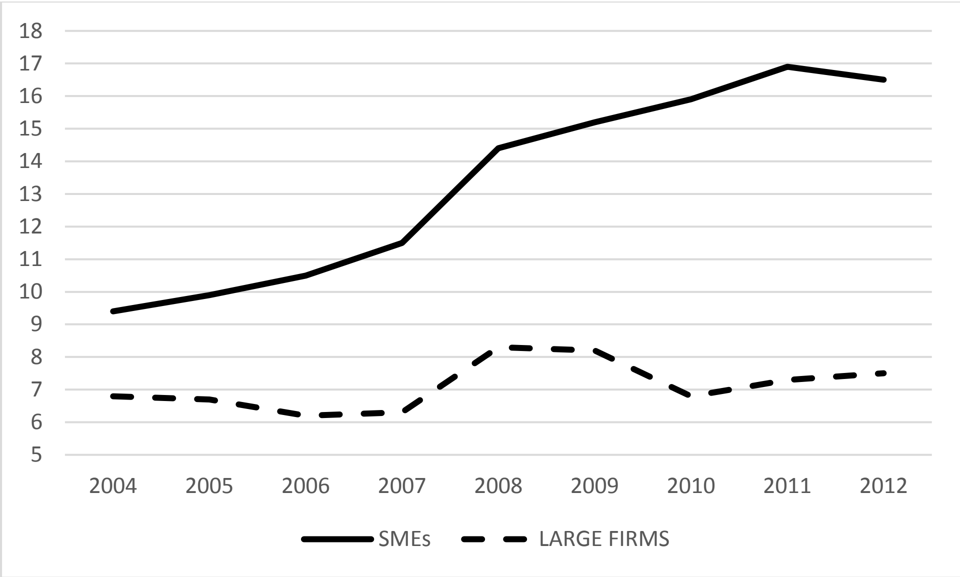
where

- N_{jtS} is the number of SMEs in industry j, N_{jtL} the number of large firms in industry j, and N_{jt} the total number of firms in industry j;
- $\omega_{njtS} = \left(\frac{\theta_{njt}}{\hat{\theta}_{jtS}}\right)^{\frac{1}{1-\eta}}$ and $\hat{\theta}_{jtS} = \left(\sum_{n=1}^{N_{jtS}} \theta_{njt}{}^{\frac{1}{1-\eta}}\right)^{1-\eta}$;

- $\omega_{njtL} = \left(\frac{\theta_{njt}}{\hat{\theta}_{jtL}}\right)^{\frac{1}{1-\eta}}$ and $\hat{\theta}_{jtL} = \left(\sum_{n=1}^{N_{jtL}} \theta_{njt}{}^{\frac{1}{1-\eta}}\right)^{1-\eta}$;
- $\hat{\theta}_{jt} = \left(\sum_{n=1}^{N_j} \theta_{njt}{}^{\frac{1}{1-\eta}}\right)^{1-\eta}$.

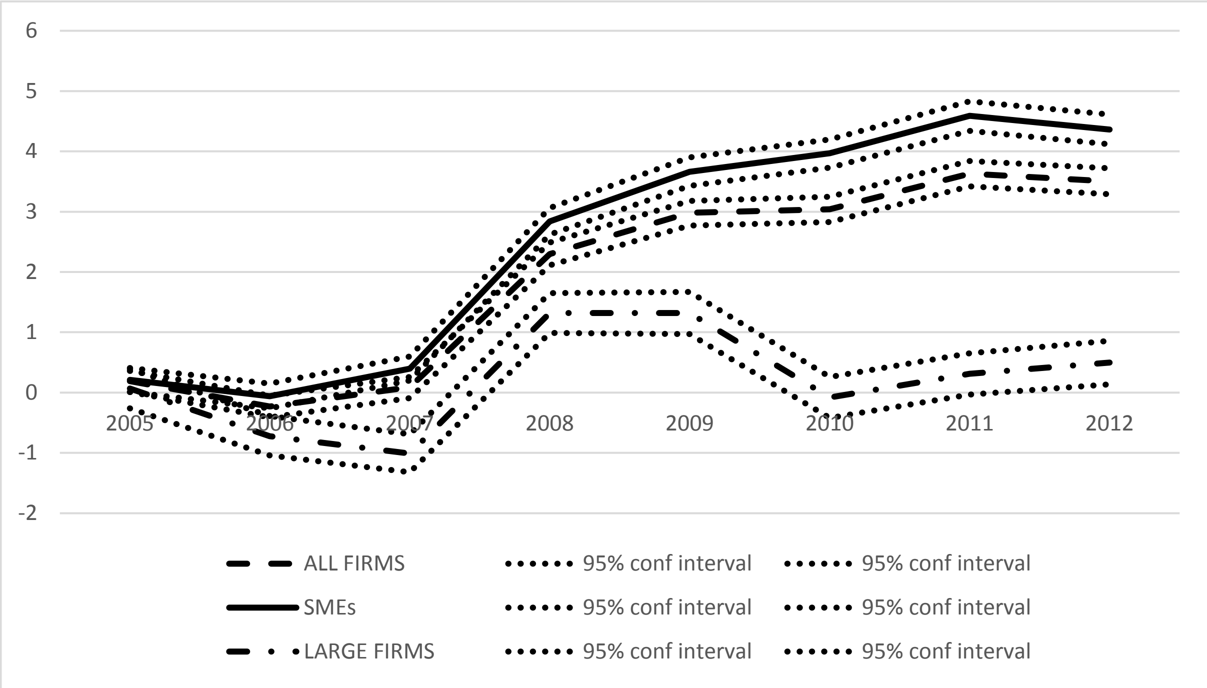
The size-specific measures of credit market frictions, Θ_{jtS} and Θ_{jtL}, are weighted by the relative aggregate productivity of each size-category. As we did when estimating Θ_t, we implement the size decomposition at the industry level and then aggregate using industry employment shares by size category to obtain an aggregate estimate of credit frictions for SMEs and large firms separately.

