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The Equilibrium Impact of Credit Frictions: Evidence from Default Risk Using Firm-Level Data
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ABSTRACT

This paper examines the impact of credit frictions arising from firm-level default risk on aggregate economic performance. We build a micro-to-macro model with heterogeneous firms and sector-specific production functions, showing that perceived default risk is a sufficient statistic for credit frictions. Using UK administrative data (2004–2019) matched to S&P risk measures, counterfactual estimates reveal that relaxing frictions raises output by 25% and wages by 23%. Ignoring equilibrium wage adjustments overstates output gains, while fixed-capital misallocation approaches understate them. Most gains reflect aggregate capital accumulation. Credit frictions remain above pre-crisis levels, reshape firm size dynamics, increase misallocation across firms, and dampen productivity growth over time.

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1 Introduction

The period following the global financial crisis brought renewed attention to the role of credit frictions in shaping aggregate economic outcomes. Tighter borrowing conditions raised the cost of capital and redirected investment away from its most productive uses. This focus intensified following the COVID-19 pandemic, which featured unprecedented credit interventions across advanced economies and was subsequently followed by a sharp increase in interest rates.

This paper develops a framework for assessing how credit frictions ration and allocate capital, and how these frictions propagate from firms to industries and ultimately to the aggregate economy. We begin by proposing a theoretical micro-to-macro model in which credit contracts depend on firms' default risk. In this setting, default risk emerges as a sufficient statistic summarizing firm-specific credit frictions. Firms are heterogeneous in both productivity and default risk, generating rich interactions between financial conditions and production decisions. We then take this framework to novel firm-level panel data on idiosyncratic default risk to quantify the aggregate consequences of credit frictions.

Our baseline empirical analysis draws on administrative panel data covering the universe of UK firms between 2004 and 2019, matched to firm-level probabilities of default (PDs). These PDs are generated using a proprietary algorithm developed by S&P, which is widely used by institutional lenders to inform credit contracts. The algorithm combines firm-level balance sheet information with time-varying expert assessments of industry conditions and macroeconomic risks, and is calibrated to observed default events. Importantly, we rely exclusively on information available at the time each PD is produced. We match these measures to our firms, generating a dataset of 23 million firm-year observations.[1]

To understand how idiosyncratic default risk affects aggregate outcomes, we develop a model that begins with a microeconomic setting in which firms and lenders interact under the threat of default. A firm's probability of default summarizes its borrowing conditions and therefore acts as the sufficient statistic for credit frictions. We then embed this firm-level heterogeneity in a framework reminiscent of Lucas (1978), allowing

[1] Administrative data are essential because accounting regulations do not require all firms to disclose key information, such as employment. We use the Business Structure Database, which covers the population of registered firms and draws on information collected by HMRC.

firms to choose their factor inputs optimally given productivity and credit constraints. Aggregating across firms yields closed-form expressions characterizing sectoral output, equilibrium wages, and aggregate production.

A key feature of our approach is that credit frictions enter the aggregation through an employment-weighted average of firm-level distortions. This allows us to construct a transparent and theoretically grounded measure of aggregate credit frictions using minimal firm-level information. While our headline results exploit data on the firm population, we use richer information from the Annual Business Inquiry and Annual Business Survey (ABI/ABS) to estimate sector-specific production parameters. The model further highlights that reducing credit frictions can substantially raise equilibrium wages, as improved access to capital shifts out labor demand. Accounting for this general equilibrium channel proves crucial for the quantitative conclusions.

Our analysis focuses on firms operating in the UK "market economy" [2] We estimate that, on average, credit frictions reduced aggregate output by 25% between 2004 and 2019, with real wages 23% lower than under a low-friction benchmark. Moreover, credit frictions worsened over time: productivity losses were 2.6 percentage points higher at the end of the sample period than at the beginning, as substantial difference given aggregate productivity growth of only 9.8% over this period.

Beyond their level effects, credit frictions reshape the firm-size distribution. While reducing frictions stimulates growth among medium-sized firms, it leads to contractions among both very small firms (which are less productive) and large firms (which are less credit constrained), driven by higher equilibrium wages. Sectoral responses likewise depend on production technologies: capital-intensive and very credit constrained sectors experience large output gains, whereas some labor-intensive and relatively unconstrained sectors actually contract when wages rise (e.g., Professional Services).

The paper contributes both substantively and methodologically. Substantively, we provide new evidence on the magnitude and evolution of credit frictions and their aggregate consequences. Methodologically, we demonstrate how widely used credit-rating tools can be integrated into a structural framework to study financial frictions at scale. In the

[2] The market economy excludes agriculture, mining, public administration, education, health, finance, and real estate. As with these other excluded sectors, output is challenging to measure in financial services, although the sector remains central to aggregate outcomes through its role in credit allocation.

UK context, our findings speak directly to longstanding concerns that the financial sector fails to allocate capital efficiently to non-financial firms. We show that default-related credit frictions were particularly severe during the global financial crisis, accounting for more than half of the productivity decline between 2008 and 2009. Although conditions subsequently improved for large firms, frictions remained elevated for smaller firms.

More broadly, our results highlight the potentially large gains from improving credit allocation, while emphasizing that such gains operate largely through higher wages induced by capital deepening. These benefits extend well beyond the mechanics of financial markets alone.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 outlines the theoretical framework. Section 4 describes the data and presents summary statistics. Section 5 explains how the model is taken to the data and reports the core empirical results. Section 7 concludes. Online Appendices provide additional details on the data (A), theory (B), and empirical robustness (C).

2 Related Literature

Our paper lies at the intersection of three strands of research: theories of credit market frictions, micro-empirical studies of financial constraints, and the literature on misallocation and aggregate productivity.

Credit market frictions. A large theoretical literature studies financial frictions arising from asymmetric information, limited commitment, and imperfect enforcement, following seminal contributions by Stiglitz and Weiss (1981) and Gale and Hellwig (1985). These frictions restrict access to capital and shape real economic outcomes. Such mechanisms have been incorporated into macroeconomic models in influential work by Bernanke and Gertler (1986) and Kiyotaki and Moore (1997), and have been used to explain persistent cross-country income differences and poverty traps (Banerjee and Newman (1993)). More recent quantitative macro models emphasize the role of credit frictions in shaping development paths and capital accumulation, for example in Buera and Shin (2013) and Moll (2014).

A common feature of many macro models is that default is either ruled out in equilibrium or plays no explicit allocative role. In contrast, we focus directly on default risk as the primitive friction underlying borrowing conditions. This allows us to connect the theory more directly to observed lending practices, where default probabilities are routinely used to price credit risk.

Micro evidence on financial constraints. A substantial micro-empirical literature documents how financial frictions affect firm investment, employment, and technology adoption. For example, Midrigan and Xu (2014) emphasize how financial constraints slow structural transformation, while Gilchrist et al. (2013) use corporate bond spreads to measure firm-specific borrowing costs among large U.S. firms. A related literature exploits quasi-experimental shocks to credit supply, such as parent-company cash-flow shocks (Lamont (1997)), pension funding rules (Rauh (2006)), housing collateral (Chaney et al. (2012), Gan (2017)), or bank-specific liquidity shocks (Khwaja and Mion (2008)).

Following the global financial crisis, many studies used bank–firm linkages to trace the real effects of credit contractions, for instance through exposure to Lehman Brothers in the U.S. (Chodorow-Reich (2014)) or major European banks (Huber (2018); Anderson et al. (2019)). While these designs offer compelling causal identification, they typically focus on partial-equilibrium firm-level outcomes and do not easily aggregate to economy-wide general equilibrium effects.

Misallocation and aggregate productivity. Our paper is also closely related to the misallocation literature initiated by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), which uses dispersion in marginal products to infer productivity losses due to distortions. Subsequent contributions, including Bartelsman et al. (2013), Asker et al. (2014), and Gopinath et al. (2017), emphasize the importance of firm-level wedges in shaping aggregate TFP.

This literature typically abstracts from the micro-foundations of distortions and often holds aggregate factor supplies fixed. By contrast, we model credit frictions explicitly, allow aggregate capital to respond endogenously, and account for general equilibrium wage adjustments. We show that failing to account for increases in aggregate capital supply leads to substantial *under*-estimates of the output gains from relaxing distortions, whereas failure to allow for aggregate wage responses leads to substantial *over*-estimation of gains. Related work by Baqaee and Farhi (2020) studies distortions in a general equilibrium framework with factor supplies fixed, whereas our framework naturally decomposes output losses into misallocation and capital deepening effects when credit frictions are relaxed.

Measurement of financial frictions. Finally, our paper contributes to the growing literature that seeks to measure financial frictions using firm-level data. Unlike approaches that infer distortions from revenue-based measures—potentially confounding measurement error with misallocation (e.g. Bils et al. (2021); Collard-Wexler and De Loecker (2016))—we use a widely deployed credit-scoring algorithm to measure default risk directly. This enables us to link theory to observables that are central to real-world lending decisions and to study the full population of firms, including SMEs that do not directly access public debt markets.

Contribution. Our contribution is threefold. First, we provide an explicit theory of credit frictions grounded in firm-level default risk, a central object in real-world lending but one that is largely absent from macroeconomic models of financial frictions. Default risk serves as a sufficient statistic for borrowing conditions and delivers transparent aggregation results that link micro-level distortions to aggregate outcomes.

Second, we combine this theory with novel firm-level data on default probabilities produced by a widely used credit-risk algorithm, allowing us to measure credit frictions directly rather than infer them from revenue-based wedges. This approach enables us to study the entire firm population, including small and privately held firms that are typically excluded from studies relying on public credit spreads.

Third, our framework nests misallocation effects within a general equilibrium setting that allows aggregate capital and wages to adjust endogenously. This reveals that a substantial share of the output costs of credit frictions operates through suppressed capital accumulation rather than misallocation alone, and that equilibrium wage responses fundamentally reshape firm- and sector-level outcomes. By integrating credit risk measurement, firm heterogeneity, and general equilibrium effects, the paper offers a quantitatively grounded and policy-relevant assessment of the aggregate consequences of credit frictions.

3 Conceptual Framework

3.1 Firms

Let n be a firm in sector s which produces using the production function:

$$Y_{nst} = \theta_{nst}\left(L_{nt}^{1-\alpha_s} K_{nst}^{\alpha_s}\right)^{\eta_s} \tag{1}$$

where θ_{nst} is firm-specific productivity at date t.[3] The parameters $\{\alpha_s, \eta_s\}$ vary at the sector but not firm. Firms hire labor in a single labor market at wage w_t but the price of capital is firm-specific and is denoted by $(\rho + \delta) / \tau_{nst}^K$ where $\tau_{nst}^K = 1$ is a firm specific "wedge" representing capital market imperfections, ρ is the cost of capital and δ is the depreciation rate. A "perfect" capital market is where $\tau_{nst}^K = 1$. Throughout, we will focus on the case where capital market frictions result in a higher cost of capital for each firm compared to borrowing at the risk-free rate ρ, i.e. $\tau_{nst}^K < 1$.[4]

We normalise output price $P = 1$ without loss of generality.[5] Then, firms choose labor and capital to maximize profits, yielding the following expression for output as a function of factor prices:

$$Y_{nst} = \theta_{nst}^{\frac{1}{1-\eta_s}} \left(w_t\right)^{-\frac{(1-\alpha_s)\eta_s}{1-\eta_s}} c_s \tau_{nst} \tag{2}$$

where c_s=$\left[\left(1-\alpha_s\right)\eta_s\right]^{\frac{(1-\alpha_s)\eta_s}{1-\eta_s}} \left(\frac{\alpha_s \eta_s}{\rho+\delta}\right)^{\frac{\alpha_s\eta_s}{1-\eta_s}}$ collects exogenous parameters, $\{\eta_s, \alpha_s, \rho, \delta\}$ and $\tau_{nst} \equiv \left(\tau_{nst}^K\right)^{\frac{\alpha_s\eta_s}{1-\eta_s}}$ represents the firm-specific capital market friction.

Sector-specific output is derived by summing equation (2) across all N_s firms within a sector s to obtain:

$$Y_{st} = \sum_{n=1}^{N_s} Y_{nst} = \left(w_t\right)^{-\frac{(1-\alpha_s)\eta_s}{1-\eta_s}} C_s T_{st}, \tag{3}$$

where

$$T_{st} = \sum_{n=1}^{N_s} \omega_{nst} \tau_{nst} \tag{4}$$

[3]We choose a Cobb-Douglas production function for analytical convenience. Our approach can be used for more general production functions such as CES as we show below (details in Appendix C.4).

[4]We focus on wedges on capital wedges where we have good measurement, but our theory easily generalises to labour wedges, τ_{nst}^L, modeled in a symmetric way. The earlier version of our paper details this more general approach.

[5]See Hsieh and Klenow (2009)) showing the close relationship between the extension of Lucas (1978) we use here and a standard Dixit-Stiglitz monopolistic competition model where firms will have common and fixed markups.

serves as a sufficient statistic for the sector-specific frictions in the credit market in sector s. Firm-specific frictions are weighted by productivity, where the weight is given by:

$$\omega_{nst} \equiv \frac{\theta_{nst}^{\frac{1}{1-\eta_s}}}{\sum_{m=1}^{N_s} \theta_{mst}^{\frac{1}{1-\eta_s}}} \tag{5}$$

The exogenous prices and parameters are now collected in C_s.[6] Using this, we can then derive an expression for economy-wide output, Y_t by summing equation (3) across all sectors. We will show below that all of the relevant elements of these expressions can be measured in the data that we have available.

3.2 Wages

Equilibrium wages are endogenous and are determined by the labor market clearing condition based on labor demand across all S sectors. The market-clearing wage is now given by:

$$\bar{L}_t = \sum_{s=1}^{S} (w_t)^{-\left[\frac{1-\alpha_s\eta_s}{1-\eta_s}\right]} (1-\alpha_s)\eta_s C_s T_{st}, \tag{6}$$

where $\bar{L}_t$ is the (exogenously given) stock of labor. Using this, we find a direct relationship between the wage and sector-specific credit market frictions. Specifically, consider a change in sector s's distortion, represented by T_{st}, on the wage:

$$\frac{\partial \log w_t}{\partial \log T_{st}} = \frac{(w_t)^{-\left[\frac{1-\alpha_s\eta_s}{1-\eta_s}\right]} (1-\alpha_s)\eta_s C_s T_{st}}{\sum_{r=1}^{S} (w_t)^{-\left[\frac{1-\alpha_r\eta_r}{1-\eta_r}\right]} \left[\frac{(1-\alpha_r\eta_r)(1-\alpha_r)\eta_r}{1-\eta_r}\right] C_r T_{rt}} > 0. \tag{7}$$

To interpret equation (7), recall that as T_{st} approaches one, the capital market distortion goes to zero. So higher T_{st} corresponds to a lower capital market distortion in sector s and this increases the economy-wide wage. The magnitude of this effect depends on a sector's capital intensity, α_s, its returns to scale, η_s and its relative size represented by T_s and C_s. Below, we will explore this quantitatively below using our empirical measure of firm-specific credit frictions τ_{nst}.

[6]

$$C_s \equiv ((1-\alpha_s)\eta_s)^{\frac{(1-\alpha_s)\eta_s}{1-\eta_s}} \left(\sum_{n=1}^{N_s} \theta_{nst}^{\frac{1}{1-\eta_s}}\right) \left(\frac{\alpha_s\eta_s}{\rho+\delta}\right)^{\frac{\alpha_s\eta_s}{1-\eta_s}}.$$

3.3 Output Losses Due to Credit Frictions

To study output losses due to credit frictions, we compare our measured credit frictions to a counterfactual benchmark $\hat{T}_{st}$ for each sector s built from an underlying set of firm specific benchmarks $\hat{\tau}_{nst}$. We consider cases where the benchmark is one of reduced credit frictions compared to what we measure in the data. At the sector-specific level, this benchmark is:

$$\hat{T}_{st} = \sum_{n=1}^{N_s} \omega_{nst} \hat{\tau}_{nst} > T_{st} = \sum_{n=1}^{N_s} \omega_{nst} \tau_{nst}. \tag{8}$$

Associated with the benchmark is a wage $\hat{w}_t$ derived from the labor market clearing condition in equation (6) at the benchmark level of credit market frictions.

