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Evergreening ☆

Miguel Faria-e-Castro [a,*], Pascal Paul [b,c], Juan M. Sánchez [a]

[a] Federal Reserve Bank of St. Louis, United States
[b] Federal Reserve Bank of San Francisco, United States
[c] Leibniz Institute for Financial Research SAFE, Goethe University Frankfurt, Germany

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ABSTRACT

We develop a simple model of concentrated lending where lenders have incentives for evergreening loans by offering better terms to firms that are close to default. We detect such lending behavior using loan-level supervisory data for the United States. Banks that own a larger share of a firm's debt provide distressed firms with relatively more credit at lower interest rates. Building on this empirical validation, we incorporate the theoretical mechanism into a dynamic heterogeneous-firm model to show that evergreening affects aggregate outcomes, resulting in lower interest rates, higher levels of debt, and lower productivity.

"Owe your banker £1,000 and you are at his mercy; owe him £1 million and the position is reversed." — J. M. Keynes (1945)

1. Introduction

Following the outbreak of COVID-19 in early 2020, firm profits declined sharply, and governments supported businesses by providing them with subsidized credit. At the same time, concerns emerged that banks would "evergreen" loans—the practice of granting further credit to firms close to default to keep such firms alive. Similar to the government credit programs, such lending behavior may stabilize an economy in the short run, preventing bankruptcies and worker layoffs. After the crisis passes, however, it may contribute to less productive firms remaining in business, leading to the creation of "zombie firms" and depressing aggregate productivity and economic growth (Peek and Rosengren, 2005; Caballero et al., 2008). For the United States, such worries were frequently dismissed on the basis that evergreening is typically associated with economies experiencing depressions with undercapitalized banking systems, such as Japan in the 1990s, and the U.S. was not thought to be in such a position (Gagnon, 2021).

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* Corresponding author.
E-mail addresses: miguel.fariaecastro@stls.frb.org (M. Faria-e-Castro), pascal.paul@sf.frb.org (P. Paul), juan.m.sanchez@stls.frb.org (J.M. Sánchez).

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Assessing whether banks evergreen loans requires a general theory that formalizes such lending behavior. In this paper, we illustrate the economic mechanism that results in evergreening using a stylized model of bank lending. Equipped with this basic framework, we address the following questions. First, is evergreening a general feature of financial intermediation instead of being specific to economies that resemble Japan in the 1990s? If so, can we find empirical evidence for such lending distortions even for the U.S. economy over recent years, when banks were operating with relatively high capital ratios? And finally, what are the macroeconomic implications of evergreening for aggregate outcomes?

We begin our analysis by modifying a simple model of bank-firm lending along two realistic dimensions. First, we assume that a bank owns a firm's legacy debt, resulting in losses in case of firm default. Second, we posit that the bank behaves as a Stackelberg leader and internalizes how the offered lending terms influence a firm's decision to default on existing liabilities. The presence of such concentrated lending can reverse typical lending incentives. In contrast to standard intuition, lenders may offer relatively *better* terms to less productive and more indebted firms closer to the default boundary. By providing more attractive conditions on a new loan contract, a bank raises the continuation value of a firm, thereby reducing the likelihood of default and increasing the chance of repayment of existing debt. All else being equal, larger outstanding debt raises the threat of default and improves a borrower's position vis-à-vis its lender, as captured by the Keynes quote above. Within our static framework, firms with "worse" fundamentals—more debt and lower productivity—pay lower interest rates and invest more. Importantly, the proposed mechanism is distinct from well-known corporate finance theories, such as risk-shifting or debt overhang, and does not hinge on information asymmetries, unhealthy lenders, or depressed aggregate conditions.