FIGURE 1: Aggregate probability of default at the 1-year horizon (in %) – by firm size



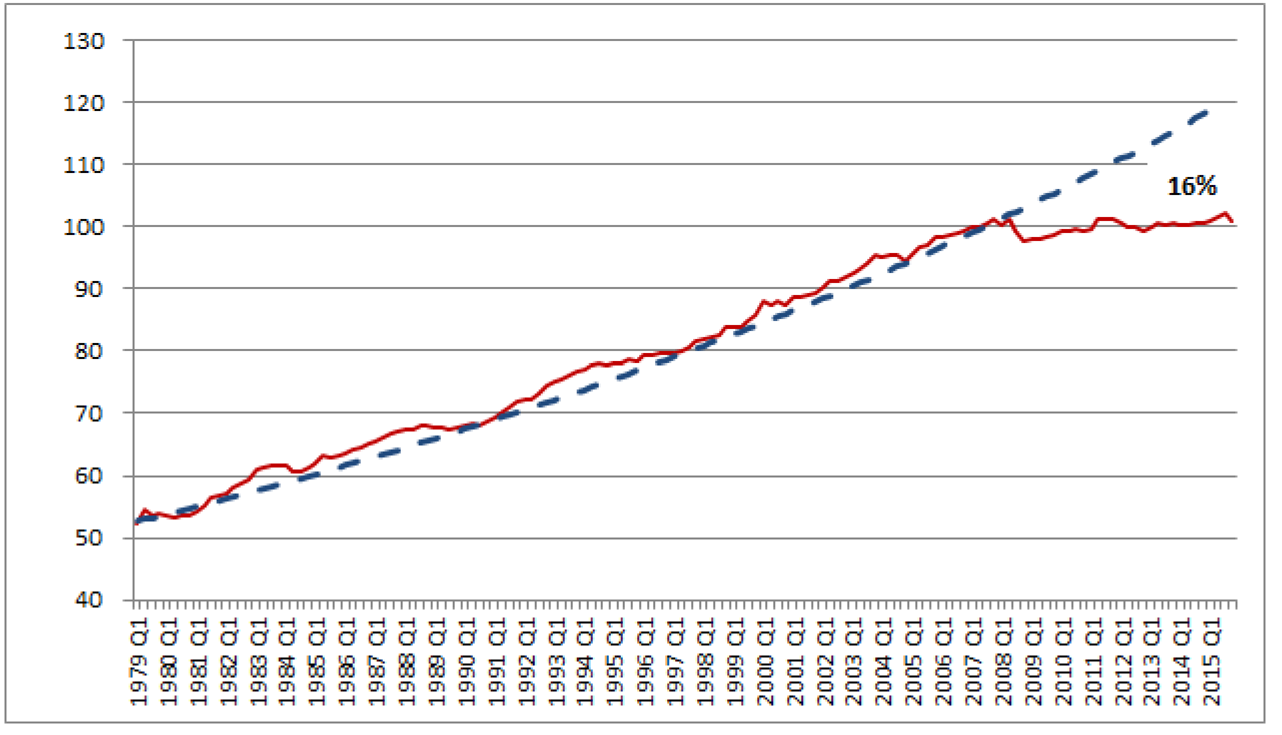
Note: A firm's probability of default is the probability that it will default on its payments at the one-year horizon estimated using S&P's PD Model and historical default rates from S&P's CreditPro. SMEs (solid line) are Small and Medium-sized Enterprises defined as firms with fewer than 250 employees. 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 2: Firm-level probabilities of default at the 1-year horizon – by firm size (controlling for industry)