Using this, we can express the ratio of actual output compared to the benchmark in sector s as:

$$\frac{\hat{Y}_{st}}{Y_{st}} = \frac{\hat{T}_{st}}{T_{st}} \left[\frac{\hat{w}_t}{w_t} \right]^{-\left[\frac{(1-\alpha_s)\eta_s}{1-\eta_s} \right]}. \tag{9}$$

This has a natural economic interpretation. The first part of equation (9) is a positive *direct* effect from removing credit frictions ($\frac{\hat{T}_{st}}{T_{st}}$), while the second indirect effect is due to the wage being higher. This second term will actually depress output in a sector, and all the more so in sectors that are labor intensive, i.e. α_s is lower. This second term is important economically and, as we shall see significant empirically. As wages rise due to a less distorted capital market, some sectors will contract when economy-wide credit frictions are removed, especially if the direct effect is small, i.e. $T_{st} \simeq \hat{T}_{st}$.

To proceed to the aggregate level, we derive a closed-form expression for the ratio of aggregate output compared to the benchmark. This can be expressed as a weighted mean of the sectoral ratios from equation (9). Thus:

$$\frac{\hat{Y}_t}{Y_t} = \frac{\sum_{s=1}^{S} \hat{Y}_{st}}{\sum_{s=1}^{S} Y_{st}} = \sum_{s=1}^{S} \nu_{st} \left(\frac{\hat{Y}_{st}}{Y_{st}} \right) \tag{10}$$

where $\nu_{st} = Y_{st}/Y_t$ are the theoretically consistent weights which, as we show below, can be derived from observables. As a final step, we can express equation (10) as the percentage change in aggregate output when moving from the actual level of credit market frictions to the counterfactual benchmark as:

$$\frac{\hat{Y}_t - Y_t}{Y_t} = \frac{\hat{Y}_t}{Y_t} - 1 \tag{11}$$

The output gains from moving to the low friction benchmark are, of course, lower when the initial situation has lower frictions.

We now have the necessary ingredients to take to the data and our main quantitative contribution will be to show how equation (11) can be estimated from micro-data, using a credit scoring tool to measure existing frictions, and comparing it to a low friction benchmark. We specify the latter as a situation where all firms above the fifth percentile of default risk have their risk assessment reduced to this this level. We apply this heterogeneously, i.e. looking at the distribution of default risk within each SIC four-digit industry. This counterfactual benchmark is not extreme; it equates roughly to all firms having no worse than a BB- credit rating. Moreover, it ensures that in the low-default benchmark that we use, firms never have an "out-of-sample" level of default risk, relative to their peers in the same industry.[7]

To measure credit frictions empirically, we use assessments of firm-level default risks from the S&P credit rating software tool. The next subsection connects this to how firm's allocate capital in a model of how credit works when default is endogenous.

3.4 Equilibrium Credit Market Frictions

Our approach to credit market frictions allows for firm success or failure, leading to the possibility of default.[8] Let the capital available to each firm be denoted by K_{nst}. This comprises a firm's initial assets, denoted by A_{nst}, and the amount that it is able to borrow, denoted by B_{nst}. Assets A_{nst} represent the health of a firm's balance sheet. Such assets can be directly productive as well as serving as collateral.

The possibility of default is central to credit market frictions in our framework and there are two underlying states: "success"and"failure". Repayment occurs when a firm is successful and makes a profit while default corresponds to a case where the firm fails and makes no profit, thus lacking the capacity to repay its loan.[9] The theoretical model maps directly to the kind of assessment that our credit-rating tool tries to measure, creating a useful and direct connection between the theory and empirics.

[7] See subsection 5.4 for a more detailed discussion of this benchmark counterfactual. Appendix C.1 considers alternative counterfactual benchmarks as a robustness test.

[8] The approach is a simplified version of the model developed in Besley and Burchardi (2012) who allow for default to be endogenous.

[9] This two state specification makes debt and equity equivalent with a state of default being a case where shareholders lose their investment and repayment being one where they receive a dividend.

If a firm invests capital K and is successful, then its profit is used to repay its debt. The relevant profit function is derived from equation (1), and is given by:

$$\Pi^s(\theta, w, K) = [1 - (1-\alpha_s)\eta_s]\,\theta^{\frac{1}{1-(1-\alpha_s)\eta_s}} \left[\frac{w}{(1-\alpha_s)\eta_s}\right]^{\frac{-(1-\alpha_s)\eta_s}{1-(1-\alpha_s)\eta_s}} K^{\left(\frac{\alpha_s\eta_s}{1-(1-\alpha_s)\eta_s}\right)}. \tag{12}$$

This function is sector-specific due to variation in production technologies across sectors. We suppose that capital depreciates in production process at rate δ and hence the value of the assets that remain on the firm's balance sheet are $(1-\delta)K$.

If the firm is unsuccessful, it defaults on its loan. In this case, we allow the lender to seize the firm's assets. However, we suppose that a fraction, Δ, of the value of these assets cannot be recovered, possibly because recovery is costly via the legal system or because, once installed, capital is sunk and cannot costlessly be deployed elsewhere. This means that the lender receives $(1-\Delta)K$ from a firm with assets K in the case of default. If $\Delta = 0$, the full value of the assets is recovered, while if $\Delta = 1$ the assets are worthless.

We will focus on the case where a firm has insufficient liquid assets on its balance sheet to finance its capital needs and hence needs to enter the credit market to augment its capital stock. A *credit contract* comprises an amount lent to each firm in every period, B_{nst}, and a repayment amount, R_{nst}.[10] Firms repay their loans with probability ϕ_{nst}. This is determined by such things as the quality of the firm's management. Lenders must assess this when deciding whether to lend money to the firm and on what terms. While human judgment is important, we know that when lenders assess these risks, they frequently turn to credit rating tools.

We represent how a credit contract is negotiated between a firm and a lender using the following stylized protocol, which applies in each time period:

1. Firm n in sector s at date t enters the period with a balance sheet comprising assets A_{nst}, a default probability ϕ_{nst} and an ouside option of $\bar{U}_{nst}$.

2. Lenders propose a contract $\{B_{nst}, R_{nst}\}$ and firm's accept it if its expected payoff exceeds $\bar{U}_{nst}$, in which case it has capital $K_{nst} = A_{nst} + B_{nst}$.

[10]Thus, R_{nst}/B_{nst} is what we conventionally refer to as the "interest rate"which depends on both dimensions of the specified contract rather than being determined directly. This is purely for analytical convenience.

3. If the firm is unsuccessful, it produces nothing and defaults on its loan. In this case, the lender receives only the residual value of the firm's assets $(1-\Delta)(A_{nst}+B_{nst})$.

4. If the firm is successful, then it pays R_{nst} and the value of its assets depreciates to $(1-\delta)(A_{nst}+B_{nst})$.

We now analyze the optimal credit contract, dropping firm-specific subscripts and considering only a generic firm in sector s with characteristics $\{\phi,\theta,A,\bar{U}\}$. If the firm borrows B and has to make repayment R, then its expected payoff from the contract is

$$\phi\left[\Pi^{s}(\theta,w,A+B)+(1-\delta)(A+B)-R\right]. \tag{13}$$

The expected payoff of a lender that lends to such a firm is correspondingly

$$\phi\left(R-(1+\rho)B\right)+(1-\phi)\left[(1-\Delta)A-(\Delta+\rho)B\right], \tag{14}$$

where ρ is now the funding rate that the lender faces. In the event of repayment, the profit is $R-(1+\rho)B$ and if there is default, it depends on the assets that can be reclaimed by the lender as well as the cost of accessing funds.

The optimal credit contract maximizes (14) subject to (13) being greater than an outside option $\bar{U}_{nst}$. We will focus on the case where this outside option is binding. Setting (13) equal to $\bar{U}$ to solve R and substituting this into (14) means that the optimal amount lent to a firm can be describe by a function $\hat{B}^{s}(\phi,\theta,A)$ that maximizes

$$\phi\Pi^{s}(\theta,w,A+B)-\left[\rho+\phi\delta+(1-\phi)\Delta\right]B+\left[1-\delta\phi-(1-\phi)\Delta\right]A. \tag{15}$$

Assuming an interior solution, this yields capital available to the firm of:

$$\Pi_{K}\left(\theta,w,A+\hat{B}^{s}(\phi,\theta,A)\right)=\frac{\delta+\rho}{\tilde{\tau}(\phi)} \tag{16}$$

where

$$\tilde{\tau}(\phi)=\frac{1}{1+\frac{(\Delta+\rho)(1-\phi)}{(\delta+\rho)\phi}}<1\text{ for all }\phi<1. \tag{17}$$

is our theory-driven measure of the credit friction that entered our model firm decision making in equation (2). Although we have specified this as the lender choosing the allocation of capital, it is "as if" the firm is deciding how much capital to choose when ut faces a cost of capital $\frac{\delta+\rho}{\tilde{\tau}(\phi)}$.

Equation (16) is key to driving capital allocation and says that a firm's marginal product of capital is set equal to a risk-adjusted sum of the depreciation rate and the lender's cost of funds.[11] It plays a key role in linking the default probability to capital allocation. To get a feel for what equation (17) implies, suppose that a firm has a 90% repayment probability (so $\phi = 0.9$) and that $\rho = \delta = 0.05$ so that the marginal product of capital in the absence of default would be 10%. Then with $\Delta = 1$, the marginal cost of capital would be approximately 22%, which is around double the no default case. Even with a repayment probability of 95%, the marginal cost of capital would be around 16%. So we expect significant distortions in capital allocation from reasonable repayment probabilities.

4 Data

4.1 Data Sources

We now describe our data sources that permit us to implement the core ideas from the theory and estimate the aggregate consequences of credit frictions. Here, we sketch the main aspects of the data, with further details available in online Appendix A.

Business Structure Database (BSD). We use micro-data from the Business Structure Database (BSD), which provides annual snapshots of the population of *all* registered UK firms. These data report the number of employees in each firm, for every year, as well as the firm's four-digit UK SIC industry (equivalent to a US 6 digit NAICS code). We consider only firms that operate in the "market sector" i.e. we drop agriculture, mining and quarrying, local and central government, education, health care, financial services, real estate and non-profit organizations. This subset of firms in the market-sector is our primary source for measuring the aggregate output gap attributable to credit frictions. Appendix Table B.1 reports the sample properties. In an average year, we cover 1.46 million firms and 15.6 workers.

[11] To make this explicit, note that (17) can be used to rewrite the right hand side of equation (16) as

$$\delta + \rho + \tilde{\rho}\,(A, \theta)$$

where $\tilde{\rho}\,(A, \theta) = (1 + \rho)\left[\frac{1-\phi}{\phi}\right]$ is a firm-specific credit spread similar to Gilchrist et al. (2013), which is a decreasing function of the repayment probability.

Annual Business Survey (ABS). The ABS surveys all 'large' firms (those with 250 employees or more) as well as a stratified sample of 'SME's' (those firms with fewer than 250 employees). These data are similar in structure and content to the U.S. Annual Survey of Manufacturing (ASM), except they also contain data on the non-manufacturing sectors. Like the ASM, ABS contains information on value added, sales, investment and the wage bill. Our main use of the ABS is to estimate sector-specific production parameters.

S&P Default Risk Algorithm. A unique feature of our study is the use of a credit-scoring algorithm developed and maintained by S&P. This algorithm, called the 'PD Model' is used to construct annual measures of each firm's probability of default (PD). The PD model works by taking in firm-level financial statements, and combines this information with it's own proprietary information on industry and macroeconomic risk. The algorithm is calibrated annually using historical data on actual firm defaults. Importantly for us, the PD model is widely used by financial institutions when evaluating their own portfolio of loans and lending behavior.[12]

When we apply S&P's algorithm, only the historical information set is used, thus making it a forward-looking estimate of default risk from the perspective of when the assessment is made. Thus, for a firm's financial reports lodged in April 2010, our use of the algorithm produces the same measure of default risk that one would have recovered had a lender fed these financial statements into the PD Model at that date. We use the continuous version of the default risk provided by the model, but winsorise at the 99^{th} percentile.[13]

Firm Accounting data from Historical Orbis. To use S&P's 'PD Model', we collect the universe of financial statements from Bureau Van Dijk's (BvD) Historical Orbis database. This covers the full set of registered companies, including SMEs as well as large public and private firms. Importantly, Historical Orbis contains comprehensive data on firms who exited after 2003, so does not condition on survivors. We then map these financial

[12]Some larger financial institutions will also use their own in-house algorithms to price risk based on default probabilities alongside S&P's model. Discussions with a number of personnel at these institutions tell us that these in-house models will rarely–if ever–price risk lower than S&P's PD model, as this leaves them open to serious scrutiny from prudential regulators (who also use S&P's product).

[13]This allows for borrowing costs of insolvent firms to be bounded, reflecting unsecured or private borrowing options. Note that the continuous default risk measure is often banded into discrete categories that are reported by the financial media, such as "aaa" for safer assets and "bbb" for more risky ones (see notes to Figure 2 for the exact bands).

statements into the financial inputs used by the PD Model.[14] The model then combines this with it's own proprietary information about prevailing conditions and returns a measure of the one-year ahead probability of default.

4.2 Descriptive Evidence

After matching the default probabilties from the PD model to the firm-level data, we we can see how default risk varies over time and across our sample. We begin in 2004 when the comprehensive Orbis data are first available and end in 2019 ahead of the COVID pandemic. Figure 1, shows an employment-weighted average measure of default risk. We mark three key events – the global financial crisis ("GFC"), the "Draghi Moment" (when as head of the European Central Bank, Mario Draghi promised to do "whatever it takes" to save the Euro) and the Brexit Vote. The Figure offers a guide to the level of default risk perceived by many lenders at the time, filtered through the lens of the S&P model. It shows that there was a reduction in default risk in the years leading up to the financial crisis, falling to a low of 4.5% in 2007. By 2019, however, this had risen by almost a full percentage point to to 5.4%. Notably, there was a big upward shift in default probabilities during the financial crisis and subsequent Eurocrisis, which had a strong effect as the Eurozone is Britain's largest trading partner. The Draghi Moment in 2013 reversed the elevated levels, but default risks started rising again in the lead-up and in the aftermath of the 2016 Brexit vote. S&P appear to be assessing firms in a way consistent with the various economic and political shocks hitting the UK.

Table 1 reports the same basic facts Figure 1 (column (2) reproduces the exact numbers underling the Figure), but broken down between large firms with 250 or more employees, and SMEs. Roughly half of employees are in SMEs (see Table B.1). Larger firms have a much lower average probability of default than SMEs, with employment-weighted means of 1.8% versus 8% versus 5.1% for all firms pooled (see columns (4), (6) and (2) respectively). The unweighted means in column (1) are substantially higher at 11.0% overall, reflecting the fact that smaller firms both face higher default risk and constitute the vast majority of the firm population. The increase in default risk over our sample period has also been greater for SMEs (rising from 10.1% to 12.2%) than for

[14] The full set of accounting items used are: EBIT, income tax expense, interest expense, total revenue in the previous year, cash flow from operation, net property plant and equipment, retained earnings, total assets, cash and short-term investments, current liabilities, total debt, total liabilities, net income, earnings from continuing operations, total depreciation and amortization, total deferred taxes, and other non cash items. S&P's model can also accommodate missing values, and will impute such values as needed.

larger firms (rising from 3.5% to 4.2%).[15]

Figure 2 looks at the data in terms of the underlying credit scores that go into to computing default risk. It compares the distribution of such ratings in 2004 (light red bars) and 2019 (dark blue bars). Panel (a) shows that employment is concentrated among firms with intermediate credit ratings, with the modal categories falling in the "bb" to "b" range in 2004 (corresponding to default probabilities of 0.72% to 5.35% Panel (b) demonstrates that the firm count distribution is more heavily weighted toward lower credit ratings, with the modal category being "b-" (5.35% to 8.84% default probability) in both years. This reflects the facts SMEs have higher default probabilities. As we would expect from Figure 1, there was a marked deterioration in credit-worthiness between the start and end years: the share of firms in the lowest rating categories ("ccc" and below) increased substantially, while the share in investment-grade categories ("bbb-" and above) declined. This rightward shift in the distribution is evident in whether we look at employment or firm counts, though it appears more pronounced with the latter because, as noted above, credit conditions worsened particularly for smaller firms.

The patterns in Figures 1 and 2, and Table 1 make intuitive sense. But to appraise their quantitative importance for output, wages and employment, we will need to process them through the theoretical approach outlined above.

5 From Theory to Measurement

Our theoretical model suggests a simple but precise mechanism for how default risk assessment in credit markets affect firm decisions through the cost of capital that they face. Lenders will only lend up to a point where the marginal product of capital equals to the risk adjusted cost of capital. Our credit rating tool gives us a way of modeling credit risk and hence how firm decisions are affected. To explore these ideas quantitatively, we now show how all of the key magnitudes can be measured using our firm-level data.