To assess whether such lending behavior can be found in practice, we turn to the Federal Reserve's Y-14 data set, which provides detailed loan-level information for the United States. We make use of the fact that the data include banks' risk assessments for each borrower, in particular firms' probabilities of default which we use to measure firm financial distress. Using the fixed effects approach by Khwaja and Mian (2008), we show that banks that own a larger share of a firm's debt lend relatively more to distressed firms at lower interest rates. These effects persist at the firm level, affecting total debt and investment. We obtain these results even outside of a recession when banks were relatively well capitalized, and further show that other prominent theories of evergreening or zombie lending based on bank capital positions cannot explain our findings. Thus, we view our mechanism as a general feature of financial intermediation as opposed to being specific to economies that find themselves in a severe recession with an undercapitalized banking system.

Building on this empirical evidence, we embed the theoretical mechanism into a dynamic heterogeneous-firm model based on the one developed by Hopenhayn (1992), augmented with debt, default, and financial frictions as in Hennessy and Whited (2007), Gomes and Schmid (2010), or Clementi and Palazzo (2016). The dynamic model improves on the static one by endogenizing the joint distribution of firm productivity, debt, and capital, and allows us to study the macroeconomic effects of evergreening. Calibrating the model to U.S. data, we show that evergreening arises in equilibrium and affects firm borrowing and investment decisions. On the one hand, evergreening allows lenders to recover their investments more frequently, and these benefits are passed on to borrowers in the form of lower interest rates. As a result, incumbent firms increase their debt and capital by 1 to 3 percent across different model specifications. On the other hand, the firms that are saved and invest more are the ones that are less productive and prevent new firms from entering. In turn, this reduces aggregate total factor productivity (TFP) by around 0.25 percent relative to an economy with dispersed lenders.

The dynamic model delivers additional insights. We decompose measured TFP losses into three components: firm size, average firm productivity, and misallocation. Most of the drop in TFP is due to firm size: firms are relatively larger in an economy with evergreening, which causes productivity losses under decreasing returns-to-scale production technologies. We further find that firms that benefit from subsidized lending tend to be larger, more leveraged, and less productive—all features that the literature typically associates with zombie firms. However, subsidized firms are also riskier and pay higher interest rates than non-subsidized firms, though lower rates relative to a counterfactual economy without evergreening. Given these differences, we compare various classifications of zombie firms against our measure of whether a firm is subsidized. Definitions based on characteristics such as leverage and productivity as in Schivardi et al. (2022) tend to correlate with our measure. In a final exercise, we replicate the cross-sectional regression estimates based on model simulations and show that the mechanism generates comparable real effects as in the data.

Related literature Our paper relates to the literature on evergreening and zombie lending that emerged from Japan's "lost decade," which started with the collapse of stock and real estate markets in the early 1990s. For this period, Peek and Rosengren (2005) provide evidence of evergreening by showing that poorly performing firms typically experienced an increase in their credit. Lending surges were also associated with weakly-capitalized banks or if banks and firms had strong corporate affiliations.[1] Similarly, Caballero et al. (2008) document a rise in the share of zombie firms, which they define as businesses that pay interest rates below comparable prime rates. Consistent with a model of creative destruction, they show that job creation and destruction declined and productivity growth stalled in industries that experienced an increase in the share of zombie firms. The presence of zombie firms also spilled over to other firms. In industries with a higher share of zombies, healthy firms experienced a fall in their investment and employment, while their productivity relative to zombies increased.

Building on these seminal contributions, several papers have documented similar evidence of evergreening and real economy effects of zombie firms.[2] These studies span several countries with varying economic conditions. Still, they generally share two main findings: that evergreening is more prevalent among weakly capitalized banks during severe recessions and that zombie firms adversely impact healthy firms and impede firm exit and entry, hindering productivity growth within industries (see Acharya et al., 2022, for a recent survey). We contribute to this literature in the following three ways.