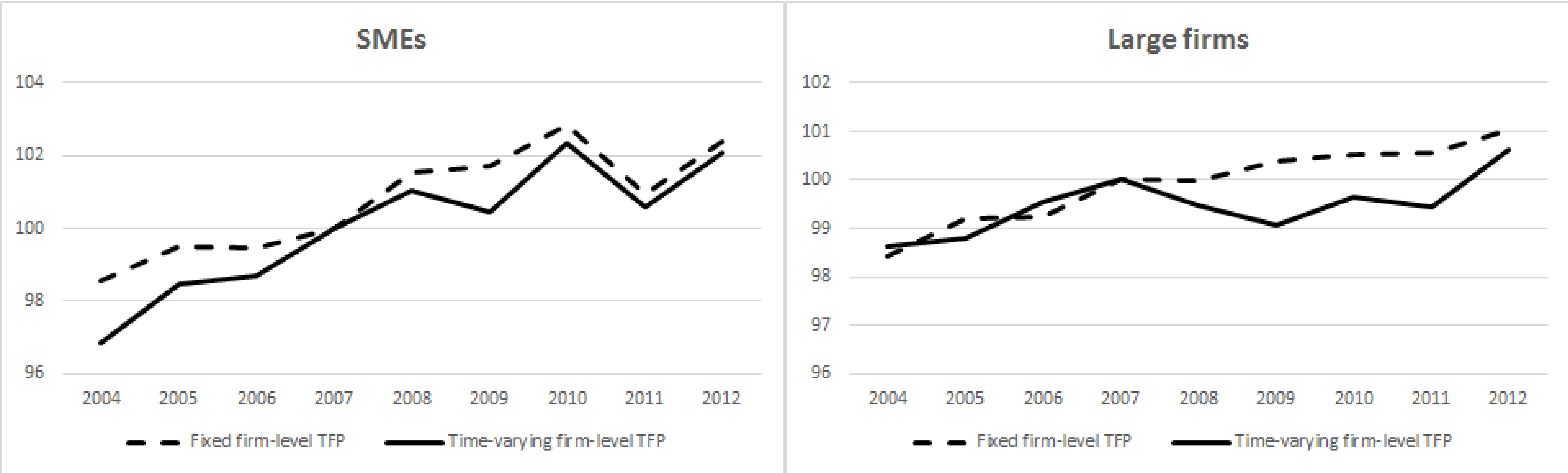
Note: Coefficients(*100) on year dummies from regression of firm-level 1-year default probabilities on year and industry dummies (reference year=2004). A firm's probability of default is the probability that a firm will default on its payments within 1 year. Industry fixed effects are at the three-digit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

FIGURE 3: 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 dashed line assuming a historical average growth of 2.3% per annum (the average over the period Q1 1979 Q1 to Q2 2008).

FIGURE 4: Evolution of TFP based on Solow residual with α=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).

TABLE 1: Employment in the market sector – by size

	Total employment	SME employment	% of total	Large firm employment	% 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 A.1 for more details on the sampling frame and weights). SMEs are firms with strictly fewer than 250 employees.

TABLE 2: Firm performance and lagged repayment probabilities

Panel A: Common samples - cross-section with year and 3-digit industry fixed effects

	(1) Log(employment)	(2) Log(real GVA)	(3) Log(capital stock)	(4) Log(real net capex)	(5) Log(total assets)	(6) Log(fixed assets)	(7) Log(capital-labour ratio)	(8) Log(capex-labour ratio)	(9) Log(capex-capital stock ratio)
Repayment probability	3.180***	4.097***	4.200***	4.696***	5.057***	5.693***	1.012***	1.527***	0.515***
	(0.067)	(0.072)	(0.088)	(0.095)	(0.091)	(0.105)	(0.051)	(0.061)	(0.050)
N	81664	81664	81664	81664	81664	81664	81664	81664	81664

Panel B: Common samples - panel with year and firm fixed effects

	(1) Log(employment)	(2) Log(real GVA)	(3) Log(capital stock)	(4) Log(real net capex)	(5) Log(total assets)	(6) Log(fixed assets)	(7) Log(capital-labour ratio)	(8) Log(capex-labour ratio)	(9) Log(capex-capital stock ratio)
Repayment probability	0.104***	0.608***	0.087***	0.913***	0.401***	0.385***	-0.021	0.820***	0.834***
	(0.025)	(0.045)	(0.021)	(0.095)	(0.037)	(0.056)	(0.026)	(0.094)	(0.087)
N	61168	61168	61168	61168	61168	61168	61168	61168	61168

Note: 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. We regress firm-level characteristics on the firm's repayment probability at the one-year horizon from Standard and Poor's PD model estimated using data at *t-1*. The sample is the full "calibration" sample but the size of the regression sample is determined by data availability and is indicated in each table under "N". Both panels condition on a sub-sample with non-missing values on all 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). All data (except repayment probabilities) are winsorised (at the top and bottom 1% of the sample distribution). The dependent variables are the logarithm of employment, real GVA, the capital stock, real net capex (capital expenditures), total assets, fixed assets, the capital-labour ratio, the capex-labour ratio, and the capex-capital stock ratio. Time period is 2004 to 2012. The data are from the ABI/ABS, except total assets and fixed assets which are from BVD Orbis. There is a full set of year dummies in all the models.