[15] Appendix Figure C.1 shows binscatters of the firm-level default rate at the beginning and end of our sample period. Panel (a) shows a strong positive relationship between the current default rate and the empirical one year ahead firm exit rate. This validates the fact that the PD model is informative about real behaviour. The slope in 2019 is closer to the 45 degree line than 2004, showing that the increase in aggregate default probabilities is not simply due to an actual increase in exit rates, but a perception of greater riskiness of non-payment. Panel (b) shows a strong positive relationship between expected default rates and debt-equity ratios. Again, there seems to be a larger estimate of the default probability in 2019 even for the same level of debt, especially for the most highly leveraged firms.

This will, in turn, allow us to have a theory-based measure of the aggregate impact of credit market frictions.

The measurement proceeds in five steps. First, we leverage default risk as a sufficient statistic to empirically measure idiosyncratic capital distortion. Second, we estimate production function parameters for each industry using micro-data. Third, we use our theoretical model to aggregate the impact of credit market frictions up to the sectoral level. Fourth, we impose the equilibrium labor market condition to solve for the wage with a given level of sector-specific credit market frictions. Finally, we construct measures of output loss.

5.1 Firm-level Credit Frictions

To estimate firm-level credit frictions empirically, we start from the estimated repayment probabilities (ϕ_{nst}) which are computed for each firm from S&P's PD Model. Using this along together with equation (17), yields:

$$\tau_{nst}^{K} = \tilde{\tau}\left(\phi_{nst}\right) = \frac{1}{1 + \frac{(\Delta+\rho)(1-\phi_{nst})}{(\delta+\rho)\phi_{nst}}}. \tag{18}$$

In order to create an estimate of τ_{nst}^{K}, we set $\rho = \delta = 0.05$ and $\Delta = 1$.[16] For each firm, the resulting capital distortion lies in the unit interval.[17] Equation (18) is key input into what follows, representing firm-level variation in credit frictions derived from the underlying default probability estimates.

5.2 Production Function Parameters: Theory and Estimates

To obtain sector-specific estimates of the production function parameters, the capital elasticity (α_s) and returns to scale (η_s), we take two key structural relationships implied by our model to the ABS data. The first relationship is based on the sector-specific labor

[16] Appendix C.2 tests the sensitivity of our findings to these values.

[17] We also winsorize at the 1% level which serves to limit the extent to which measured credit frictions can distort production. It implies a minimum credit score of "cc" (a choke price), and can be motivated by the presence of unsecured borrowing. Including these firms makes no difference to the results in practice, as firms for which this choke price binds have very little employment.

share, χ_s, the ratio of the wage bill to value added, VA:[18]

$$\chi_s = \frac{\sum_{n=1}^{N_s} \text{WageBill}_{ns}}{\sum_{n=1}^{N_s} VA_{ns}} \tag{19}$$

The second structural relationship uses the (conditional) relationship between employment and the capital market friction in the micro-data. We run sector-specific regressions across firms of the form:

$$\log(L_{nst}) = \beta_s \log\left(\tau^K_{nst}\right) + \iota_{\text{industry}} + \iota_{\text{year}} + \varepsilon_{nst} \tag{20}$$

where ι_{industry} and ι_{year} are four-digit SIC-code industry and year dummies and ε_{nst} is an error term that aim to absorb the unobserved productivity term. Using our model, we can relate β_s estimated in equation (20) by noting that the theory implies that:[19]

$$\beta_s = \left(\frac{\alpha_s \eta_s}{1-\eta_s}\right). \tag{21}$$

Putting these two elements together yields estimates of the parameters of interest for each of our eight sectors:

$$\alpha_s = \frac{\beta_s(1-\chi_s)}{\beta_s + \chi_s}, \;\; \eta_s = \frac{\chi_s + \beta_s}{1+\beta_s}, \tag{22}$$

where χ_s is data and β_s is obtained from econometrically estimating equation(20).

Table 2 reports our baseline sector-specific estimates as well as an aggregate pooled estimate ("All Industries" row). We also include standard calibration values on the final row of this table for comparison (e.g., Hsieh and Klenow (2009)) . There are some important insights from these estimates. First, there is meaningful heterogeneity in production parameters across sectors. The capital elasticity (α_s) ranges from 0.28 in Professional Services (M) to 0.47 in Wholesale/Retail (G), while returns to scale (η_s) varies from 0.79 in Manufacturing (C) to 0.87 in Professional Services.

A criticism of the estimates in Table 2 is that we may not have not adequately controlled

[18]We pool data across all time-periods, and construct a weighted sum using survey weights from the ABI/ABS sample

[19]This is implied by the firm's first order condition, $w_t = (1-\alpha_s)\eta_s Y_{nst}/L_{nst}$, which can be rearranged to give $\log L_{nst} = G_{nst} + \frac{\alpha_s \eta_s}{1-\eta_s}\log(\tau^K_{nst})$, where G_{nst} collects productivity and wage terms, specifically θ_{nst} and w_t.

for firm productivity, θ_{nst}, in equation (20). Consequently, as a robustness check, we recovered the persistent component of firm productivity from explicitly estimating a value added production function for each sector separately using the method of Ackerberg et al. (2015) (see Appendix C.3 for details). As is standard, the productivity term is treated as a first-order Markov process and modeled non-parametrically and the intermediate input equation is inverted to control for this unobserved productivity term in the production function routine (as suggested originally by Levinsohn and Petrin (2003). We included this estimate of θ_{nst} as an additional control in equation (20). As expected, the recovered productivity term entered positively and significantly in the employment regressions in all sectors. Its inclusion only had a small quantitative effect on the estimated β_s, the coefficient on the critical credit friction term. Importantly, as we show in Appendix Table C.5, the new implied structural estimates of α_s and η_s are almost identical to baseline estimates in Table 2. Hence, we believe we are doing a reasonable job in our baseline at controlling for firm productivity.

5.3 Sector-level Credit Frictions

To obtain a measure of the aggregate consequences of credit frictions, we can look at the mean credit friction in a sector obtained by averaging across firms using firm-specific productivity weights, ω_{nst}, as in equation (5). This is given by substituting in our empirical estimate of the friction $\tilde{\tau}$, for their theoretical counterparts:

$$T_{st} = \sum_{n=1}^{N_s} \omega_{nst} \tilde{\tau} \left(\phi_{nst}\right)^{\frac{\alpha_s \eta_s}{1-\eta_s}} . \tag{23}$$

The weight, ω_{nst}, is defined in equation (5) and is given by:

$$\omega_{nst} = \frac{\gamma_{nst} T_{st}}{\tilde{\tau} \left(\phi_{nst}\right)^{\frac{\alpha_s \eta_s}{1-\eta_s}}} \tag{24}$$

where γ_{nst} is the employment share of firm n in sector s. Since $\sum_{n=1}^{N_{st}} \omega_{nst} = 1$, we now have the empirical counterpart to equation (23):

$$T_{st} = \left[\sum_{n=1}^{N_s} \gamma_{nst} \tilde{\tau} \left(\phi_{nst}\right)^{-\frac{\alpha_s \eta_s}{1-\eta_s}} \right]^{-1} , \tag{25}$$

which is our measure of sector-level credit market frictions. Note that these sectoral credit friction terms are measured independently from the productivity terms in our model.[20]

5.4 The Low Credit Friction Benchmark

To measure the output loss due to credit market imperfections, we need a benchmark. Our baseline approach considers a world where there is a common perceived default risk within each four-digit industry which is set at the 5^{th} percentile of the probability of default distribution. This gives *all* firms the same access to credit as the "best" firms within the sector in which it operates. These benchmark default risk measures follow equation (25) and are denoted by $\hat{T}_{st}$. By construction, moving to this benchmark reduces credit frictions compared to the PD estimates that we have derive form the S&P credit rating tool and will therefore have a positive effect on output. This will increase labor demand and lead to higher equilibrium wages which will, in turn, push down output and employment, especially in firms where credit frictions were low in the status quo.

We estimate the output losses factoring in both allocative and general equilibrium effects for a specific choice of benchmark. But the framework can be used straightforwardly to assess a variety of low credit friction counterfactuals. We conduct some robustness tests in Appendix C.1 to illustrate how the findings vary. For example, we consider a 'frictionless' counterfactual, where all firms borrow at the risk free rate so that the user-cost of capital becomes $\rho + \delta = 0.1$ for *all* firms. We also consider a number of other "best-in-class" benchmarks including one with a lower-bound at the 5^{th} percentile within wider industry groups, using two-digit industry codes and within each year.

5.5 Equilibrium Wages

We determine the wage level endogenously given a set of credit frictions by assuming that it is set to clear the labor market as in equation (6). To estimate the output loss relative to the benchmark, we need to estimate what the wages would be in the low friction benchmark, i.e. when frictions are at $\widehat{T_{st}}$ by solving for the aggregate la,bor demand in this case and contrasting it to the credit frictions that we have estimated T_{st}. To do so, it suffices to solve for the *ratio* of low friction wages to market wages given by:

$$1 = \sum_{s=1}^{S} \left\{ \Gamma_{ts} \left(\frac{\widehat{w_t}}{w_t} \right)^{-\frac{1-\alpha_s \eta_s}{1-\eta_s}} \left(\frac{\widehat{T_{st}}}{T_{st}} \right) \right\} \tag{26}$$

[20] We view this as a key strength of our approach, and contrasts with approaches that imputes distortions from dispersion in revenue products such as Gopinath et al. (2017).

where $\Gamma_{st} = {}^{L_{st}}/_{L_t}$ is the share of aggregate employment in sector s in year t. Since we can measure all the relevant components of equation (26), we are able to solve numerically for ${}^{\widehat{w}_t}/_{w_t}$.

5.6 The Aggregate Output Gap

Finally, we show how the aggregate output loss due to credit frictions can be calculated. As noted above, we measure this as the percentage increase in aggregate output if the economy moved to the low credit friction benchmark. To estimate this, we combine equations (9)-(11), yielding the following expression:

$$\frac{\hat{Y}_t - Y_t}{Y_t} = \sum_{s=1}^{S} \nu_{st} \left(\frac{\hat{w}_t}{w_t}\right)^{-\frac{(1-\alpha_s)\eta_s}{1-\eta_s}} \left(\frac{\hat{T}_{st}}{T_{st}}\right) - 1 \tag{27}$$

where the output weights $\nu_{st} = \frac{\Gamma_{st}/[(1-\alpha_s)\eta_s]}{\sum_{r=1}^{S}\Gamma_{rt}/[(1-\alpha_r)\eta_r]}$ are calculated using sectoral employment shares Γ_{st} and production parameters.

Equation (27) corresponds to a thought experiment that asks through the lens of our model, what would happen to aggregate output if financial frictions were reduced. It allows for sector-specific heterogeneity in both credit frictions and production parameters, and decouples the direct impact of relaxing frictions with the indirect effect due to increased equilibrium wages.

An attractive feature of equation (27) is that the loss from credit frictions is specified in terms of a minimal set of observables together with our specification of the low friction benchmark. The measure depends on the credit frictions by sector, the estimated production function parameters and the impact of credit market frictions on wages. As well as looking at aggregate effects, the next section will also explore some decompositions by firm size and sector.

6 Results

We begin by quantifying the full general equilibrium effects of credit frictions on the economy based on equation (27). We contrast this with two alternative scenarios (i) holding wages constant - equivalent to infinitely elastic labor supply, analogously to what the baseline model has for capital, and (ii) holding aggregate capital constant - with both aggregate factor supplies fixed (this allows us to identify the pure reallocation effect as distinct from a scale of capital effect). We also discuss the heterogeneity of the impacts of relaxing credit frictions across firm size and across sectors.

6.1 The Aggregate Impact of Credit Frictions

Table 3 documents the gains from relaxing credit frictions for each year. Column (1) indicates the number of firms in the sample per year. Column (2) contains output changes, showing our headline finding in the final row that moving to our low friction benchmark would lead to an increase in GDP of 24.8%. So credit frictions are a quantitatively significant source of inefficiency. The time series profile broadly mirrors Figure 1, and shows a substantial increase after the financial crisis and around the Brexit vote. Appendix C.5 compares our output loss series with the ECB's Loan Supply Index in the Eurozone (Altavilla et al., 2019), a measure of lending frictions. The two time series show a strong correlation until the Brexit vote where output losses worsened in our UK series, but frictions continued to ease in the Eurozone.

Potential gains have risen from 23.7% in 2004 to 26.3% at the end of our sample period in 2019. This increased output loss of 2.6% compares to an actual increase in GDP per hour of 9.8% over this period (Office of National Statistics), implying that productivity growth would have been substantially higher but for the increase in credit frictions.[21] The loss was particularly severe around the financial crisis and its aftermath, with increased frictions reducing output by 5.9 percentage points (= 27.5% - 21.6%) between 2007 and 2013.

Column (3) of Table 3 shows the effects of credit frictions on the wage and shows that we would expect real wages to be 23.4% higher on average in the low friction benchmark, with a time series profile closely following the pattern of output losses. Note that average wages gain in the counterfactual is 1.4 percentage points (24.8% - 23.4%) lower than that of output, a small difference that is entirely due to sectoral heterogeneity. As we will describe later, the more credit-constrained sectors will now take a larger share of output, and these tend to be the ones with lower labor shares. This shows the advantage of a multi-sector model over a one sector macro model.

[21] In other words, productivity growth 2019-2004 would have been 12.65% = (9.8*1.026) instead of 9.8%, a difference of 2.85 percentage points.

Column (4) of Table 3 shows what would happen if, instead of allowing for a general equilibrium response, we fix the real wage (labelled "No Wage Effects"). This would be the case, for example, if labor supply were perfectly elastic rather than in fixed supply.[22] In this case, there would be a larger output effect as none of the benefits of lower frictions would accrue to workers. Output is now 133% higher, over five times larger than in column (2). This illustrates why general equilibrium effects matter and highlights why approaches that do not consider this possibility miss an important dimension of what happens when credit frictions are lowered.

6.2 Factor Reallocation versus Capital Deepening

The output gain of around 25% has two elements: (i) a reallocation effect when inputs are moved towards firms who have lower credit market frictions and (ii) a capital deepening effect due to a higher aggregate capital stock. We now show the relative importance of these by comparing our baseline results to a benchmark where the aggregate capital stock is fixed as is standard in much of the existing literature on capital misallocation such as Baqaee and Farhi (2020). To model this, we solve for the rental cost of capital, ρ that keeps the aggregate capital stock fixed in the low credit friction counterfactual (details in Appendix B). Doing this allow us to isolate a pure reallocation effect since we can consider how much output would have increased if credit frictions are lowered but with no expansion in the capital stock.

Column (5) of Table 3 shows that the reallocation effect of relaxing credit frictions is on average a 9.7% increase in output and a 9.3% increase in wages which is around two-fifths of the overall output (39% = 9.7/24.8) and wage gain (40% = 9.3/23.4). Thus, pure misallocation of labor and capital does have a material effect on economic output, but capital deepening accounts for most of output gain from reducing credit frictions. This offers a new window on the existing misallocation literature which generally assumes away scale of capital effects.

Although the capital deepening effect dominates reallocation in the cross section, the importance of reallocation has been growing over time, particularly after the global financial crisis. For example, the fraction of output losses due to misallocation has risen by five percentage points from 35% (= 8.4/23.7) in 2004 to 40% (= 10.6/26.3) in 2019. As

[22] One could think of this as a model with open borders where immigration fully responds to an increase in labor demand.

we saw in our discussion of column (1), there has been an increase in output losses due to credit frictions of 2.6 percentage points (26.3% - 23.7%) over this period with the losses from misallocation rising by 2.2 percentage points (10.6% - 8.4%). Hence, increases in misallocation due to credit frictions account for 85% (= 2.2/2.6) of the increased productivity losses.

This raises the question of which set of results on output gains should be the main focus. Although stylized, the assumptions of a fixed labor supply and an elastic capital stock seem reasonable as a first approximation to the UK economy. But our approach can be modified to handle a range of possibilities. Moreover, if the supply of capital was only partially elastic, then the output effects would be bounded by what we find in columns (2) and (5) of Table 3 (from 9.7% to 24.8%). Thus, if the capital stock only adjusted by half of what we had in core results, the output gains would be approximately 17.3%.