First, we provide a novel theory of evergreening that shows that lenders may be incentivized to recoup their investments by keeping less productive firms alive. Thus far, relatively few papers formalize the ideas of evergreening or zombie-lending theoretically, and a common modeling approach is still lacking. Previous theories have relied on information asymmetries (Rajan, 1994; Puri, 1999; Hu and Varas, 2021), on the premise that banks gamble for resurrection (Bruche and Llobet, 2013; Acharya et al., 2021b), or that banks delay the recognition of loan losses (Begenau et al., 2021). In contrast, our mechanism assumes full information and does not rely on bank regulation, capital-constrained lenders, or depressed aggregate conditions. Thus, it is not specific to economies that resemble Japan in the 1990s—with undercapitalized banks and a deep recession—but rather describes a general feature of financial intermediation.

[1] Within the bank, loan officers may engage in evergreening if they face a lower likelihood of being exposed (Hertzberg et al., 2010). Banks also reduce zombie-lending after on-site inspections (Bonfim et al., 2022).

[2] Among others, examples are Giannetti and Simonov (2013), Storz et al. (2017), McGowan et al. (2018), Acharya et al. (2019), Andrews and Petroulakis (2019), Acharya et al. (2020), Bittner et al. (2021), Schmidt et al. (2020), Acharya et al. (2021a), Chari et al. (2021), Banerjee and Hofmann (2022), and Artavanis et al. (2022).

The mechanism is also different from the classic problem of debt overhang (Myers, 1977), where equity holders are reluctant to invest in profitable investment projects as benefits could be reaped by existing debt holders, hindering further borrowing. In our framework, more indebted firms receive better loan conditions, enabling them to borrow and invest relatively more — the opposite result. Similarly, our mechanism is related to the idea of sequential lending with non-exclusive contracts as in Bizer and DeMarzo (1992). Contrary to sequential banking, where firms borrowing from multiple lenders tend to overborrow, dilute the stakes of preexisting lenders, and have higher default probabilities, our model predicts that firms that borrow from a single (concentrated) lender tend to borrow more but face lower probabilities of default, relative to the case where they would be borrowing from multiple (dispersed) lenders.

Nevertheless, our theory shares some similarities with mechanisms that have been proposed in the literature. For example, Bolton et al. (2016) show that relationship lenders can screen out good borrowers and provide them with relatively cheap financing in a crisis. Cetorelli and Strahan (2006) find that less competition among banks is associated with fewer firms that are larger on average, and Giannetti and Saidi (2019) show that a higher indebtedness of banks to specific industries is associated with stronger incentives to provide credit in times of distress. We share with Becker and Ivashina (2022) the observation that zombie lending may not only be due to bank risk-shifting motives but is also determined by costly corporate insolvency, an important assumption of our framework. Using cross-country firm- and loan-level information, Becker and Ivashina (2022) show that weak insolvency regimes give rise to more zombie lending in crisis years. We also have in common with Hu and Varas (2021) the idea that evergreening may not only be present with capital-constrained lenders but also with healthy ones. In their model, a relationship lender may roll over loans even after bad news about a firm arrives, at the prospect that a market-based lender with less information may lend to such a weak firm in the future.

Our second contribution is quantifying the aggregate effects of evergreening with a calibrated heterogeneous-firm model. Few papers have provided similar assessments, and the results hinge on the specifics of the micro-foundations. In Acharya et al. (2021b), excessive forbearance induces low-capitalized banks to risk-shift and lend to less productive firms, depressing overall output. Tracey (2021) considers a setting in which heterogeneous firms have the option to enter a loan forbearance state, which results in a larger number of less productive firms and lower output. In contrast, in our model, firms do not enter explicit restructuring states to be subsidized by the lender. We find that evergreening depresses TFP primarily thanks to an increase in average firm size.[3]

Last, we contribute to the empirical literature with a new identification approach to detect evergreening behavior and by focusing on large U.S. banks at a time when those were relatively well capitalized—in contrast to prior studies that concentrated on distressed European and Japanese institutions.[4] Blattner et al. (2023) use Portuguese data to show that low-capitalized banks extended relatively more credit to borrowers with underreported loan losses following an unexpected increase in capital requirements. Schivardi et al. (2022) find that weakly capitalized banks in Italy issued relatively less credit to healthy firms—but not zombie firms—during the Eurozone crisis. Consistent with our mechanism, Jiménez et al. (2022) find that Spanish firms were more likely to obtain a public guaranteed loan from banks with higher preexisting debt exposure during the COVID-19 crisis.