TABLE 3: The Effect of Credit frictions on Aggregate Output

	Overall		SCALE		TFP	
	$\hat{\Theta}_t$	Percentage Loss of output	$\hat{\Theta}_t^S$	Percentage Loss of output	$\hat{\Theta}_t^T$	Percentage Loss of output
	(1)	(2)	(3)	(4)	(5)	(6)
2004	0.907	3.191	0.910	8.982	0.997	0.319
2005	0.903	3.33	0.906	9.351	0.997	0.343
2006	0.905	3.273	0.908	9.182	0.996	0.351
2007	0.903	3.346	0.906	9.392	0.997	0.345
2008	0.875	4.357	0.879	12.135	0.996	0.426
2009	0.865	4.726	0.87	13.045	0.995	0.545
2010	0.864	4.773	0.869	13.14	0.994	0.584
2011	0.854	5.129	0.86	14.047	0.993	0.655
2012	0.849	5.318	0.855	14.497	0.993	0.728
Average	0.881	4.160	0.885	11.530	0.995	0.477

Note: All estimates assume that η = ¾ and α=1/3. The credit friction, $\hat{\Theta}_t$, is the estimate of aggregate credit market frictions derived in Equation (10). Output loss is the proportionate fall in output as a result of credit frictions calculated using Equation (14). $\hat{\Theta}_t^S$ is the scale component defined in Equation (17) and $\hat{\Theta}_t^T$ is the TFP component defined in Equation (16).

TABLE 4: The Effect of Credit frictions on Aggregate Output and Productivity: Broken down by firm size (α=1/3)

	PANEL A: SMEs						PANEL B: Large firms					
	Overall		SCALE		TFP		Overall		SCALE		TFP	
	$\hat{\Theta}_t$	Percentage Loss of output	$\hat{\Theta}_t^S$	Percentage Loss of output	$\hat{\Theta}_t^T$	Percentage Loss of output	$\hat{\Theta}_t$	Percentage Loss of output	$\hat{\Theta}_t^S$	Percentage Loss of output	$\hat{\Theta}_t^T$	Percentage Loss of output
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
2004	0.895	3.619	0.899	10.113	0.996	0.396	0.931	2.339	0.933	6.724	0.999	0.14
2005	0.888	3.869	0.892	10.766	0.996	0.445	0.932	2.334	0.933	6.712	0.999	0.137
2006	0.888	3.894	0.892	10.814	0.995	0.471	0.934	2.238	0.936	6.437	0.999	0.138
2007	0.884	4.032	0.888	11.21	0.995	0.457	0.934	2.257	0.935	6.478	0.998	0.15
2008	0.855	5.097	0.86	14.049	0.994	0.555	0.911	3.052	0.913	8.706	0.998	0.19
2009	0.84	5.657	0.846	15.432	0.993	0.705	0.909	3.12	0.911	8.862	0.998	0.23
2010	0.838	5.739	0.844	15.608	0.992	0.757	0.913	2.983	0.915	8.494	0.998	0.209
2011	0.828	6.084	0.835	16.461	0.992	0.842	0.907	3.186	0.91	9.049	0.998	0.227
2012	0.822	6.307	0.83	16.993	0.991	0.915	0.906	3.23	0.909	9.137	0.997	0.268
Average	0.860	4.922	0.865	13.494	0.994	0.616	0.920	2.749	0.922	7.844	0.998	0.188

Note: All estimates assume that η = ¾ and α=1/3. The credit friction, $\hat{\Theta}_t$, is the estimate of aggregate credit market frictions derived in Equation (12). Output loss is the proportionate fall in output as a result of credit frictions calculated using Equation (14). $\hat{\Theta}_t^S$ is the scale component defined in Equation (17) and $\hat{\Theta}_t^T$ is the TFP component defined in Equation (16). Panel A is for SMEs, i.e. firms with strictly fewer than 250 employees. Panel B is for large firms, i.e. firms with 250 employees or more.

TABLE 5: The Effect of Credit frictions on Aggregate Output (including Labor Market Distortions)

	Overall		SCALE		TFP	
	$\hat{\Theta}_t$	Percentage Loss of output	$\hat{\Theta}_t^S$	Percentage Loss of output	$\hat{\Theta}_t^T$	Percentage Loss of output
	(1)	(2)	(3)	(4)	(5)	(6)
2004	0.430	3.023	0.534	8.629	0.805	0.184
2005	0.406	3.114	0.513	8.925	0.791	0.141
2006	0.376	3.142	0.481	8.857	0.781	0.302
2007	0.372	3.044	0.473	8.672	0.787	0.202
2008	0.331	3.975	0.430	11.187	0.771	0.305
2009	0.334	4.364	0.435	12.202	0.767	0.373
2010	0.310	4.341	0.402	11.983	0.771	0.549
2011	0.310	4.613	0.401	12.725	0.773	0.555
2012	0.284	4.733	0.370	13.004	0.768	0.612
Average	0.347	3.817	0.449	10.687	0.779	0.326

Note: All estimates assume that η = ¾ and α=1/3. The credit friction, $\hat{\Theta}_t$, is the estimate of aggregate credit market frictions derived in Equation (12). Output loss is the proportionate fall in output as a result of credit frictions calculated using Equation (14). $\hat{\Theta}_t^S$ is the scale component defined in Equation (17) and $\hat{\Theta}_t^T$ is the TFP component defined in Equation (16).