6.3 The Firm Size Distribution

We now explore how credit frictions affect the firm-size distribution. Since reducing frictions creates winners and losers, once effects on wages are considered, the effects are nuanced. To illustrate this, Figure 3 shows how the distribution of employment changes once frictions are lowered. It plots the share of jobs by firms in different firm-size bins in the data (light pink bars) and the low friction benchmark (dark blue bars). It is well know that the firm-size distribution is highly skewed with 36% of jobs in "very large" firms (those with over 1,000 employees), while only 8% of employment is in "micro" firms with two employees or less. When we relax credit frictions, the share of employment in very large firms shrinks by 16 percentage points to 21%, whereas firms with between two and 250 employees increase their employment share in the economy by about 20 percentage points. The share of jobs in larger firms with 250 to 1,000 employees stays roughly the same.

Intuitively, the finding in Figure 3 is due to SMEs facing larger credit frictions than other firms and hence gaining most from reducing such frictions (see Table 1). In contrast, large firms face have lower credit frictions benefit less and hence suffer as the equilibrium wage increases. This wage effect is dominant for this group of firms and they shrink as a share of total employment. At the other end of the size distribution, firms with two or less employees also see their share of employment fall in half to 4%. This makes sense too, since although this group gains a lot from lower credit frictions they have very low productivity on average, so the higher equilibrium wage means they effectively exit and their former employees are reallocated to more productive firms further up the firm-size distribution.

Figure 3 illustrates how our framework that builds up from the micro-data on credit frictions allows a rich exploration of the equilibrium effects of credit frictions on the firm-size distribution. Broadly, it suggests that credit frictions make the firm size distribution more unequal. Directly, SMEs are kept inefficiently small, but indirectly the low equilibrium wages caused by credit frictions allows small unproductive firms to survive.

In Figure 4 we show how output shifts across the SME vs. large firm segments when we reduce credit frictions. Output gains are driven by the SME segment which increases by 77% in 2019, whereas large firm output shrinks by 26%. The equivalent numbers in 2004 were 67% and 23%. This illustrates the greater credit frictions faced by SMEs, and how this has became worse over time. It may therefore seem surprising that reallocation of factors towards SMEs generates such a positive effect on aggregate output, as much of the misallocation literature argues that there is too little output allocated to large firms.[23] This is because in our framework, (i) size reflects not only productivity, but also credit frictions which holds back some productive SMEs from expanding and (ii) the lower equilibrium wages due to credit frictions effectively subsidizes larger firms.

6.4 Sectoral Differences

We now explore how credit fictions affect the structure of production in the economy by looking at how different sectors are affected. The sectoral distribution of average output gains are shown in column (1) of Table 4. There are two key factors behind these findings. First, the worse is a sector's credit frictions (i.e., the lower is τ_s^K in column (2)), the more it will benefit from a lowering of credit frictions. Second, the more capital-intensive is the sector, (a lower χ_s, in Table 2) the more the sector will benefit from lower credit frictions. But the general equilibrium effect is also heterogeneous by sector with more labor-intensive sectors being more affected by an increaese in the wage.

The gains from lowering credit frictions line up as expected if we group sectors into those

[23]Our model does not have size-dependent regulations which affect larger firms more severely. These are much less important in the UK than in other countries such as Italy and France (e.g., Garicano et al., 2016).

with above and below average values of frictions and labor shares. To illustrate, first consider the two sectors with above average credit frictions and capital shares: Construction (F) and Wholesale and Retail (G).[24], hence a higher capital friction. They experience large gains from relaxing credit frictions: 81% for Construction and 39% for Wholesale and Retail compared to the average gain of 25%. This can be contrasted with the two sectors that are below the industry average for both capital shares and credit frictions: Professional Services (M) and Administrative and Support Services (N).[25] They are also the only two sectors that actually *reduce* their output when credit credit frictions are reduced, as the losses from higher labor costs outweigh the direct gain. The other four sectors are more mixed (above average on one of labor share and τ^K and below average on the other)[26], and as we would expect, their output gains from reduced credit frictions are generally middling.[27]

In summary, our framework makes clear that there are structural effects from the pattern of credit frictions with some sectors likely to expand with fewer credit frictions while others expand. While the patterns are intuitive once the mechanisms are understood, the precise quantitative effects require the kind of framework that we have put forward which allow us to build up the sectoral effects from the underyling micro-data.

6.5 Robustness and Extensions

There are many ways in which the robustness of our findings can be assessed and we detail some of these in Appendix C, giving an overview here.

We first considered alternative benchmarks for low credit frictions (see Appendix Table C.1 where our baseline is in column (2)). Rather than the "best in class" defined as the 5^{th} percentile of the four-digit industry, we consider an extreme benchmark of an entirely frictionless economy without default where $\tau^K_{nst} = 1$. This generates a much larger output gain of 34.9% compared with our baseline gain of 24.8%. We also considered

[24]Sectors F and G have labor shares, χ_s, of 47% and 44% respectively compared to a sector average of 50%, so a higher implied capital share. Their mean τ^K are 0.27 and 0.25 compared to the average of 0.32

[25]Sectors M and N have labor shares of 62% and 57% respectively compared to the aggregate average of 50%. Their mean τ^K are both 0.37 compared to the industry average of 0.32. Hence, they have relatively low capital shares and credit frictions.

[26]ICT (sector J) has a larger gain of 48% than one might expect from this analysis, as it has below average credit frictions. But it also has the second lowest labor share of all sectors which sufficiently offsets this.

[27]We show these results visually in Appendix Table (C.2) with binscatters of output losses by sector-year vs. the output-capital elasticity in Panel (a) and the mean friction in panel (b).

within year rather than across all years as a best in class, and using broader two-digit industries (instead of four-digit). These all generated very similar losses to our baseline.

Second, we considered alternative magnitudes of the parameters of the production function. Table C.2 reproduces our baseline calibration in column (1) while column (2) uses a "pooled" regression version rather than sector specific values (i.e., $\alpha = 0.40$ and $\eta = 0.83$ from Table 2. The output gains fall only slightly to 24.2% which implies that sectoral parameter heterogeneity does not materially affect the core findings. This is encouraging since finer levels of industry disaggregation give us a smaller sample of firms to estimate the relevant parameters and introduce less precision to the estimates. We also considered a more "standard" macro calibration (i.e., $\alpha = 0.33$ and $\eta = 0.85$), which gives somewhat lower aggregate output losses of 19.5%. This suggests that there is value in using our estimated production function parameters from the relevant micro-data. Following on from this, we look look more broadly across alternative parameter values in Table C.3. As expected, the gains are sensitive to the output-capital elasticity parameter, α which are the fundamental determinant of over losses from capital frictions with gains ranging from 19% to 33% (for values between 0.35 and 0.45). The output gains are less sensitive to different returns to scale, η, ranging between 22% and 29% (for 0.8 to 0.85).
Third, we look at varying the other key calibration parameters in lower rows of Table C.3. Since interest rates have varied significantly over the last 20 years, it is reassuring that output losses are in a tight range of 24% to 26% when we move from cost of funds (ρ) from as low as 1% to as high as 9%. A lower capital depreciation rate (δ) creates more potential output gains of 30% when moving from our baseline to 5% to 3%, and a lesser gain of 18% when we increase depreciation rates higher. An important parameter is the loss to a lender after a default (loss-given-default), (Δ). Our baseline assumes no recovery rate of capital after default, but even if we assume a much higher rate of recovery (Δ = 0.8 instead of the baseline 1.0), output gains are still a substantial 20%. Our sense is that output gains from reducing credit frictions is substantial for all reasonable ranges of the key parameters.

Fourth, we relax the assumption that the production function is Cobb-Douglas rather than CES (details are in Appendix C.4). As is well well-known (e.g., Karabarbounis and Neiman, 2021), with a CES production function, a regression of the labor share of value added on the firm specific cost of capital allows one to recover an estimate of the elasticity of substitution, σ.[28] Using the same panel data as Table 2, we find that the

[28] In our context, the only firm-specific variation in the cost of capital over time is the capital wedge

econometric estimate of $\sigma = 1.02$.[29] Hence, the deviations from Cobb-Douglas (where $\sigma = 1$) appear quantitatively minor, so we feel comfortable with assuming a unitary elasticity of substitution in our baseline approach.

Finally, we considered a variety of other ways to deal with some of the missing values on capital frictions in Appendix **??**. We show that, if anything, our baseline method underestimates the overall output losses compared to these alternative approaches.

7 Conclusion

This paper develops a theoretically-grounded approach to credit market frictions using firm-level data. We combine rich administrative data with S&P's proprietary credit-scoring algorithm to measure market perceptions of the default risk for the universe of market sector UK firms between 2004 and 2019. This allows us to study different sectors and firm sizes, including SMEs, which often go unstudied. We also are able to study the general equilibrium implications for wages. Overall, the approach opens a new window on studying the costs of credit frictions in affecting the real economy.

We have used our approach to assess the impact of default risk on aggregate economic performance. We find that credit frictions depress economic output by about 25% on average. Most of this (three-fifths) is due to a lower aggregate capital stock, with the remainder due to reallocation of labor and capital when frictions are reduced. We estimate that real wages are are average 23% lower, and approaches that ignore these equilibrium effects on factor practices massively overestimate the output effects of relaxing credit frictions. We also highlight that large firms (and very small unproductive firms) benefit from the status quo level of credit frictions, because they enjoy the benefits of lower labor costs which outweigh their financial constraints. There is considerable heterogeneity in the impact of credit frictions across sectors, with low labor share firms benefiting more strongly from lower frictions. We also show that credit frictions increased sharply after the global financial crisis and are still elevated. We estimate that productivity would have grown substantially more over our sample period (an additional 2.6 percentage points instead of the actual 9.8%) but for worsening credit frictions. In contrast to the

induced by credit frictions.

[29]There is some variation across sectors in σ. Subsection C.4 shows that the unweighted mean across sectors is 0.99, although it does range as low as 0.7 in Professional, Scientific and Technical services and as high as 1.2 in Accommodation and food services.

cross section, the vast majority of this time series deterioration is due to reallocation.

We have focused on a specific measurable aspect of credit market frictions and the fact that we anchor the empirical analysis in a simple model permits us to estimate of what output would be in the absence of default risk. But beyond the specific factors that we study, we acknowledge that there may be other aspects of frictions in capital markets that are not picked up by a focus on default risk. It does not, for example, assess the possibility that "zombie firms", i.e. those which benefit from lender forbearance, depress output and productivity (see Andrews and Petroulakis (2019)). Having some firms with excess capital relative to the efficient allocation could create an additional source of output loss.

Our model is stylized and could be developed in several different directions. We do not explicitly consider forward-looking behavior. In future work, it would be interesting to study what happens if firms may choose to accumulate assets in order to get better future access to credit markets. Firms could also make productivity-enhancing investments such as R&D, not just for their direct benefits but to be be perceived more favorably by lenders. It would also be interesting to endogenise savings implications of reducing credit frictions by modeling the household sector.

Other future work could also integrate our approach with the literature on how bank connections affected the impact of the global financial crisis - see e.g. Chodorow-Reich (2014), Huber (2018), and Anderson et al. (2019). Although these papers have cleaner causal identification of the impact of the crisis on firms, it is harder to aggregate these up to general equilibrium output effects - which is the focus of our paper (see Catherine et al. (2022) for a similar point). In our framework, these connected firms might suffer a larger exogenous change in their default probabilities, ϕ_{nst}, and therefore their capital taxes, τ^K_{nst}. These designs could be used as instruments for the treatment effects which could in turn be exploited as well-identified micro-moments to offer a richer application of our model.[30]

Overall, our results underline that firm-level assessments of default risk create insights in understanding credit frictions and credit shocks. Moreover, the approach highlights the value of automated scoring tools used by lenders for assessing the impact of credit

[30] See Nakamura and Steinsson (2018) for a general argument for this approach in modern macroeconomics and Herreno (2019) for an application to bank lending cuts.

market frictions using firm-level data. The framework can be applied with parsimonious data requirements and opens up the "black box"of credit frictions in a novel way linked to an underlying theory.

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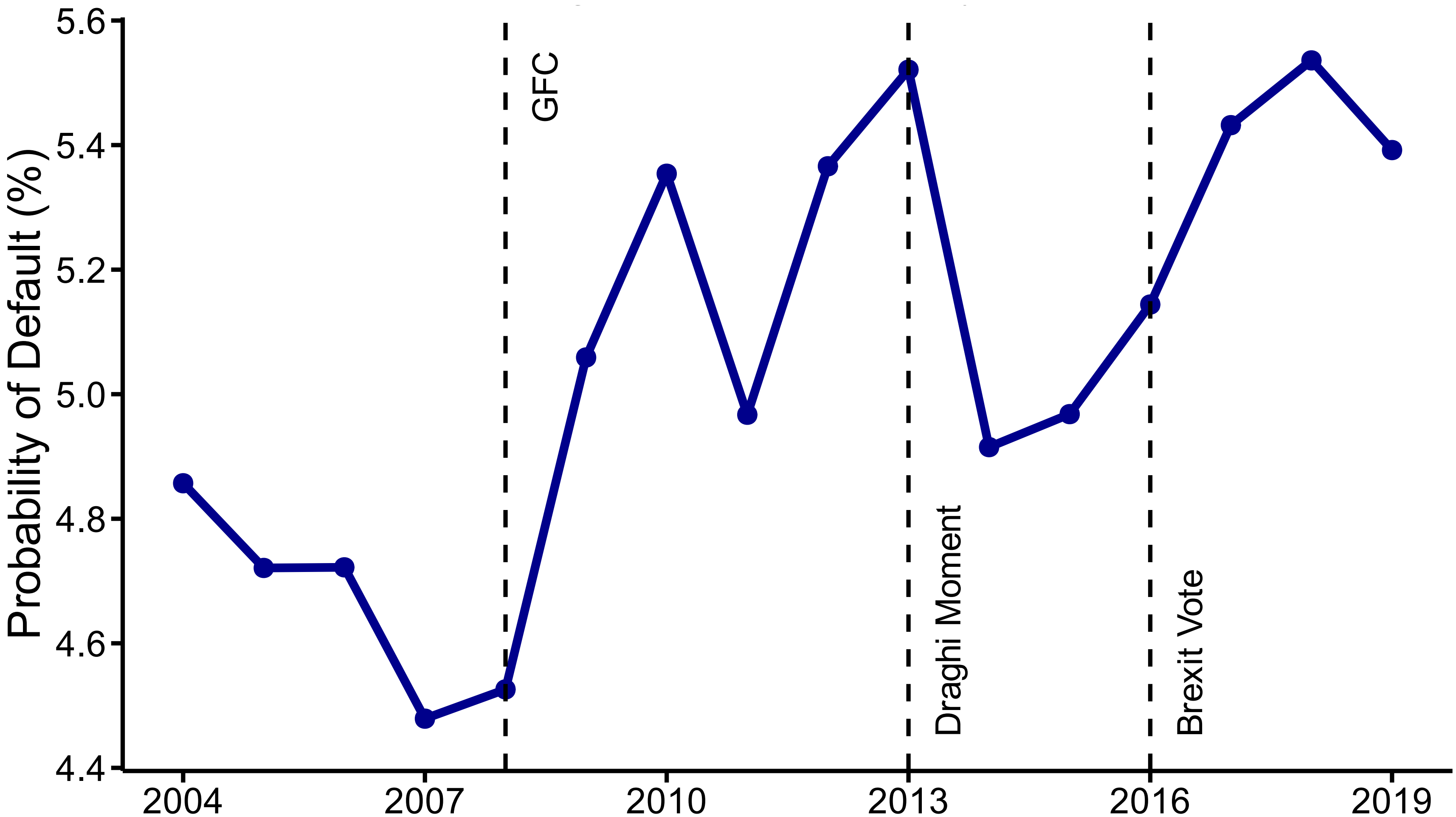
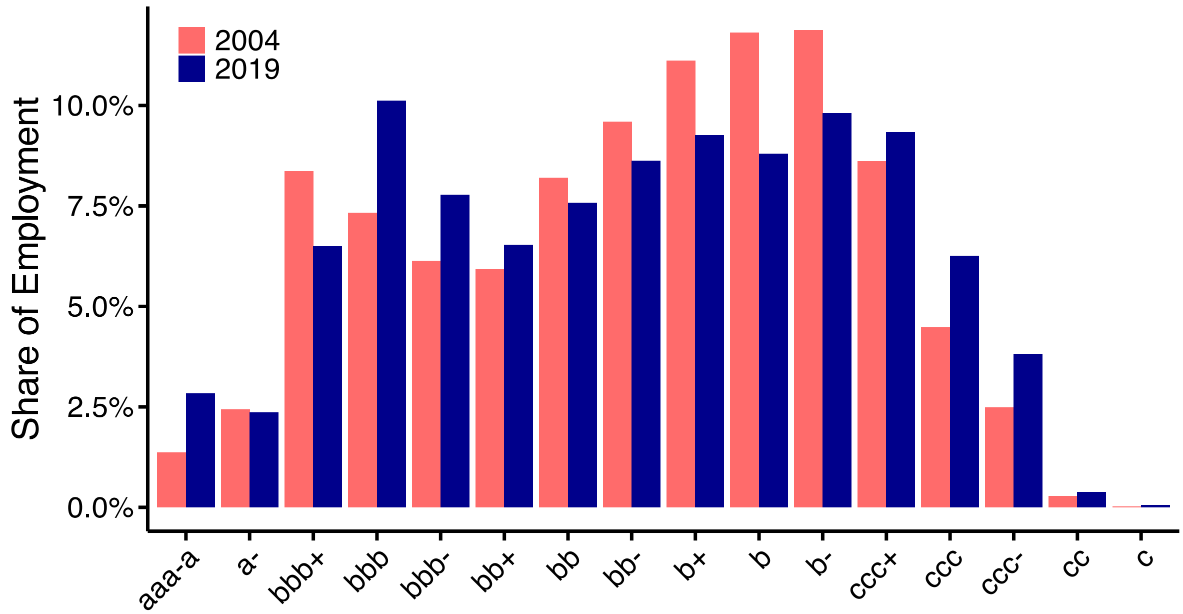
Figure 1: Employment-weighted Default Risk has risen since the Financial Crisis