2. Static model

In this section, we develop a simple model of bank-firm lending. We begin by presenting the problem of a firm that decides how much to borrow and invest, taking the interest rate on new credit as given. The firm has preexisting liabilities on which it may choose to default. We then compare the equilibrium outcomes of two economies: (i) one with dispersed lending and (ii) one with concentrated lending, where a single lender owns the firm's outstanding debt and internalizes how loan conditions affect the firm's decision to default on its legacy debt.

Environment There are two periods $t = 0, 1$. There are two types of agents: firms, indexed by their pre-determined states (z, b), where z is productivity and b is legacy debt, and lenders, who are risk-neutral and have deep pockets.

2.1. Firm problem

At the beginning of $t = 0$, the firm may choose to default and obtain a zero value. If it remains in business, the firm has a continuation value equal to $V(z, b; Q)$, which is a function of the legacy debt b, productivity z, and the price of new debt Q that is offered by the lender at $t = 0$, and which the firm takes as a given. The firm therefore defaults if and only if $V(z, b; Q) < 0$. For simplicity, we assume that there is no default at $t = 1$. This assumption is relaxed in the dynamic model.

If the firm does not default, it repays its existing liabilities b, borrows Qb', and invests k' at $t = 0$. At $t = 1$, the firm produces according to a decreasing returns-to-scale technology $z(k')^\alpha$, where $\alpha \in (0, 1)$, and repays debt b' borrowed at $t = 0$. Additionally, the firm faces a borrowing constraint at $t = 0$ that takes the form $b' \leq \theta k'$, where $\theta > 0$.[5] The firm's value, conditional on not defaulting, is

$$V(z, b; Q) = \max_{b', k' \geq 0} -b - k' + Qb' + \beta^f [z(k')^\alpha - b'] \quad \text{s.t.} \quad b' \leq \theta k' \quad , \tag{2.1}$$

where β^f is the firm's discount factor.[6] Appendix A.1 describes the solution to the firm's problem. Under the assumption that the constraint is binding (which we later verify), we characterize the firm's optimal default decision in the following proposition.

Proposition 1. *Firm optimal policies and value (k', b', V) are (i) increasing in Q, (ii) increasing in z. Firm value V is decreasing in b. Additionally, there exists a $Q^{\min}(z, b)$ such that the firm defaults if and only if $Q < Q^{\min}(z, b)$. $Q^{\min}(z, b)$ is (i) strictly increasing in b, (ii) strictly decreasing in z, and (iii) satisfies* $\lim_{b\to\infty} Q^{\min}(z, b) = \beta^f + 1/\theta$.

Equipped with the solution to the firm's problem for a given price of debt Q, we now proceed to study two different forms of determining Q and characterize the equilibria that result from each of them.

[3] Our findings relate to Gopinath et al. (2017) who show that a decline in interest rates results in lower aggregate TFP in a model calibrated to Southern Europe in the 2000s (see also Gilchrist et al., 2013; Liu et al., 2022; Asriyan et al., 2021; and Cingano and Hassan, 2022).

[4] We connect to an extensive body of work that measures how bank health affects the allocation of firm credit (Khwaja and Mian, 2008) and firm outcomes (Chodorow-Reich, 2014). Related to our application, Favara et al. (2022b), and Ma et al. (2021) have used the Y-14 data in this context to investigate the effects of bank capitalization and lender expectations.

[5] Appendix A.2 shows that all our results hold under more general borrowing constraints of the type $b' \leq g(k')$, which nest standard specifications of earnings-based constraints, for example.

[6] We assume that the firm owns no preexisting stock of capital that would allow it to produce at $t = 0$ and faces no costs of issuing equity. This is without loss of generality: preexisting capital and production in the first period are equivalent to rescaling the net liabilities b. Adding a linear equity issuance cost also increases net liabilities in the first period and introduces an additional distortion as the marginal cost of investment rises, but it does not affect our results.