TABLE 6: The Effect of Capital Market and Labor Market distortions on Manufacturing Output using capital stock estimates

	Overall		SCALE		TFP	
	$\hat{\Theta}_t$	Percentage Loss of output	$\hat{\Theta}_t^S$	Percentage Loss of output	$\hat{\Theta}_t^T$	Percentage Loss of output
	(1)	(2)	(3)	(4)	(5)	(6)
2004	0.14	43.191	0.196	77.284	0.718	19.291
2005	0.13	43.522	0.179	77.162	0.698	21.118
2006	0.12	44.017	0.176	77.721	0.698	21.244
2007	0.12	44.304	0.17	78.266	0.708	20.508
2008	0.12	44.267	0.165	78.247	0.707	20.417
2009	0.13	43.378	0.188	76.96	0.699	21.212
2010	0.11	44.895	0.152	78.758	0.704	21.226
2011	0.11	44.172	0.155	78.122	0.705	20.468
2012	0.1	45.45	0.139	78.874	0.682	23.163
Average	0.119	44.133	0.169	77.933	0.702	20.686

Note: All estimates assume that η = ¾ and α=1/3. The credit friction, $\hat{\Theta}_t$, is the estimate of aggregate credit market frictions derived in Equation (12). Output loss is the proportionate fall in output as a result of credit frictions calculated using Equation (14). $\hat{\Theta}_t^S$ is the scale component defined in Equation (17) and $\hat{\Theta}_t^T$ is the TFP component defined in Equation (16).

TABLE 7: Aggregate labour productivity, Index 2007 = 100

	ABI/ABS market sector	Calibration Sample	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/datasets/uknonfinancialbusinesseconomyannualbusinesssurveysectionsas).

TABLE 8: Annual labour productivity growth (in %) by firm size and sector

	All firms	SMEs	Large firms	Manufacturing	Non-manufacturing
2005	4.80	7.10	2.60	4.10	5.64
2006	3.70	5.60	1.80	1.43	4.54
2007	6.90	5.60	8.00	15.25	4.88
2008	-0.60	-0.40	-0.90	2.35	-0.93
2009	-8.10	-8.60	-7.80	-5.20	-8.68
2010	7.70	8.50	7.10	7.95	7.93
2011	2.00	1.00	3.00	6.96	0.69
2012	0.90	1.80	0.00	-3.12	2.56

Note: Labour productivity is defined as real gross value added per employee. Manufacturing corresponds to Section D SIC 1992. SMEs are firms with strictly fewer than 250 employees. Large firms are firms with 250 employees or more.

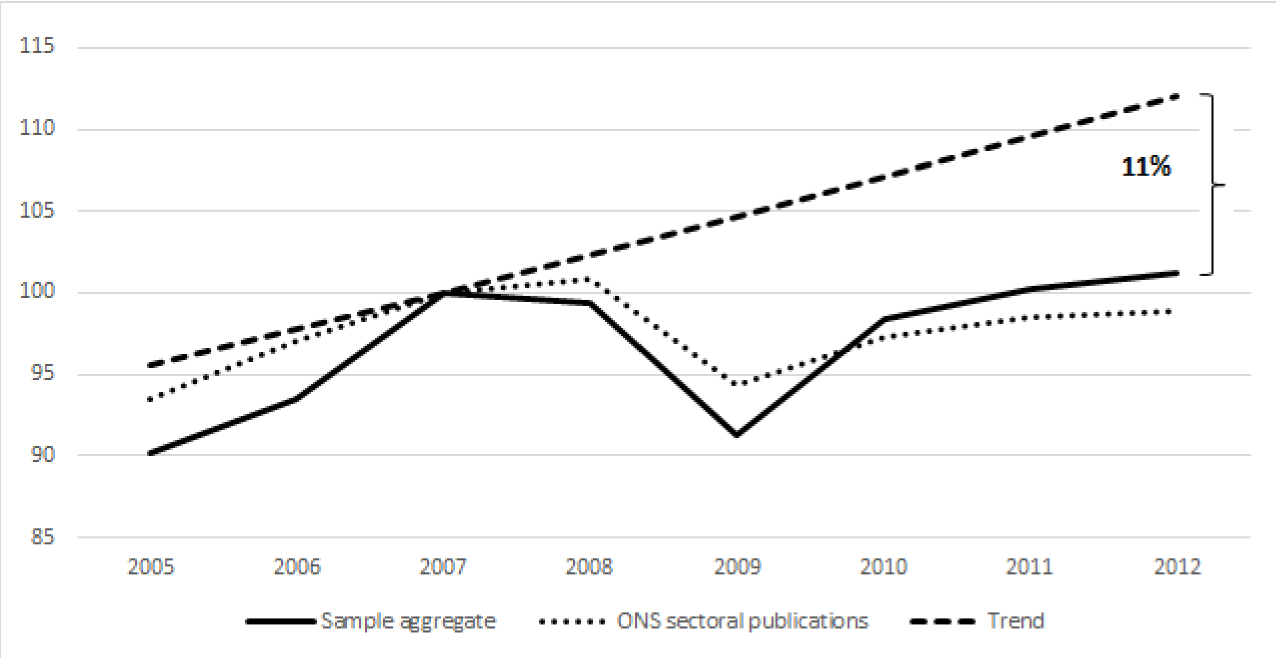
TABLE 9: The Effect of Credit frictions on Aggregate Labor Productivity