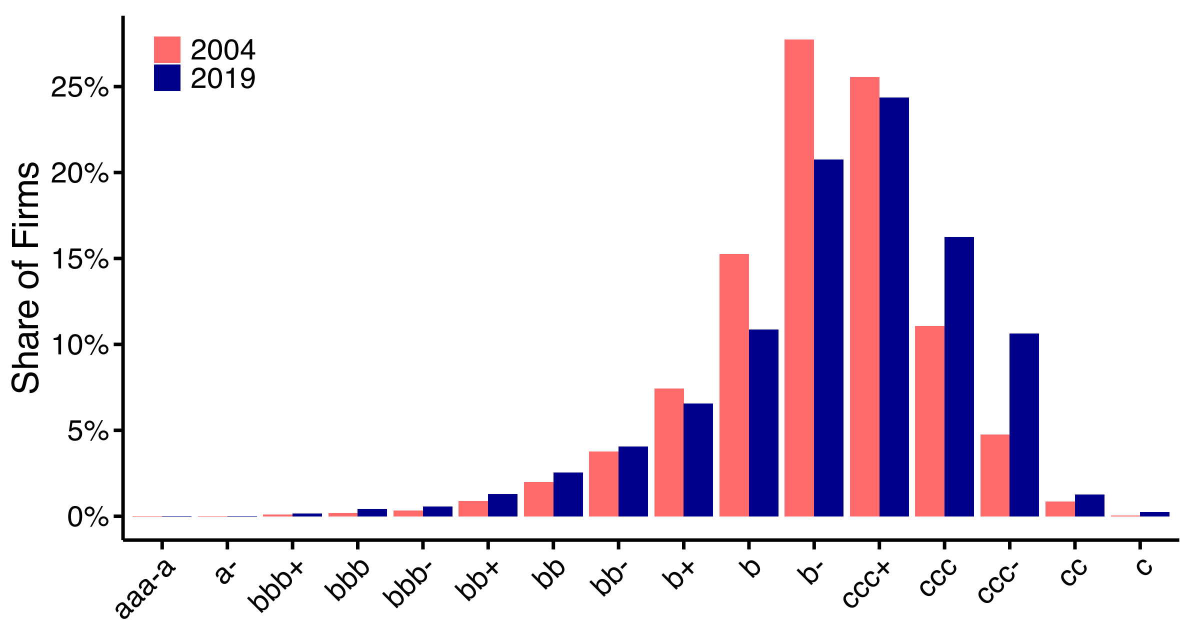
Note: A firm's default probability (PD) is given by the probability that it will default on its payments at the one-year horizon according to S&P's PD Model, using historical information sets only in each year. Firm-level default probabilities are aggregated using employment weights. The sample is the UK market sector (see Table 1 for underlying sample sizes). Vertical lines highlight the start of the Global Financial Crisis, GFC, in 2008, Draghi Moment in 2013 and Brexit Vote in 2016.

Figure 2: Distribution of Employment and Firms by S&P Credit Score, 2004 vs 2019

(a) Employment

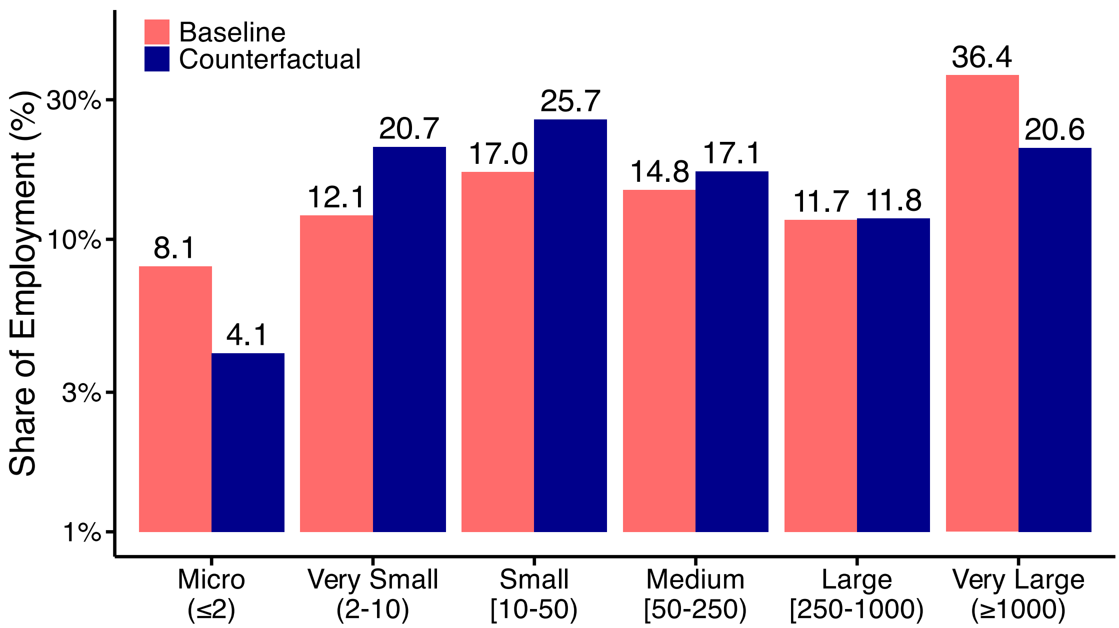


(b) Firms



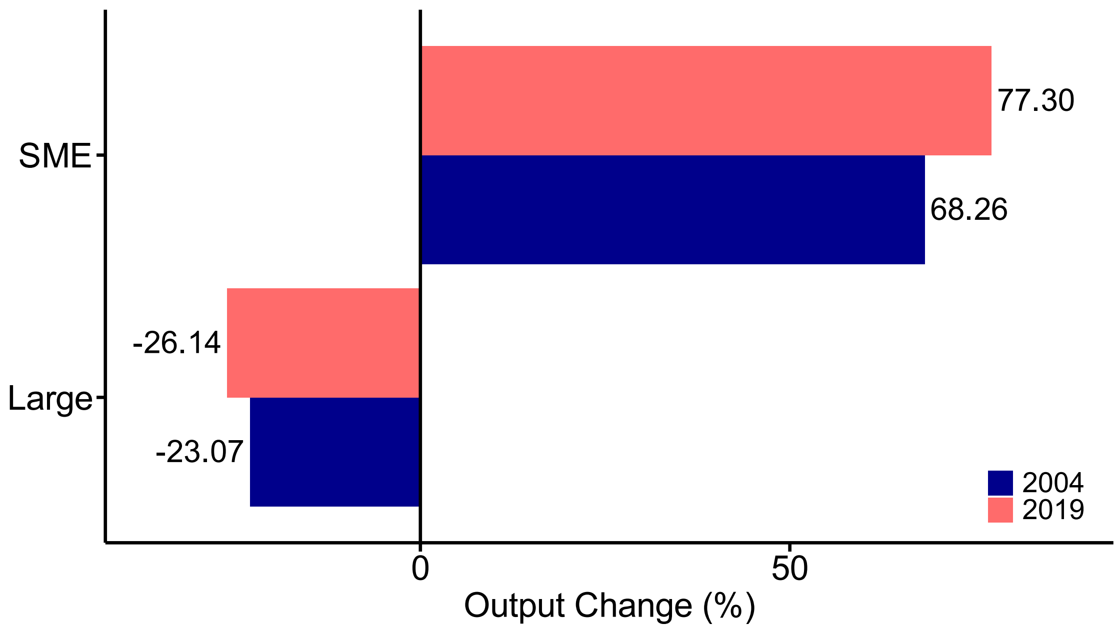
Note: Figure shows the distribution of employment (Panel (a)) and firms (Panel (b)) by S&P credit scores. The credit rating bins with 1-year probability of default ranges are: aaa-a (0-0.058%), a- (0.058-0.097%), bbb+ (0.097-0.16%), bbb (0.16-0.26%), bbb- (0.26-0.44%), bb+ (0.44-0.72%), bb (0.72-1.19%), bb- (1.19-1.96%), b+ (1.96-3.24%), b (3.24-5.35%), b- (5.35-8.84%), ccc+ (8.84-14.61%), ccc (14.61-24.13%), ccc- (24.13-39.86%), cc (39.86-65.84%), and c (65.84-100%). Highest ratings have been merged into aaa-to-a to avoid ONS disclosure thresholds.

Figure 3: Changes in the Firm Size Distribution



Note: Figure reports the share of total employment for each of six firm-size classes, ranging from 'Micro' ($\leq$ 2 employees) to 'Very Large' ($>$ 1,000 employees), comparing the baseline to the low friction counterfactual. 2019 values.

Figure 4: Output Change in the Low Friction Benchmark by Firm Size Group



Note: Figure reports the output growth achieved when moving from the baseline level of credit frictions to the low friction benchmark, broken down into the growth for 'SME' firms ($\leq$ 250 employees) and 'Large' firms ($>$ 250 employees). We report this for both 2004 and 2019.

Table 1: Firm-Level Default Probability (%), 2004-2019

Year	All Firms		Large Firms		SME Firms	
	(1)	(2)	(3)	(4)	(5)	(6)
	Unweighted Mean	Employment Weighted Mean	Unweighted Mean	Employment Weighted Mean	Unweighted Mean	Employment Weighted Mean
2004	10.1	4.9	3.5	1.8	10.1	7.6
2005	10.0	4.7	3.3	1.7	10.0	7.4
2006	9.8	4.7	3.5	1.8	9.8	7.4
2007	9.7	4.5	3.2	1.6	9.8	7.2
2008	10.0	4.5	3.1	1.6	10.0	7.3
2009	10.8	5.1	3.8	1.9	10.8	8.0
2010	11.4	5.4	3.8	1.9	11.4	8.5
2011	11.1	5.0	3.3	1.6	11.2	8.1
2012	11.7	5.4	3.7	1.8	11.8	8.7
2013	11.9	5.5	3.9	1.9	12.0	8.8
2014	10.9	4.9	3.5	1.7	10.9	7.9
2015	10.9	5.0	3.5	1.9	10.9	7.8
2016	11.4	5.1	3.7	1.9	11.4	8.2
2017	11.9	5.4	4.0	2.0	12.0	8.5
2018	12.3	5.5	4.1	2.1	12.4	8.7
2019	12.2	5.4	4.2	2.1	12.2	8.4
Average	11.0	5.1	3.6	1.8	11.0	8.0

Note: This table presents the mean of 'Probability of Default', the one year horizon probabilities calculated using S&P's proprietary algorithm across all registered UK firms. Columns (1)-(2) show two different mean calculations: the unweighted arithmetic mean and employment-weighted arithmetic mean. Columns (3)-(4) report the same calculations for 'Large' firms (250+ employees), columns (5)-(6) report these values for SMEs (under 250 employees).

Table 2: Micro-econometric Estimates of Production Parameters

Industry Section:	(1) Sample Size N	(2) Labor Share χ_s	(3) Regression Coefficient $\widehat{\beta}_s$	(4) Standard Error $SE(\widehat{\beta}_s)$	(5) Implied Parameters α_s	(6) η_s
C: Manufacturing	118,187	0.48	1.52	0.02	0.40	0.79
F: Construction	55,045	0.47	1.79	0.03	0.42	0.81
G: Wholesale and retail trade	152,499	0.44	2.13	0.03	0.47	0.82
H: Transportation and storage	26,050	0.54	2.16	0.06	0.37	0.85
I: Accommodation and food service	26,937	0.58	1.94	0.07	0.32	0.86
J: Information and communication	35,788	0.46	1.83	0.05	0.43	0.81
M: Professional, scientific and technical	51,936	0.62	1.86	0.05	0.28	0.87
N: Administrative and support service	46,554	0.57	1.71	0.04	0.32	0.84
All Industries:	512,996	0.50	1.87	0.01	0.40	0.83
Standard Calibration:	-	0.57	1.89	-	0.33	0.85

Note: This table reports the results of our estimation of sector-specific production parameters α_s and η_s. We estimate these parameters separately for each sector section (defined by UK SIC 2007 section groups). Column (1) reports the sample size and column (2) labor share of value added. Column (3) reports the OLS coefficient of the elasticity of employment (L_{nst}) with respect to the capital distortion term (τ^K_{nst}). This is from a firm-level panel data regression of log employment on $log(\tau^K_{nst})$ with four-digit industry and time dummies. Column (4) are the standard errors (clustered at the firm-level). We use equation (22) along with the values in column (2) and (3) to identify the structural parameters reported in columns (5) and (6). "All Industries" are the results when pooled across all industries. The final row reports commonly used standard calibration values in the literature for comparison.

Table 3: Aggregate Output Gains from Relaxing Credit Frictions

	(1)	(2)	(3)	(4)	(5)	(6)
		Baseline		No Wage Effects	Pure Reallocation Effect	
Year	N	Output Growth (%)	Wage Growth (%)	Output Growth (%)	Output Growth (%)	Wage Growth (%)
2004	1,369,417	23.7	22.2	119.7	8.4	7.9
2005	1,387,790	22.9	21.6	115.7	8.3	7.9
2006	1,405,668	22.8	21.5	115.9	8.4	8.0
2007	1,375,914	21.6	20.3	108.1	8.2	7.7
2008	1,422,240	22.0	20.7	111.2	8.5	8.0
2009	1,391,461	25.1	23.6	131.9	9.5	9.1
2010	1,352,148	26.5	25.1	143.5	10.2	9.8
2011	1,317,958	24.4	23.1	129.8	9.8	9.5
2012	1,353,627	26.6	25.1	145.4	10.4	10.1
2013	1,367,230	27.5	25.9	152.2	10.7	10.3
2014	1,436,061	24.3	23.0	130.6	10.0	9.6
2015	1,490,503	24.3	23.0	131.7	10.0	9.7
2016	1,559,449	25.3	23.9	139.2	10.3	10.0
2017	1,634,874	26.8	25.4	150.8	10.8	10.4
2018	1,647,648	27.0	25.7	154.3	10.9	10.7
2019	1,687,135	26.3	24.9	148.2	10.6	10.4
Average	1,449,945	24.8	23.4	133.0	9.7	9.3

Note: This table reports the aggregate consequences of relaxing credit frictions to our "low credit friction" counterfactual. Column (1) reports the sample size. Columns (2) and (3) report the general equilibrium percentage changes in output and wages respectively in our baseline setting (labor supply fixed and aggregate capital perfectly elastic). Column (4) reports output growth when wages are fixed (perfectly elastic labor supply). Columns (5) and (6) hold aggregate capital fixed (as well as aggregate labor), isolating pure reallocation effects. Our "low credit friction" counterfactual imposes a ceiling on default risk at the fifth percentile within each 4-digit SIC industry.