2.2. Dispersed lending

In the first economy we consider, there is a continuum of lenders willing to lend to the firm. These lenders are risk-neutral, have deep pockets, and discount payoffs with factor $\beta^k > \beta^f$. Since we assume that there is no default at $t = 1$, perfect competition in the lending market requires that the offered contract satisfies

$$Q = \begin{cases} \beta^k & \text{if } \beta^k \geq Q^{\min}(z,b) \\ 0 & \text{otherwise} \end{cases} .$$

In this equilibrium, all non-defaulting firms borrow at the same interest rate, regardless of (z, b), which implies that marginal products of capital (MPK) are equalized. More productive firms invest more and borrow more, but credit quantities and prices are independent of the amount of legacy debt b.

2.3. Concentrated lending

We now analyze the equilibrium with concentrated lenders. There are two key differences in relation to the dispersed lending economy. First, the lender internalizes how its choice of Q affects the firm's default decision. Second, lending is non-anonymous because the lender owns the preexisting debt b and understands that this debt is lost in the case of default. We use the terms "lender" and "bank" interchangeably. The lender's problem is given by

$$W = \max_{Q \geq \beta^k} \mathbb{I}[V(z,b;Q) \geq 0] \times \left[b - Qb'(z;Q) + \beta^k b'(z;Q)\right] \quad ,$$

where $\mathbb{I}$ is an indicator function denoting no default at $t = 0$. If the firm defaults at $t = 0$, the lender makes zero profits.[7] Otherwise, the lender recovers b, lends Qb', and obtains b' at $t = 1$, discounted at β^k. Finally, the lender's choice of Q is constrained to be above β^k, as we assume that the firm may access a competitive debt market like the one previously described. We can equivalently write the bank's problem as

$$W = \max_{Q \geq \max\{\beta^k, Q^{\min}(z,b)\}} \left[b + b'(z;Q)(\beta^k - Q)\right] \quad .$$

From this formulation and the fact that $\partial b'(z;Q)/\partial Q > 0$, it is evident that the bank's objective function is strictly decreasing in Q (subject to the constraint on the choice of Q). For this reason, it is optimal for the bank to offer the lowest possible Q as long as $W \geq 0$. The following propositions characterize bank optimal lending.

Proposition 2. *Let $Q^{\max}(z,b)$ denote the maximum Q at which the bank is willing to lend. $Q^{\max}(z,b)$ solves the implicit equation $W(z,b;Q^{\max}) = 0$ and satisfies the properties (i) $Q^{\max}(z,b) > \beta^k$ iff $b > 0$, (ii) it is increasing in b, (iii) it is decreasing in z.*

Proposition 3. *The bank's optimal policy can be written as*

$$Q^*(b,z) = \begin{cases} \beta^k & \text{if } Q^{\min}(z,b) \leq \beta^k \leq Q^{\max}(z,b) \\ Q^{\min}(z,b) & \text{if } \beta^k \leq Q^{\min}(z,b) \leq Q^{\max}(z,b) \\ 0 & \text{otherwise} . \end{cases}$$

Let $\bar{b}(z)$ be such that $Q^{\min}(\bar{b}(z), z) = \beta^k$ and $\hat{b}(z)$ such that $Q^{\min}(\hat{b}(z), z) = Q^{\max}(\hat{b}(z), z)$, then (i) $\bar{b}(z) < \hat{b}(z), \forall z$, (ii) $Q^*(b,z)$ is increasing in b, strictly if $b \in [\bar{b}(z), \hat{b}(z)]$, and (iii) $Q^*(b,z)$ is decreasing in z, strictly if $b \in [\bar{b}(z), \hat{b}(z)]$.

[7] For simplicity we assume that there is no recovery in case of default. Our results are qualitatively robust to assuming that there is some recovery as long as it is not full, i.e., default is costly for the lender. We relax this assumption in the quantitative dynamic model, where we allow for partial recovery in case of default.