	All firms		SMEs		Large firms	
	$\hat{\Theta}_t$	LP growth contribution	$\hat{\Theta}_t$	LP growth contribution	$\hat{\Theta}_t$	LP growth contribution
2004	0.907		0.895		0.931	
2005	0.903	-0.144	0.888	-0.259	0.932	0.005
2006	0.905	0.059	0.888	-0.027	0.934	0.098
2007	0.903	-0.075	0.884	-0.144	0.934	-0.019
2008	0.875	-1.052	0.855	-1.116	0.911	-0.817
2009	0.865	-0.387	0.84	-0.591	0.909	-0.071
2010	0.864	-0.05	0.838	-0.087	0.913	0.142
2011	0.854	-0.374	0.828	-0.367	0.907	-0.209
2012	0.849	-0.200	0.822	-0.238	0.906	-0.046
Average	0.881	-0.278	0.860	-0.354	0.920	-0.115

Note: Labour productivity is defined as real gross value added per employee. Manufacturing corresponds to Section D SIC 1992. SMEs are firms with strictly fewer than 250 employees. Large firms are firms with 250 employees or more. All estimates assume that $\eta = 3/4$ and $\alpha=1/3$. The credit friction, $\hat{\Theta}_t$, is the estimate of aggregate credit market frictions derived in Equation (12). "LP growth contribution" is the contribution of changes in $\hat{\Theta}_t$ to annual labor productivity growth derived in Equation (24).

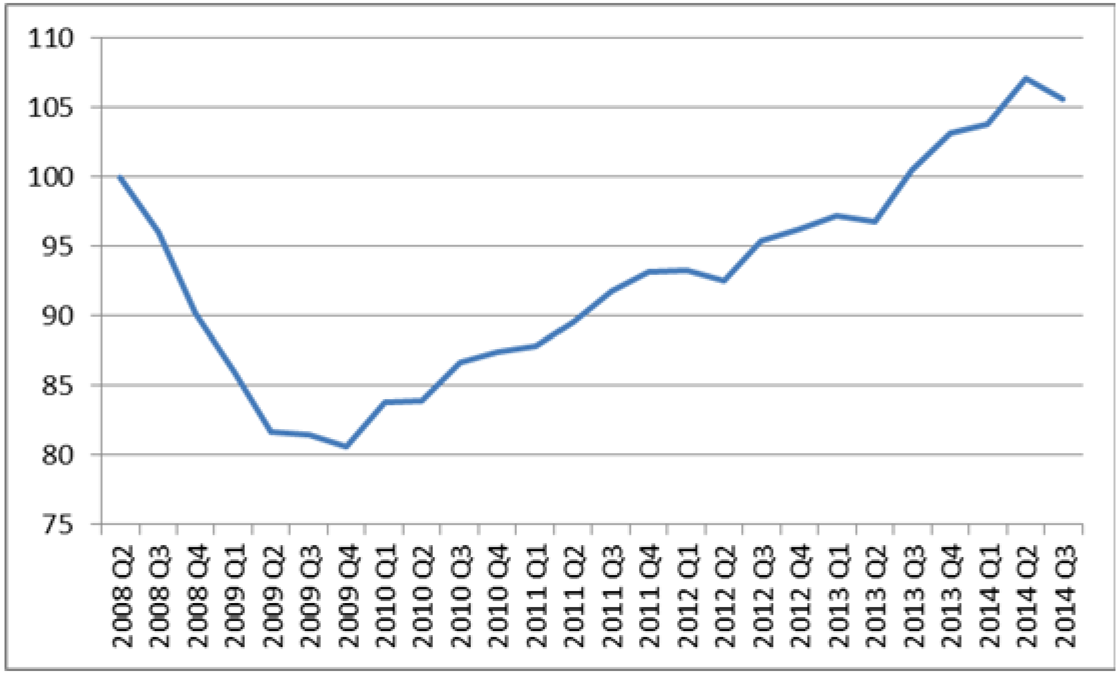
Appendix

FIGURE A1: 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 Q1 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/datasets/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).

FIGURE A2: 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.

TABLE A1: Market sector employment and number of establishments by size (average 2004-2012)

		Employment (millions)	Number of establishments (thousands)
MICRO	**(1-9)**	3.2	1,289
SMALL	**(10-49)**	2.6	132
MEDIUM	**(50-249)**	2.4	24
LARGE	**(250+)**	7.5	5
TOTAL		15.7	1,450

Source: IDBR (Inter-Departmental Business Register) and authors' calculations. These are 2004-2012 averages.