Table 4: Sectoral Output Gains from the Low Friction Benchmark

	(1) Output Gains (%)	(2) Average Distortions
C: Manufacturing	13.2	0.42
F: Construction	81.1	0.27
G: Wholesale & Retail Trade	39.2	0.25
H: Transportation & Storage	12.3	0.25
I: Accommodation & Food Services	5.1	0.29
J: Information & Communication	48.1	0.35
M: Professional, Scientific & Technical	-8.0	0.37
N: Administrative & Support	-5.1	0.37

Note: Column (1) report output gains, representing $((\hat{Y}_{st} - Y_{st})/Y_{st}) \times 100$, i.e., the percentage change in sectoral output achieved by moving from the baseline distorted economy to a 'low credit friction' counterfactual. Column (2) reports the mean of firm-level capital wedges (τ^K) within each sector, where $\tau^K = 1$ would be zero credit frictions, so a lower value implies greater credit frictions

The Equilibrium Impact of Credit Frictions: Evidence from Default Risk using Firm-level Data

Appendix — For Online Publication Only

A Data

A.1 Business Structure Database (BSD)

Our primary dataset is the Business Structure Database (BSD), which provides annual snapshots of the UK's official business register - the Inter-Departmental Business Register (IDBR). The IDBR is a comprehensive list of UK incorporated businesses and other businesses registered for tax purposes, maintained by the Office for National Statistics (ONS, UK Census Bureau). It excludes the crop and animal production part of agriculture, public administration and defense, activities of households as employers, undifferentiated goods and services-producing activities of households for own use, and activities of extraterritorial organizations and bodies.

The BSD/IDBR contains basic information for all businesses such as employment, sales, and industry, and is structured at the "enterprise reference unit" level. While the IDBR itself is a continuous rolling business register (analogous to the U.S. Longitudinal Business Database), we access it through the BSD, which provides annual snapshots that are also used by the ONS as sampling frames for various representative surveys, including the ABI/ABS (see below). Our BSD extract includes annual data from 2004-2019.

The market sector we analyze includes the following sectors: Manufacturing (C), Construction (F), Wholesale and retail trade (G), Transport and storage (H), Accommodation and food service activities (I), Information and communication (J), Professional, Scientific and Technical Activities (M) and Administrative and Support Services (N). The sectors we drop are those where output is 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.

Our market sector sample covers an average of 1.5 million firms and around 16 million workers per year (see Table B.1).

A.2 Annual Business Survey (ABI/ABS) data

The Annual Business Survey (ABS) is the main survey of the UK non-financial business economy conducted by the Office for National Statistics (ONS). Until 2008, the ABS was known as the Annual Business Inquiry (ABI). ABI/ABS includes a rich set of variables that have been used to calculate UK productivity statistics including gross nominal output, value added, labor, capital investment, intermediate goods and services inputs and the wage bill.

The surveys are a census of large businesses (those with over 250 employees) and a stratified random sample of smaller businesses. The ABI/ABS contains sampling weights which reflect the survey 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 (we use these to calculate sector labour share, for example). We primarily use these data to identify our structural estimates of industry-specific production parameters.

A.3 Data on Default Probabilities

We use Bureau Van Dijk's (BVD) Historical Orbis database to obtain financial statement data required by Standard and Poor's PD Model. Orbis is a worldwide digital database containing accounts of publicly and privately traded firms. We extract all active and inactive UK firms from this database for the period 2004-2019.

Standard and Poor's PD Model is a proprietary algorithm that combines firm-level accounting information with S&P's assessment of industry risk, macroeconomic conditions, and sovereign risk to generate annual default probabilities. The algorithm generates a continuous measure of default probabilities which we use in the paper. It also aggregates these into the well-known S&P's rating symbols (aaa to c, encompassing 21 categories).

The model uses up to 19 accounting items as inputs, though the exact requirements vary by public/private status and broad sector (manufacturing, services, infrastructure). Key inputs include: total revenue, total equity, EBIT, income tax expense, interest expense, cash flow, net property plant and equipment, retained earnings, total assets, cash and short-term investments, current liabilities, total debt, total liabilities, net income, and various other financial metrics.

Importantly, we apply the algorithm using only historical information available at each point in time. For example, to calculate the expected default probability of a firm in

2007, the algorithm sees only financial information from this period and also uses S&P's proprietary algorithm trained on observed defaults for previous years. This ensures our measures reflect contemporaneous market perceptions of default risk.

The algorithm can generate default probability measures even with incomplete data. For publicly listed firms, total equity is required; for private firms, either total revenue or a combination of fixed assets, total assets, current liabilities, and total liabilities suffices. This flexibility allows us to generate default risk measures for 95% of the 16.6 million firm-year observations in Orbis, yielding approximately 15.8 million usable observations when matching to the administrative data.

A.4 Matching

To link our default probability measures to administrative data, we rely on the company registration number (CRN) which is assigned to all registered firms in the UK. The matching process involves several steps and addresses multiple challenges arising from differences in how firms are defined across databases.

The UK Data Service maintains correspondences between CRNs (used in Orbis) and enterprise reference numbers ("Entrefs", used in the BSD/IDBR). However, this matching is imperfect because the two systems are maintained independently. The IDBR identifies business units according to functional units relevant for government statistics, while a CRN is created whenever a company's management registers a new business name. Consequently, there is no necessary one-to-one correspondence between entrefs and CRNs.

The UK Data Service successfully matched 2,372,326 CRNs to entrefs, representing 12.3 million entref-year observations. From these, we drop observations with consolidation code C2 (consolidated accounts of a company-headquarter that also has unconsolidated accounts) to avoid double counting, following Kalemli-Ozcan et al. (2015).

In most cases, the matching process links administrative data with company financials one-to-one. However, some matches are one-to-many, with a single administrative firm linked to multiple company financials.[31]

[31] This is a well-known challenge owing to the fact that a 'firm' takes a slightly different definition in administrative data vs. company financials. The key difference arises because administrative data defines firms according to payroll tax definitions, whereas company financials are defined by each registered legal entity.

When a single administrative firm is linked to multiple company financials, we assign the lowest PD from the set of matched company financials to the administrative firm.[32]

This matching strategy successfully links S&P's probability of default measure to more than half the universe of administrative firms, covering over 64% of total employment. This is about the same for SMEs (64.1%) as for large firms (63.5%).

As noted in the main text, due to missing values of the credit friction measures for a minority of our population of firm-years, we imputed some values using an expectation-maximization with bootstrapping (EMB) algorithm. This estimates the joint distribution of our capital distortion term along with (log) employment, (log) fixed assets, (log) EBITDA, (log) total liabilities, (log) total assets, (log) firm age, firm industry, year, firm size-group, and entry/exit dummy variables. We also include one lead and one lag of the friction term (in the panel where it exists), and (log) employment.

We implement this using the Amelia II R package, adding restrictions to ensure that our imputed friction term τ^K remains bounded on the unit interval, and impose an empirical prior based on 1% of the total sample size. A total of five imputed datasets we constructed and our baseline results used the cell-level mean of these imputed credit friction terms. We also looked at individual draw output gains, and applied Rubin's rules to measure imputation standard errors (Rubin, 1987). We found similar estimates to our baseline estimates, and found that the between-imputation differences one tenth of a percentage point in all years. As a robustness check, we also replicated out baseline measures using non-imputed data only (see Table C.4) and found only modestly higher output gains associated with this non-imputed sample.

[32] Cases where multiple company financials are matched to a single administrative firm are driven by companies with a nested ownership structure. Our approach which takes the minimum default probability from the set of matched companies thus assumes perfect internal capital markets, so that all companies in the company group can access capital markets at the borrowing cost of its least constrained entity (usually the ultimate corporate owner).

B Decomposing Output Losses into Reallocation and Capital Deepening Effects

We introduce a *pure reallocation* setting in which aggregate factor supplies are fixed and exogenous. This is distinct from our baseline model, where the aggregate capital stock expands when credit frictions are relaxed. Our baseline model allows for both a "scale" effect through greater aggregate capital stock (capital deepening), alongside a "reallocation" effect where there is a redistribution of the share of factor inputs. In this Appendix, we isolate the latter reallocation effect by assuming there is a fixed and exogenous aggregate capital stock. Assuming that all aggregate factor supplies are fixed and perfectly inelastic is a standard assumption in the misallocation literature (e.g., Baqaee and Farhi, 2020).

The estimates of this procedure are in Table 2 columns (5) and (6), and enable a decomposition of the aggregate output effect into misallocation and a scale of capital effect - the latter is the difference between columns (2) and (5). Capital deepening accounts for two-fifths of the overall 25% output gain effect in the cross section, but only 15% of the time series change.

B.1 Set Up

As usual we allow for sector technologies to differ in their production parameters (α_s, η_s). Firms face common factor prices (w_t, r_t) and firm-specific capital wedges $\tau^K_{nst} \in (0, 1]$. $r_t = \rho_t + \delta$ which is the endogenous rental rate of capital that clears the capital market which has fixed supply $\bar{K}$. This gives us a slightly different form for sectoral output:

$$Y_{st} \;=\; C_{st}\, w_t^{-\frac{(1-\alpha_s)\eta_s}{1-\eta_s}}\; r_t^{-\frac{\alpha_s\eta_s}{1-\eta_s}}\; T_{st}, \qquad T_{st} \equiv \sum_n \omega_{nst}\,(\tau^K_{nst})^{\frac{\alpha_s\eta_s}{1-\eta_s}}, \tag{B.1}$$

where

$$C_{st} \equiv \big[(1-\alpha_s)\eta_s\big]^{\frac{(1-\alpha_s)\eta_s}{1-\eta_s}}\big[\alpha_s\eta_s\big]^{\frac{\alpha_s\eta_s}{1-\eta_s}} \sum_n \theta_{nst}^{\frac{1}{1-\eta_s}}.$$

The sectoral demand for capital and labor are given by:

$$L_{st} = (1-\alpha_s)\eta_s \frac{Y_{st}}{w_t} = (1-\alpha_s)\eta_s\, C_{st}\, w_t^{-\frac{1-\alpha_s\eta_s}{1-\eta_s}}\, r_t^{-\frac{\alpha_s\eta_s}{1-\eta_s}}\, T_{st}, \tag{B.2}$$

$$K_{st} = \alpha_s\eta_s \frac{1}{r_t}\sum_n \tau^K_{nst} Y_{nst} = \alpha_s\eta_s\, C_{st}\, w_t^{-\frac{(1-\alpha_s)\eta_s}{1-\eta_s}}\, r_t^{-\frac{1-(1-\alpha_s)\eta_s}{1-\eta_s}}\, T^K_{st}, \tag{B.3}$$

with

$$T^K_{st} \equiv \sum_n \omega_{nst}\,(\tau^K_{nst})^{\frac{1-(1-\alpha_s)\eta_s}{1-\eta_s}}. \tag{B.4}$$

A convenient identity linking (B.1)–(B.4) is

$$T_{st} \;=\; \frac{T^K_{st}}{\sum_n (Y_{nst}/Y_{st})\,\tau^K_{nst}}, \qquad \text{with } \frac{Y_{nst}}{Y_{st}} \propto \omega_{nst}\,(\tau^K_{nst})^{\frac{\alpha_s\eta_s}{1-\eta_s}}. \tag{B.5}$$

Pure reallocation: fixed factor supplies

Let total supplies be fixed at $(\bar{L}_t, \bar{K}_t)$. Define baseline sector shares

$$\Gamma_{st} \equiv \frac{L_{st}}{\bar{L}_t}, \qquad \Psi_{st} \equiv \frac{K_{st}}{\bar{K}_t}, \tag{B.6}$$

computed at reference wedges $\{T_{st}, T^K_{st}\}$ and prices (w_t, r_t). Consider counterfactual wedges $\{\widehat{T}_{st}, \widehat{T}^K_{st}\}$ that reallocate factors while keeping $(\bar{L}_t, \bar{K}_t)$ fixed. Market clearing requires

$$1 = \sum_{s=1}^{S} \Gamma_{st} \left(\frac{\widehat{w}_t}{w_t}\right)^{-\frac{1-\alpha_s\eta_s}{1-\eta_s}} \left(\frac{\widehat{r}_t}{r_t}\right)^{-\frac{\alpha_s\eta_s}{1-\eta_s}} \frac{\widehat{T}_{st}}{T_{st}}, \tag{B.7}$$

$$1 = \sum_{s=1}^{S} \Psi_{st} \left(\frac{\widehat{w}_t}{w_t}\right)^{-\frac{(1-\alpha_s)\eta_s}{1-\eta_s}} \left(\frac{\widehat{r}_t}{r_t}\right)^{-\frac{1-(1-\alpha_s)\eta_s}{1-\eta_s}} \frac{\widehat{T}^K_{st}}{T^K_{st}}. \tag{B.8}$$

Equations (B.7)–(B.8) determine the price ratios $\widehat{w}_t/w_t$ and $\widehat{r}_t/r_t$.

Aggregate output. From (B.1), sectoral output ratios are

$$\frac{\widehat{Y}_{st}}{Y_{st}} = \left(\frac{\widehat{w}_t}{w_t}\right)^{-\frac{(1-\alpha_s)\eta_s}{1-\eta_s}} \left(\frac{\widehat{r}_t}{r_t}\right)^{-\frac{\alpha_s\eta_s}{1-\eta_s}} \frac{\widehat{T}_{st}}{T_{st}}.$$

Let $\nu_{st} \equiv Y_{st}/Y_t$ be baseline output weights. Using $Y_{st} = \frac{w_t}{(1-\alpha_s)\eta_s} L_{st}$ from (B.3),

$$\nu_{st} = \frac{\Gamma_{st} / \left[(1-\alpha_s)\eta_s\right]}{\sum_{r=1}^{S} \Gamma_{rt} / \left[(1-\alpha_r)\eta_r\right]}. \tag{B.9}$$

Aggregate output then satisfies

$$\frac{\widehat{Y}_t}{Y_t} = \sum_{s=1}^{S} \nu_{st} \left(\frac{\widehat{w}_t}{w_t}\right)^{-\frac{(1-\alpha_s)\eta_s}{1-\eta_s}} \left(\frac{\widehat{r}_t}{r_t}\right)^{-\frac{\alpha_s \eta_s}{1-\eta_s}} \frac{\widehat{T}_{st}}{T_{st}}. \tag{B.10}$$

Table B.1: Sample Size of Firms and Employment from Business Structure Database from the Market Sector

Year	All		SME			Large		
	Employment	Firms	Employment	% of Employment	Firms	Employment	% of Employment	Firms
2004	14,964,551	1,376,901	7,888,049	52.71	1,371,752	7,076,502	47.29	5,149
2005	14,904,267	1,393,810	7,826,383	52.51	1,388,758	7,077,884	47.49	5,052
2006	14,991,964	1,411,649	7,874,549	52.53	1,406,646	7,117,415	47.47	5,003
2007	14,904,124	1,380,881	7,766,348	52.11	1,375,982	7,137,776	47.89	4,899
2008	15,354,987	1,427,139	7,988,488	52.03	1,422,190	7,366,499	47.97	4,949
2009	15,358,240	1,396,289	7,963,124	51.85	1,391,332	7,395,116	48.15	4,957
2010	14,832,258	1,356,886	7,735,769	52.16	1,352,237	7,096,489	47.84	4,649
2011	14,498,250	1,322,655	7,506,644	51.78	1,318,067	6,991,606	48.22	4,588
2012	14,777,566	1,358,590	7,689,252	52.03	1,353,916	7,088,314	47.97	4,674
2013	14,973,057	1,372,654	7,775,166	51.93	1,367,927	7,197,891	48.07	4,727
2014	15,654,351	1,442,619	8,074,369	51.58	1,437,697	7,579,982	48.42	4,922
2015	16,129,897	1,497,406	8,381,398	51.96	1,492,259	7,748,499	48.04	5,147
2016	16,423,182	1,566,935	8,515,479	51.85	1,561,636	7,907,703	48.15	5,299
2017	16,790,430	1,644,546	8,787,745	52.34	1,639,187	8,002,685	47.66	5,359
2018	17,142,192	1,670,645	8,930,932	52.10	1,665,037	8,211,260	47.90	5,608
2019	17,459,691	1,731,074	9,067,709	51.94	1,725,310	8,391,982	48.06	5,764
Average	15,572,437	1,459,417	8,110,713	52.08	1,452,496	7,461,725	47.92	5,046

Note: This table presents annual totals of firms and employment from the UK Business Structure Database (BSD), which covers the universe of registered firms and we focus on the market sector. The market sector excludes agriculture, mining and quarrying, financial services, real estate, and public sector/non-profit organizations. Firms are classified as SME if they have fewer than 250 employees, and Large otherwise. For each year from 2004-2019, we report total employment, number of firms, and the employment share separately for All firms, SMEs, and Large firms. Employment counts and shares demonstrate that while SMEs represent over 99% of firms by count, they account for approximately 52% of total employment, reflecting the significant concentration of employment in large firms. All employment counts are expressed in absolute numbers.