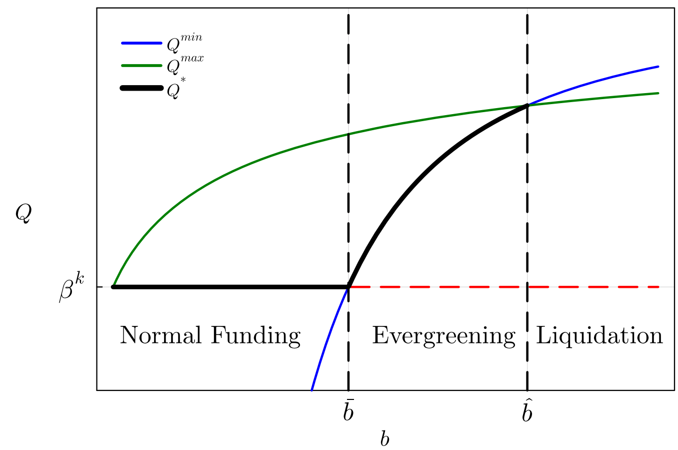

Fig. 2.1. Concentrated lending economy. **Notes:** Equilibrium allocation as a function of b, for a given z. The solid blue line is $Q^{\min}(z, b)$, the solid green line is $Q^{\max}(z, b)$, the dashed red line is β^k, and the black line is the optimal policy Q^*. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

Proposition 3 states that, as long as legacy debt is positive, $b > 0$, the bank is willing to offer better terms than those in the competitive market to the firm. Offering more favorable lending conditions allows the bank to recover b by preventing the firm from defaulting. The optimal price of debt Q^* consists of three regions, illustrated in Fig. 2.1 for a fixed z. First, as long as $Q^{\min}(z, b) < \beta^k$, the bank can offer $Q^* = \beta^k$ and guarantee that the firm does not default. In this case, the allocation in the concentrated lending economy coincides with the dispersed lending economy ("normal funding"). Second, Proposition 1 states that $Q^{\min}(z, b)$ is increasing in b and decreasing in z. Therefore, for sufficiently high b (or low z), $Q^{\min}(z, b)$ exceeds β^k. In that case, the firm exits in the dispersed lending economy. In the concentrated lending economy, however, and as long as $Q^{\min}(z, b) < Q^{\max}(z, b)$, the bank is willing to keep the firm alive by offering $Q^* = Q^{\min}(z, b) > \beta^k$. These terms are strictly better than those that the firm could obtain in the competitive market and become more favorable as b increases or z falls. We call this the "evergreening region." In the third region, $Q^{\min}(z, b) > Q^{\max}(z, b)$, and the bank decides to liquidate the firm ("liquidation"). Proposition 1 establishes that the firm's policies are strictly increasing in Q. Thus, equilibrium borrowing and investment follow a similar pattern to that of Q^* in the figure (see Appendix Fig. A.1).

Appendix A.4 contains a detailed discussion of how our mechanism relates to and is distinct from existing corporate finance theories, such as the risk-shifting, gambling for resurrection, and debt overhang. It further considers modifications of some of the assumptions of the model, in particular the nature of the contracting protocol and the absence of debt restructuring.

2.4. Discussion

The two-period model isolates the potential advantages and disadvantages of evergreening. On the one hand, evergreening saves firms with too much debt but otherwise viable investment projects that have a positive net present value and generate additional production. On the other hand, less productive firms remain in business and invest more than they otherwise would, potentially absorbing resources that could be better allocated to more productive entrants. However, the static model also leaves several questions unanswered. First and foremost, does the mechanism accurately reflect how banks make lending decisions in practice? We address this question in the next section using detailed loan-level data.