TABLE A2: Total employment and number of establishments in the market sector

	Employment (millions)	Number of establishments (thousands)
2004	15.3	1,322
2005	15.5	1,372
2006	15.6	1,410
2007	15.4	1,457
2008	16.2	1,544
2009	15.9	1,479
2010	15.3	1,459
2011	15.5	1,502
2012	15.7	1,502

Source: IDBR and authors' calculations.

TABLE A3: Match rates between ABI/ABS and data on default probabilities

	(1)	(2)	(3)
	Calibration sample	**Matched PD data**	**Percentage of calibration sample**
2004	26,155	19,107	73.05
2005	25,358	19,215	75.77
2006	21,989	17,247	78.43
2007	24,363	18,220	74.79
2006	23,614	17,428	73.80
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	84.70
TOTAL	216,540	168,514	77.82

Note: ABI/ABS surveys, Orbis and authors' calculations. The calibration sample (Column (1)) comprises all ABI/ABS market sector establishments with a positive capital stock estimate. The matched PD data (Column (2)) is the number of establishments in Column (1) which could also be matched to a default probability from the ORBIS accounting data as filtered through Standard and Poor’s PD Model. The final column has the ratio of (2) over (1). We impute default probabilities for the missing values in order to use the full number of observations in Column (1), but our results are robust to using the smaller sample in Column (2).

TABLE A4: Firm performance and lagged repayment probabilities

Panel A: Individual samples - cross-section with year and 3-digit industry fixed effects

	(1) Log(emplo yment)	(2) Log(real GVA)	(3) Log(capita l stock)	(4) Log(real net capex)	(5) Log(total assets)	(6) Log(fixed assets)	(7) Log(capital-labour ratio)	(8) Log(capex-labour ratio)	(9) Log(capex-capital stock ratio)
Repayment probability	3.586***	4.432***	4.714***	4.612***	5.583***	6.505***	1.126***	1.541***	0.543***
	-0.049	-0.054	-0.072	-0.094	-0.067	-0.079	-0.046	-0.06	-0.05
N	155915	155915	155915	90531	143430	138042	155915	90531	90531

Panel B: Individual samples - panel with year and firm fixed effects

	(1) Log(emplo yment)	(2) Log(real GVA)	(3) Log(capita l stock)	(4) Log(real net capex)	(5) Log(total assets)	(6) Log(fixed assets)	(7) Log(capital-labour ratio)	(8) Log(capex-labour ratio)	(9) Log(capex-capital stock ratio)
Repayment probability	0.093***	0.610***	0.102***	0.916***	0.393***	0.430***	0.009	0.820***	0.833***
	-0.021	-0.037	-0.018	-0.093	-0.04	-0.051	-0.022	-0.092	-0.085
N	105611	105611	105611	67273	97208	95445	105611	67273	67273

Note: 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. We regress firm-level characteristics on the firm's repayment probability at the one-year horizon from Standard and Poor's PD model estimated using data at *t-1*. The sample is the full calibration sample but the size of the regression samples is determined by data availability and is indicated in each table under "N". Both panels do not condition on non-missing values on all the variables. Panel B conditions on individual sub-samples with at least two firm-level observations. All data (except repayment probabilities) are winsorised (at the top and bottom 1% of the sample distribution). The dependent variables are the logarithm of employment, real GVA, the capital stock, real net capex (capital expenditures), total assets, fixed assets, the capital-labour ratio, the capex-labour ratio, and the capex-capital stock ratio. Data run from 2004 to 2012. The data are from the ABI/ABS, except data on total assets and fixed assets which are from BVD Orbis. There is a full set of year dummies in all the models.

TABLE A5: Exit regressions with year and firm fixed effects

	Exit
Repayment probability	-0.052***
	(0.007)
N	105,598

Notes: 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. We regress firm-level characteristics on the repayment probability (estimated using Orbis data). The "repayment probability" is measured using data at *t-1*. The sample is the full calibration sample but the exact size of the sample depends on the availability of the data and is indicated in "N". All data (except repayment probabilities) are winsorised (at the top and bottom 1% of the sample distribution).

TABLE A6: The Effect of Credit frictions on Output (Using Empirical Employment Shares)

	Overall		SCALE		TFP	
	$\hat{\Theta}_t$	Percentage Loss of output	$\hat{\Theta}_t^S$	Percentage Loss of output	$\hat{\Theta}_t^T$	Percentage Loss of output
	(1)	(2)	(3)	(4)	(5)	(6)
2004	0.936	2.008	0.938	6.181	0.998	0.182
2005	0.933	2.113	0.935	6.485	0.998	0.205
2006	0.934	2.085	0.936	6.392	0.998	0.212
2007	0.932	2.165	0.934	6.635	0.998	0.216
2008	0.91	2.879	0.912	8.773	0.997	0.268
2009	0.903	3.106	0.906	9.391	0.997	0.344
2010	0.9	3.193	0.904	9.633	0.996	0.37
2011	0.893	3.423	0.897	10.291	0.996	0.409
2012	0.889	3.568	0.893	10.681	0.995	0.459
Average	0.914	2.727	0.917	8.274	0.997	0.296

Note: All estimates assume that η = ¾. Intsead of calibrating α=1/3 for all industries, we use empirical employment shares over the sample period. The credit friction, $\hat{\Theta}_t$, is the estimate of aggregate credit market frictions derived in Equation (12). Output loss is the proportionate fall in output as a result of credit frictions calculated using Equation (14). $\hat{\Theta}_t^S$ is the scale component defined in Equation (17) and $\hat{\Theta}_t^T$ is the TFP component defined in Equation (16).