C Further Robustness Results

C.1 Alternative Benchmarks for the low friction counterfactual

The theory laid out in this paper allows us to characterize the change in aggregate economic output between any two scenarios where credit frictions differ (see equation (27)). Our main analysis considers the 'reference level' of credit frictions, i.e. the credit frictions we recover using real data on default risk as a sufficient statistic. It compares this reference level to a benchmark level of credit frictions, which is defined using a 'best-in-class' counter-factual. This counter-factual imposes a ceiling on firm-level default risk, ensuring no firm's probability of default exceeds the fifth percentile within each narrow industry group, defined using four-digit standard industry code (SIC). This is roughly equivalent to a 'BB-' floor on firms' credit-scores. This benchmark has the appealing property that no firm achieves a default risk that is out of sample relative to their industry peers.

We now consider alternative benchmarks against which the reference-level of measured credit frictions is compared. These alternative benchmarks include a *'frictionless' benchmark*, where all firms face no credit frictions (i.e. $\tau_{it}^{K} = 1$ for all firms i across all years t). We also consider alternatives to our preferred 'best-in-class' counterfactual, where we define the fifth-percentile ceiling using broader industry groups (two-digit SIC) and allowing the ceiling be defined distinctly within in each year, as opposed to across all years.

Table (C.1) reports the output gains achieved when moving from the reference level of credit frictions to each of these different benchmarks. Column (1) reports the output gains from moving to the frictionless benchmark. As expected, these gains are larger than our main specification, with output increasing by 34.9% on average when removing all dcredit frictions. We view this counterfactual as extreme, but informative as a limiting case on the potential gains from reducing credit market frictions. Column (2) reports the same results from our preferred specification, where we place a ceiling on default risk at the fifth percentile of the distribution within each narrow four-digit industry, defined simultaneously across all years. Column (3) keeps to the four digit industry benchmark but allows this ceiling-level of default risk to be different by year. We also consider coarser two-digit industries across all years in column (4) and year specific in column (5). In practice, all these three versions yield almost identical aggregate output gains to our baseline 25%.

C.2 Using Common Values of Production Function Parameters instead of Sector-specific Parameters Values

A key feature of our theoretical approach is to allow for sector-specific production parameter heterogeneity, which we estimate and report in Table 2. This approach offers additional flexibility, especially given the diverse set of capital intensities across sectors. For robustness, we also present below common production parameters (α and η) across all sectors.

When we recompute the aggregate output gain under common production parameters, imposing $\alpha_s = \alpha$ and $\eta_s = \eta$ for all sectors s, the sectoral distortion term changes. It is given by

$$T_{st} = \left[\sum_{n=1}^{N_s} \gamma_{nst} \, \tilde{\tau}(\phi_{nst})^{-\frac{\alpha\eta}{1-\eta}} \right]^{-1}, \tag{C.1}$$

and aggregate output gains are computed from

$$\frac{\hat{Y}_t - Y_t}{Y_t} = \sum_{s=1}^{S} \nu_{st} \left(\frac{\hat{w}_t}{w_t} \right)^{-\frac{(1-\alpha)\eta}{1-\eta}} \left(\frac{\hat{T}_{st}}{T_{st}} \right) - 1. \tag{C.2}$$

Two observations are useful for interpreting these results. First, the exponent inside the sectoral distortion term, $\alpha\eta/(1-\eta)$, rises in both α and η, and becomes especially sensitive as η approaches one. Second, the wage term works in the opposite direction for some parameter changes, so monotonicity in η is not a mechanical theorem of the model. Nonetheless, over the parameter range considered here, the corrected numerical results are monotone in both arguments: for fixed η, output gains rise with α; and for fixed α, output gains also rise with η. This pattern is consistent with the broader intuition that credit frictions are more consequential in production environments that are more capital intensive.

The reported output gains associated with each set of production-parameters is shown in Table C.2. Column (1) reproduces our baseline and in column (2) we use the pooled regression to obtain the structural parameters. We see that the output gains from relaxing credit frictions are similar, indicating that switching off the sector specific heterogeneity only slightly reduces the overall measured impact of credit frictions (from 24.8% to 24.2%). This fall in gains is because sectors which benefit more from lowering credit frictions tend to have a higher capital share. [33] Finally, using "standard" values in see column (3) reduces gains from reducing credit frictions to under 20%, because α = 0.33 is lower than we estimate empirically.

As discussed in the main text we examine sensitivity to alternative high and low values of all key parameters (including those of the production function) in Table C.3. Although the precise value of the magnitude of gains changes, we see material increases in output from relaxing credit frictions across all the experiments.

C.3 Alternative Econometric Estimation of Sector-specific Production Function Parameters

We consider an alternative approach to our main structural estimation approach to recover the sector-specific output elasticity respect to capital (α) and the returns-to-scale (η) parameter in Table 2. As noted in the main text, this is to address the criticism that our baseline approach of controlling for firm-level productivity θ_{nst}, through industry dummies, time dummies and an idiosyncratic error may be inadequate.

To address this we explicitly estimated a value added production function using the Ackerberg et al. (2015) for each sector separately. This approach is in the spirit of Olley and Pakes (1996) where we use a proxy variable for the unobserved persistent productivity term to eliminate the bias in estimating the parameters. We use material expenditure to construct the control function. If we can write this input demand as a strictly monotonic function of capital, labour and the persistent productivity term, we can invert this equation to proxy productivity as a non-parametric function of materials, capital and labour. We use a third order polynomial to control for this in the second stage of the Ackerberg et al. (2015) estimation routine (the first stage projects value added on a non-parametric function of factor inputs to strip out measurement error in value added). The estimation of the production function allows us to recover the persistent firm-specific productivity residual (conventionally denoted ω, a first order Markov process in the production function literature and equivalent to θ_{nst} in our framework).

Table C.5 reports the employment elasticity with respect to credit friction term (β_s) from

[33] For example, Construction ($\alpha_s = 0.42$) and Wholesale/Retail ($\alpha_s = 0.47$) show the largest output gains from removing frictions, while Professional Services ($\alpha_s = 0.28$) actually contracts due to the wage increase overwhelming the modest direct benefits. Imposing common capital intensities across all sectors reduces the measured gains from reduced frictions in these sectors.

both our baseline in Table 2 in column (3) and the alternative approach where we additionally control for an estimate of firm level productivity from the production function in column (4) of Table C.5. This term enters positively and significantly in the employment regression, as expected. The estimate of the β_s does fall, but only by a small amount (e.g., from 1.5 to 1.4 in the manufacturing sector). Crucially, columns (5) and (6) show the new estimates of the structural parameters (α and η)) implied by column (4) when combined with the labour share. These are lower than our baselines reproduced in columns (2) and (3), but the difference is minute, never greater than 0.01. In manufacturing, for example, the output elasticity with respect to capital falls from 0.40 to 0.39 and the returns to scale parameter from 0.79 to 0.78. Consequently, there is essentially no change to any of our results on output losses from this alternative approach.[34]

We also experimented with allowing for a firm specific correlated fixed effect in estimating equation (20), and also in the production function procedure either through OLS or through dynamic panel data approaches in the spirit of Bond and Blundell (2000). As is common in the literature we found that these produced very attenuated and unreasonably low estimates of the production function parameters (see e.g., Griliches and Mairesse, 1995).

C.4 CES instead of Cobb-Douglas Production Function

As an alternative to Cobb-Douglas, we considered a Constant Elasticity of Substitution (CES) production function with an elasticity of σ. This delivers a simple relationship between the firm-level labor share and the capital wedge that can be used to estimate the elasticity of substitution σ. Since the risk-free rental rate of capital $(\rho + \delta)$ is common among firms, the idiosyncratic capital wedge τ^K_{nst} provides variation to identify this equation.

Cost minimisation implies that the labor share satisfies

$$\chi_{nst} \equiv \frac{w_t L_{nst}}{(\rho + \delta)\, K_{nst} / \tau^K_{nst} + w_t L_{nst}} = \frac{(1-\alpha)\, w_t^{1-\sigma}}{\alpha \left(\frac{\rho+\delta}{\tau^K_{nst}}\right)^{1-\sigma} + (1-\alpha)\, w_t^{1-\sigma}}. \tag{C.3}$$

[34] One could ask why we do not adopt this as our baseline approach. First, it requires a more complex estimation method and there are concerns with the robustness of the proxy method approach to production functions (e.g., the discussion in Norris-Keiller et al., 2024). Second, it requires using an estimate of the capital stock which we do our core methodology. Since concerns with the availability and measurement of the capital stock is a motivation for our work we prefer the simpler approach of our baseline.

Dividing through by the wage term, $w_t^{1-\sigma}$ gives:

$$\chi_{nst} = \frac{1-\alpha}{(1-\alpha) + \alpha \left(\frac{\rho+\delta}{w_t \tau^K_{nst}}\right)^{1-\sigma}}. \tag{C.4}$$

The log-derivative of the labor share with respect to the capital wedge is

$$\frac{\partial \log \chi_{nst}}{\partial \log \tau^K_{nst}} = (1-\sigma)\big(1-\chi_{nst}\big) \tag{C.5}$$

Equation C.5 shows that, holding $(\frac{\rho+\delta}{w_t})$ fixed, the slope of $\log \chi_{nst}$ with respect to $\log \tau^K_{nst}$ is proportional to $(1-\sigma)$, with the proportionality factor given by $1-\chi_{nst}$.

Motivated by equation (C.5), we estimate regressions of the form:

$$\log \chi_{nst} = \beta_s \log \tau^K_{nst} + \kappa_n + \zeta_{jt} + \varepsilon_{nst}, \tag{C.6}$$

where κ_n are firm fixed effects, ζ_{jt} are two-digit industry by year dummies and ε_{nst} is an error term. The estimated coefficient β can be interpreted as an average of the derivative in equation (C.5). Evaluating equation (C.5) at a representative labor share $\overline{\chi}$ then provides a direct mapping from the estimated coefficient β to the CES parameter,

$$\beta = (1-\sigma)\big(1-\overline{\chi}\big) \qquad \Longrightarrow \qquad \hat{\sigma} = 1 - \frac{\hat{\beta}}{1-\overline{\chi}}. \tag{C.7}$$

Using the industry- or economy-wide labor share along with our coefficient estimates, equation (C.7) then delivers an estimate of the elasticity of substitution $\hat{\sigma}$ implied by the observed sensitivity of firm-level labor shares to the capital wedge. The Cobb–Douglas case $\sigma = 1$ corresponds to $\beta = 0$, so equation (C.6) also nests Cobb–Douglas as a special case.

We estimated equation (C.6) on the ABI/ABS data separately for each of our eight sectors as well as pooled across all observations (sample sizes are the same as Table 2). We found limited deviations from Cobb-Douglas. In the pooled regression our estimate was σ = 1.02. For the other sectors we found elasticities of substitution of 1.15, 0.79, 1.07, 0.91, 1.21, 1.02, 0.66 and 1.07 in sectors C, F, G, H, I, J, M and N respectively. So although some sectors have departures from a unitary elasticity of substitution, the mean of 0.985 suggests Cobb-Douglas is good approximation.

C.5 Alternative Imputation Methodology for missing values

As noted in the main text, due to missing values of capital frictions for a minority of our population we imputed some values using an EMB algorithm. As a robustness test we used the non-imputed sample in Table C.4. Although this has a much smaller sample size, the results are very similar with output losses of 26% compared to 25% in the baseline approach. [35]

C.6 Correlation with the Euro area Loan Supply Index

We examine how our annual estimates of the output gain from relaxing credit frictions co-move with the Euro area Loan Supply Index (LSI) of Altavilla et al., 2019, an external index of credit *supply*.[36] We are not claiming that our estimated output gain is itself a measure of credit supply. It is an equilibrium object that reflects both supply- and demand-side forces, including firm fundamentals. We benchmark against a pure supply-side index because such measures are routinely used in the literature to proxy for credit frictions, and because co-movement with them is informative about whether our measure captures variation in credit conditions of the kind that the literature attributes to supply shocks. A positive correlation is consistent with our measure picking up supply-driven tightening, but does not require that supply be the only or dominant driver.

The Euro area Loan Supply Index (LSI) is constructed from the ECB Bank Lending Survey question on credit standards applied to loans to enterprises. The construction explicitly nets out demand effects (using companion questions on loan demand), so the resulting series is interpretable as a pure supply-side shock to lending standards. The LSI is a *flow* measure of quarterly changes in lending standards. To match it to our annual stock measure of credit frictions, we cumulate it into a stock index and take the Q4 value as the annual observation. The smoothed LSI flow from Altavilla et al., 2019 is signed so that positive values indicate quarterly tightening of lending standards. We cumulate the smoothed flow starting at 100 in 2002Q4 (the first observation in this

[35] We also considered using smaller numbers of bootstrapped draws, sample weights and inverse probability weighting.

[36] We thank the authors of the paper for sharing the updated and most recent version of their series with us.

series) to construct the stock measure: the index rises during tightening episodes and falls during easing.

We align the LSI to our output-gain series with a one-year lead of the LSI, so that the Q4 value of the cumulated index for year $t-1$ is matched to our output gain for year t (e.g., the 2006Q4 LSI value is matched to our 2007 observation). We do this because our probability-of-default estimates, which underpin the output gains, measure one-year-ahead forward-looking default risk: the credit conditions prevailing at the end of one year are the relevant determinant of default risk realised over the following year. Aligning the LSI on this basis matches the timing of the two objects more closely.

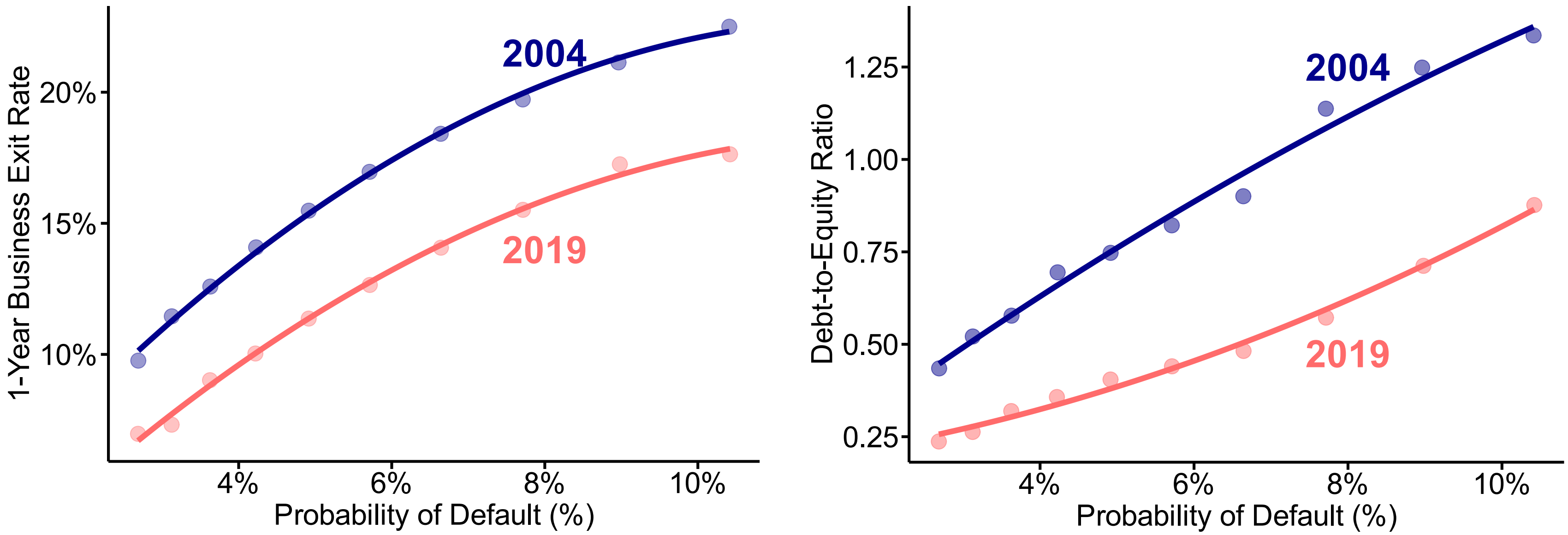
We compare the evolution of the LSI to our estimated output gains from relaxing credit frictions, i.e. the general-equilibrium total effect from column (2) of Table 3 in the main text, averaging 25% over 2004-2019. Higher values indicate greater credit frictions, matching the sign convention of the cumulated LSI (higher = tighter lending standards).