Second, the static model is silent on the macroeconomic consequences of evergreening: it assumes that firms start with certain levels of debt and productivity, but how often do firms end up with states that give rise to evergreening? Do firms potentially acquire more debt today if they know they could be saved tomorrow, a form of moral hazard? Does the survival of such firms prevent the entry of more productive ones? To answer these questions, Section 4 develops a macroeconomic framework that allows for endogenous firm entry and exit, aggregation across firms, and a counterfactual analysis between concentrated and dispersed lending economies.

Firm distress and motivation for empirical strategy The static model is simplified to clearly isolate the economic mechanism that generates evergreening in equilibrium. In particular, we abstract from any type of risk, resulting in probabilities of default that take either the value of zero or one depending on firms' initial states. In practice, firms are subject to other types of shocks that affect default beyond indebtedness and productivity. In Appendix A.5, we extend our baseline model to include idiosyncratic firm risk and show that our main qualitative results remain unchanged. Based on a numerical example, Appendix Fig. A.3 shows probabilities of default for firms with different levels of legacy debt and the same productivity. The larger b, the higher a firm's probability of default. For low levels of b, firms' default probabilities coincide between the dispersed lending economy and the concentrated lending economy. In contrast, they diverge for intermediate values of b since the single lender offers better credit conditions to the firm, thereby lowering its chance of default. These features motivate our empirical strategy in the following section. We identify distressed firms based on their default probabilities, and require that those are sufficiently elevated, so that their concentrated lenders subsidize them.

3. Empirical analysis

3.1. Identification approach

To identify the credit supply effects associated with our theory, we consider a sample of firms that borrow from multiple lenders, which allows us to control for credit demand (Khwaja and Mian, 2008). If anything, this approach makes finding evidence for our theory more challenging since the described mechanism may be stronger if a firm borrows from a single lender instead. Our empirical approach relies on cross-sectional variation in bank exposures to distressed firms. We measure bank exposures according to the share of a firm's debt that banks hold, and classify firms as financially distressed if banks assess their probability of default as elevated. Consistent with our theory, we find that banks that own a larger debt share provide distressed firms with relatively more credit at lower interest rates. We further show that these effects persist at the firm level, affecting total firm debt and investment, and that other prominent theories of evergreening or zombie lending based on bank capital positions cannot explain our findings.

3.2. Data

The main data set of our analysis is the corporate loan schedule H.1 of the Federal Reserve's Y-14Q collection (Y14 for short). These data were introduced as part of the Dodd-Frank Act following the 2007-09 financial crisis. They are typically used for stress-testing and cover large bank holding companies (BHCs).[8] For the BHCs within our sample, the data contain quarterly updates on the universe of loan facilities with commitments in excess of $1 million and include detailed information about the credit arrangements.

Importantly, the data cover banks' risk assessments for each borrower. Among the available assessments, we use the probability of default (PD) in our analysis, which measures the likelihood of a loan nonperforming over the course of the next year. That is, the PD estimates the event that a loan is not repaid in full or that the borrower is late on payments. Banks are supposed to assess the PD at the borrower rather than loan level, which also makes it comparable when multiple banks lend to the same firm.[9]

We identify a firm using the Taxpayer Identification Number (TIN). The vast majority of firms within our data are private ones. For these firms, we rely on the banks' own collections of firm balance sheets and income statements that are also part of the Y14 data. To reduce measurement error and to increase the number of observations, we take the median of firm financial variables across all banks and loans for a particular firm-date observation since these data are firm-specific. For the public firms, we instead use information from Compustat on firm financials.

We further apply several sample restrictions. First, we exclude lending to financial and real estate firms. Second, we apply a number of filtering steps that are described in Appendix B, which also includes an overview of the variables that are used. Last, we restrict the sample to 2014:Q4-2019:Q4. The start of the sample is determined by the fact that the risk assessments that we use in our analysis became available at that time. We include information up until 2019:Q4 to ensure that our results are not affected by the COVID-19 crisis. Over this sample, we cover 3,168,276 loan facility observations and 175,406 distinct firms. We identify 2,719 of those firms as public since they can be matched to Compustat. Compared with the years before the 2007-09 financial crisis, banks were relatively well capitalized over our sample period, operating with higher capital ratios and capital buffers as shown in Appendix Figs. B.1 and B.2. The U.S. economy was also growing steadily with annual real GDP growth that ranged between 1.4 and 3.8 percent with an average of 2.4 percent. Thus, we intentionally consider a sample of a steady economy with a relatively well capitalized banking system, as our theory does not hinge on poor lender health or depressed aggregate conditions.