TABLE A7: The Effect of Credit frictions on Output (Using Solow Residuals)

	Overall		SCALE		TFP	
	$\widehat{\Theta}_t$	Percentage Loss of output	$\widehat{\Theta}_t^S$	Percentage Loss of output	$\widehat{\Theta}_t^T$	Percentage Loss of output
	(1)	(2)	(3)	(4)	(5)	(6)
2004	0.900	3.454	0.901	9.868	0.998	0.157
2005	0.912	3.016	0.914	8.639	0.998	0.153
2006	0.889	3.834	0.892	10.821	0.997	0.275
2007	0.886	3.938	0.888	11.183	0.998	0.193
2008	0.867	4.630	0.869	13.101	0.998	0.178
2009	0.846	5.415	0.849	15.102	0.997	0.329
2010	0.842	5.570	0.845	15.470	0.996	0.387
2011	0.823	6.276	0.827	17.287	0.995	0.466
2012	0.817	6.516	0.821	17.890	0.995	0.502
Average	0.865	4.739	0.867	13.262	0.997	0.293

Note: All estimates assume that $\eta = ¾$ and $\alpha=1/3$. The credit friction, $\widehat{\Theta}_t$, is the estimate of aggregate credit market frictions derived in Equation (12). Output loss is the proportionate fall in output as a result of credit frictions calculated using Equation (14). $\widehat{\Theta}_t^S$ is the scale component defined in Equation (17) and $\widehat{\Theta}_t^T$ is the TFP component defined in Equation (16).

Table A8: The Effect of Capital Market and Labor Market disortions on Manufacturing Output using default probabilities

	Overall		SCALE		TFP	
	$\hat{\boldsymbol{\Theta}}_t$	Percentage Loss of output	$\hat{\boldsymbol{\Theta}}_t^S$	Percentage Loss of output	$\hat{\boldsymbol{\Theta}}_t^T$	Percentage Loss of output
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
2004	0.856	3.077	0.961	8.863	0.890	0.094
2005	0.814	3.151	0.926	9.123	0.879	0.041
2006	0.801	3.120	0.909	8.923	0.881	0.162
2007	0.766	3.035	0.871	8.617	0.879	0.236
2008	0.745	3.727	0.849	10.584	0.878	0.209
2009	0.789	4.053	0.906	11.462	0.871	0.239
2010	0.723	3.476	0.821	9.926	0.88	0.159
2011	0.668	3.715	0.765	10.547	0.873	0.211
2012	0.664	3.842	0.762	10.905	0.872	0.206
Average	0.758	3.466	0.863	9.883	0.878	0.173

Note: All estimates assume that η = ¾ and α=1/3. The credit friction, $\hat{\Theta}_t$, is the estimate of aggregate credit market frictions derived in Equation (12). Output loss is the proportionate fall in output as a result of credit frictions calculated using Equation (14). $\hat{\Theta}_t^S$ is the scale component defined in Equation (17) and $\hat{\Theta}_t^T$ is the TFP component defined in Equation (16).

TABLE A9: The Effect of Credit frictions on Aggregate Labor Productivity

	PANEL A: Empirical labor shares		PANEL B: Solow residuals	
	Theta	**LP growth contribution**	**Theta**	**LP growth contribution**
2004	0.936		0.900	
2005	0.933	-0.107	0.912	0.453
2006	0.934	0.028	0.889	-0.847
2007	0.932	-0.082	0.886	-0.108
2008	0.91	-0.732	0.867	-0.723
2009	0.903	-0.234	0.846	-0.827
2010	0.900	-0.091	0.842	-0.164
2011	0.893	-0.238	0.823	-0.751
2012	0.889	-0.15	0.817	-0.256

Note: Labour productivity is defined as real gross value added per employee. Manufacturing corresponds to Section D SIC 1992. SMEs are firms with strictly fewer than 250 employees. Large firms are firms with 250 employees or more. Estimates in PANEL A assume $\eta = ¾$ and use empirical labor shares. Estimates in PANEL B assume that $\eta = ¾$ and $\alpha=1/3$, but use Solow residuals to measure relative productivity levels. The credit friction, $\hat{\Theta}_t$, is the estimate of aggregate credit market frictions derived in Equation (12). "LP growth contribution" is the contribution of changes in $\hat{\Theta}_t$ to annual labor productivity growth derived in Equation (24).