Figure C.3 shows the two series over our sample period of 2004-19. They move quite closely together with a correlation of 0.84 until 2016, the year of the Brexit referendum. After this they diverge sharply. The cumulated LSI peaked around 110 in 2012-2013 and then declined back toward 90 as Euro area lending standards eased, while our UK measure worsened again from 2016 onwards and remained elevated through 2019. The pattern suggests that, absent the UK-specific shock around the 2016 referendum, our measure of UK credit frictions tracks Euro area lending standards quite closely.

Figure C.1: Expected Default Probabilities are higher for Firms who Subsequently Exit and for highly leveraged firms

(a) Business Exit Rate

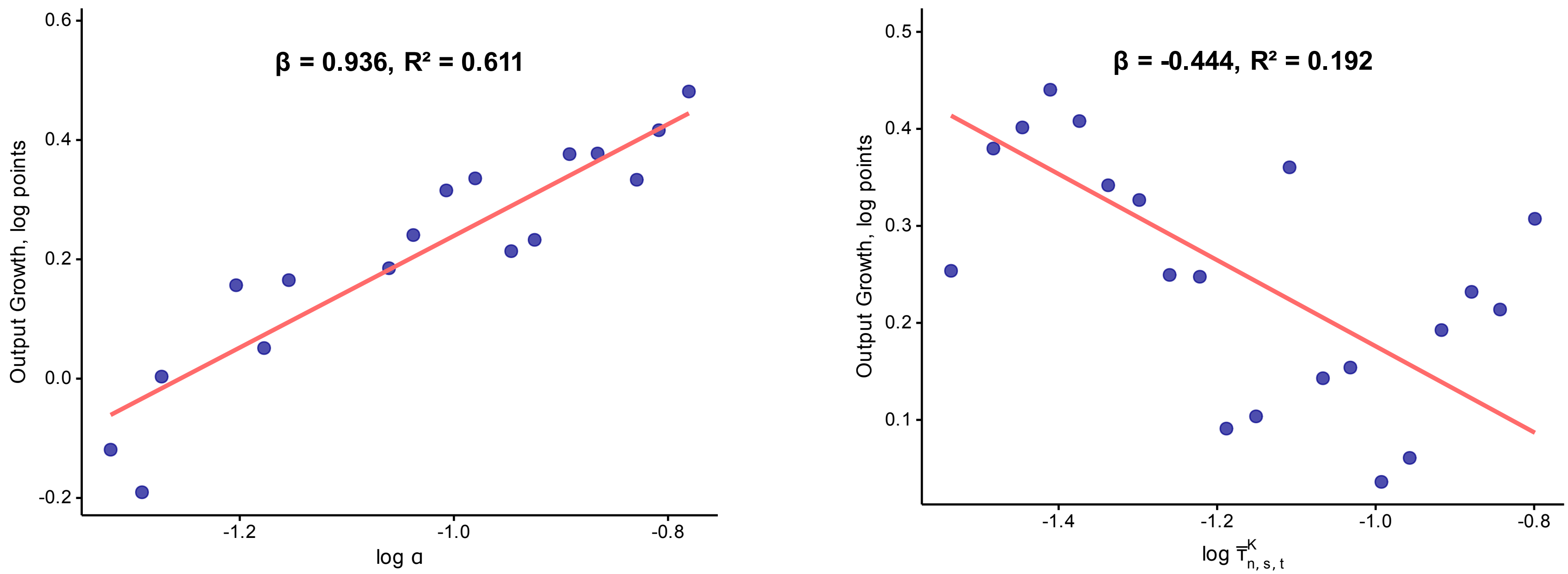
(b) Debt-to-Equity Ratio



Note: Both panels show bin-scatter plots using data from the Business Structure Database (BSD) covering UK registered firms in the market sector, linked to company accounts and parsed using S&P's proprietary PD Model. Bins are constructed using intervals over the probability of default (PD). Panel (a): Employment-weighted geometric mean of PD vs the fraction of firms alive in the previous year who exited in the focal year. Panel (b): Employment-weighted geometric mean of PD vs debt-to-equity ratio for firms with positive debt.

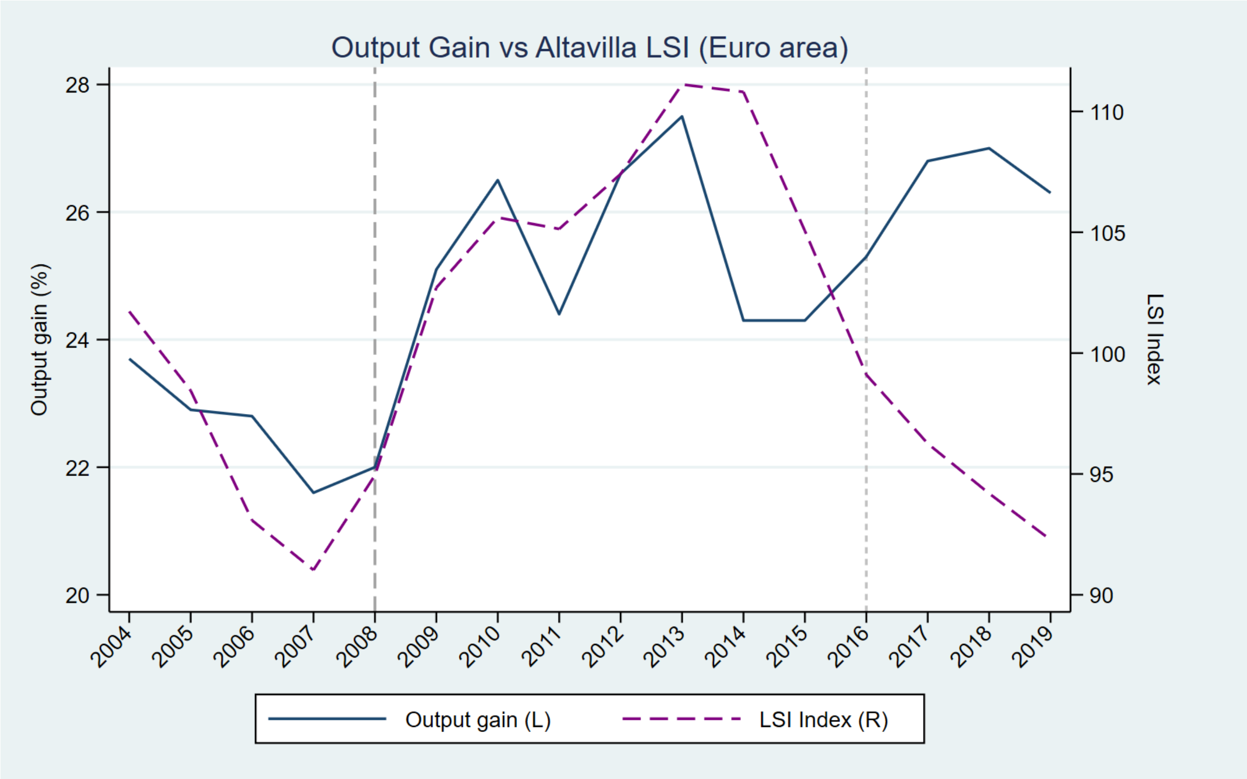
Figure C.2: Output Gains across Industry×Year cells are positively (negatively) correlated with capital intensity (average credit frictions)

(a) Capital Intensity, α (b) Mean Firm-level Friction, $\bar{\tau}^{K}_{n,s,t}$



Note: Binscatter plots showing the relationship between output gains from reducing credit frictions (log points) and (a) capital intensity in production, and (b) average firm-level distortion term. Both panels shows 20 bins with observations grouped by the x-axis variable after residualizing for year and size group fixed effects. The y-axis in both panels represents output growth in log points, $\log(Y_{cf}) - \log(Y)$. Panel (a) plots against capital intensity parameter α; panel (b) against mean firm-level capital wedge $\bar{\tau}^{K}_{n,s,t}$. Blue points represent bin means, red lines show the linear fit. Sample covers 768 size-group × industry × year observations from the UK market sector, 2004-2019.

Figure C.3: Euro area Loan Supply Index vs Output Gains from Relaxing Credit Frictions



Note: This figure plots the estimated output gains from relaxing credit frictions established in this paper (left axis, in percentage points) against the cumulated Altavilla et al. (2019) Loan Supply Index (LSI) for the Euro area (right axis; higher = cumulated tightening in lending standards). The annual observation of the cumulated index is the Q4 value. The LSI is matched to our output gain with a one-year lead: the Q4 value of the cumulated index for year $t-1$ is matched to our output gain for year t (e.g. the 2006Q4 LSI value is matched to our 2007 observation), reflecting the fact that our default-risk estimates measure one-year-ahead forward-looking default risk. Higher output gains indicate greater credit frictions. Vertical lines mark the 2008 Global Financial Crisis and the 2016 Brexit referendum.

Table C.1: Aggregate Output Gains across alternate definitions of the benchmark level of credit frictions

Year	(1) Frictionless Benchmark	Best-in-Class Benchmarks (2) Narrow Industry Groups (All Years)	(3) Narrow Industry Groups (Within-year)	(4) Broad Industry Groups (All Years)	(5) Broad Industry Groups (Within-year)
2004	33.4	23.7	22.4	24.0	22.4
2005	32.7	22.9	22.3	23.3	22.3
2006	32.6	22.8	22.7	23.2	22.8
2007	31.2	21.6	22.0	22.0	22.1
2008	31.6	22.0	22.3	22.1	22.5
2009	35.2	25.1	24.7	25.2	25.0
2010	36.8	26.5	25.6	26.6	25.8
2011	34.4	24.4	24.2	24.5	24.5
2012	37.1	26.6	25.5	26.7	25.8
2013	38.2	27.5	26.1	27.7	26.4
2014	34.5	24.3	25.0	24.5	25.3
2015	34.4	24.3	25.2	24.5	25.6
2016	35.5	25.3	25.8	25.5	26.1
2017	37.3	26.8	27.0	27.0	27.4
2018	37.4	27.0	27.2	27.2	27.6
2019	36.6	26.3	27.0	26.4	27.3
Average	34.9	24.8	24.7	25.0	24.9

Note: The Table reports the percentage increase in annual aggregate output obtained under alternative 'low credit friction' benchmarks. Column (2) reproduces our baseline counterfactual of moving to a default risk at the fifth percentile within each four-digit SIC industry. Column (1) conisders the fully frictionless benchmark. Column (3) is the same as (2) but uses a year specific benchmark. Columns (4) and (5) follow (2) and (3), but use a two-digit rather than four-digit best in class benchmark.

Table C.2: Aggregate Output Gains across alternate Production Function Parameter values (α, η)

Year	(1) Sector-specific Parameters (Estimated)	(2) Aggregate Parameters (Estimated)	(3) Aggregate Parameters (Calibrated)
2004	23.7	22.7	18.3
2005	22.9	22.0	17.8
2006	22.8	22.1	17.8
2007	21.6	20.9	16.9
2008	22.0	21.3	17.2
2009	25.1	24.2	19.5
2010	26.5	25.9	20.8
2011	24.4	23.9	19.2
2012	26.6	25.8	20.7
2013	27.5	26.6	21.4
2014	24.3	23.8	19.1
2015	24.3	23.9	19.3
2016	25.3	24.9	20.1
2017	26.8	26.4	21.2
2018	27.0	27.0	21.7
2019	26.3	26.2	21.1
Average	24.8	24.2	19.5

Note: The figure reports the percentage increase in annual aggregate output that would be obtained under a 'low credit friction' counterfactual in the UK market sector, relative to the status quo. Column (1) uses our preferred specification with production parameters that vary by sector, estimated from microdata. Column (2) also estimates production parameters from microdata, but pools across all sectors for single parameter values ($\alpha = 0.395, \eta = 0.825$). Column (3) uses well known calibration values (see Hsieh and Klenow (2009)) for capital intensity and returns to scale parameters ($\alpha = 0.33, \eta = 0.85$). All parameter values are reported in Table 2, and our strategy for estimating parameter values from microdata is outlined in Section 5.2.

Table C.3: Sensitivity of aggregate output gains to alternative parameter values

	Low value		High value	
Parameter	Value	Output gain (%)	Value	Output gain (%)
1. Output-Capital elasticity, α	0.35	18.7	0.45	32.8
2. Returns to scale, η	0.80	21.6	0.85	29.3
3. Depreciation rate, δ	0.03	30.3	0.09	18.1
4. Cost of funds, ρ	0.01	23.9	0.09	25.7
5. Loss given default, Δ	0.80	20.4	1.00	24.8

Note: Each row reports aggregate output gains, $((\hat{Y}_t - Y_t)/Y_t) \times 100$, when a parameter is moved to a an alternative lower or higher value. In the last three rows we use our baseline estimates (sector specific production parameters), but alter the value of key parameters one at a time, holding all other parameters fixed. Recall that the baseline values of these are $\delta = 0.05$, $\rho = 0.05$, and $\Delta = 1.00$, while all others are held at their baseline values. The high value of output gain for Δ is our baseline, so the baseline output losses of of 24.8%. are reproduced here for comparison. In the first two rows we use the version of the model with a single pooled value of the production parameters. These were $\alpha = 0.40$ and $\eta = 0.825$ in column (2) of Table C.2 and the penultimate row of Table 2 ("All Industries"). Rows 1 and 2 alter these common values of α and η.

Table C.4: Calculation of Output Gains from Relaxing Credit Frictions (non-imputed sample only)

	(1)	(2)	(3)
		General Equilibrium	
Year	N	Output Growth (%)	Wage Growth (%)
2004	474,610	26.6	25.4
2005	547,409	25.1	23.9
2006	587,621	25.3	24.1
2007	612,129	23.7	22.5
2008	623,875	23.7	22.6
2009	633,618	26.7	25.3
2010	643,226	27.6	26.4
2011	653,885	25.0	24.0
2012	694,961	27.3	26.0
2013	735,108	28.3	26.9
2014	798,540	25.4	24.2
2015	859,969	25.5	24.3
2016	926,029	26.7	25.3
2017	981,197	28.2	26.7
2018	1,019,368	28.3	27.0
2019	1,051,602	27.9	26.6
Average	740,197	26.3	25.1

Note: This table reports the general equilibrium consequences of relaxing credit frictions. Compared to our baseline results presented in Table 3, this table shows the losses from an identical calculation using only observations where the probability-of-default (PD) is non-missing.

Table C.5: Alternative sector specific production parameters after controlling for firm productivity through ACF Production Function Estimation

Industry Section	Baseline Estimates			Alternative Estimates		
	$\widehat{\beta}_s$	α_s	η_s	$\widehat{\beta}_s$	α_s	η_s
	(1)	(2)	(3)	(4)	(5)	(6)
C: Manufacturing	1.52	0.40	0.79	1.40	0.39	0.78
F: Construction	1.79	0.42	0.81	1.67	0.41	0.80
G: Wholesale and retail trade	2.13	0.47	0.82	1.92	0.46	0.81
H: Transportation and storage	2.16	0.37	0.85	2.04	0.36	0.85
I: Accommodation and food service	1.94	0.32	0.86	1.94	0.32	0.86
J: Information and communication	1.83	0.43	0.81	1.67	0.42	0.80
M: Professional, scientific and technical	1.86	0.28	0.87	1.73	0.28	0.86
N: Administrative and support service	1.71	0.32	0.84	1.58	0.32	0.83
All Industries (Pooled)	1.87	0.40	0.83	1.72	0.39	0.82

Note: This table compares the baseline micro-econometric estimates of sector-specific production parameters ($\widehat{\beta}_s$, α_s, and η_s) against a robustness check including the firm-specific component of persistent productivity as an additional control measured through estimating a firm-level production function using the Ackerberg et al., 2015 approach. We apply the standard two-stage estimation routine, with a third-order polynomial approximation of the control-function. Parameters are estimated separately for each sector. Columns (1) through (3) display the baseline estimates used in our main quantitative exercises from Table 2. Columns (4) through (6) report the corresponding parameters under the alternative estimation approach. Specifically, columns (1) and (4) report the estimated employment elasticity ($\widehat{\beta}_s$), while columns (2), (3), (5), and (6) report the implied structural parameters for the capital (α_s) and returns-to-scale (η_s).