3.3. Identifying credit supply effects

In equilibrium, banks and firms may match according to their need and willingness to evergreen loans. To account for such potential links between bank-firm selection and firm credit demand, we follow the fixed effects approach by Khwaja and Mian (2008) to isolate the credit supply effects associated with our mechanism. For firm i and bank j, we estimate regressions of the form

$$\begin{aligned}\frac{L_{i,j,t+2}-L_{i,j,t}}{0.5\cdot(L_{i,j,t+2}+L_{i,j,t})} =& \alpha_{i,t}+\beta_1 \text{Debt-Share}_{i,j,t} \\ &+\beta_2 \text{Debt-Share}_{i,j,t}\times \text{Distress}_{i,t}+\gamma X_{j,t}+u_{i,j,t}\end{aligned} \tag{3.1}$$

where $L_{i,j,t}$ is the aggregated amount of credit between a bank and a firm at time t, and the dependent variable measures percentage changes in credit over two quarters. Specifically, we use the symmetric growth rate as an approximation of a percentage change, which allows for possible zero observations at time t and is bounded in the range $[-2,2]$, reducing the potential influence of outliers. We include firm-time fixed effects $\alpha_{i,t}$ into our regressions, which restrict the sample to firms that borrow from multiple banks. The fixed effects control for credit demand if firms have a common demand across their lenders, and we discuss possible violations of this assumption below.

The main regressors are $\text{Debt-Share}_{i,j,t}$, defined as the ratio of outstanding credit $L_{i,j,t}$ between firm i and bank j to total firm debt $Debt_{i,t}$

[8] Until 2019, BHCs with more than $50 billion in assets were required to participate in the collection, and the size threshold was changed to $100 billion subsequently.

[9] See the U.S. implementation of the Basel II Capital Accord for the definition of default (page 69398) and the definition of probability of default (page 69403): https://www.govinfo.gov/content/pkg/FR-2007-12-07/pdf/07-5729.pdf.

Table 3.1
Credit supply to distressed firms.

	Δ Credit			Δ Interest Rate		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Debt-Share	-21.88**	-17.48**	-22.37***	0.18***	0.11	0.12*
	(8.24)	(8.58)	(7.84)	(0.05)	(0.07)	(0.06)
Debt-Share × Distress	45.60***	38.56***	44.95***	-0.93***	-0.71**	-0.72**
	(9.49)	(10.50)	(12.84)	(0.33)	(0.33)	(0.32)
Fixed Effects						
Firm × Time	✓		✓	✓		✓
Firm × Time × Pur.		✓			✓	
Bank × Time			✓			✓
Bank Controls	✓	✓		✓	✓	
R-squared	0.58	0.6	0.63	0.74	0.74	0.79
Observations	8,647	5,729	8,576	8,407	5,561	8,338
w/ Distress = 1	539	397	531	528	386	520
Number of Firms	887	642	884	867	621	864
Number of Banks	36	34	34	36	34	34

Notes: Estimation results for regression (3.1) multiplied by 100. All specifications include firm-time fixed effects that additionally vary by the loan purpose in columns (ii) and (v). Columns (iii) and (vi) include bank-time fixed effects and the remaining columns include various bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), loan share (loans/assets), leverage (liabilities/assets), Tier 1 capital buffer (ratio minus requirement), banks' income gap, and the ratio of unused credit lines to assets. Standard errors in parentheses are two-way clustered by bank and firm. Sample: 2014:Q4 - 2019:Q4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

at time t, and the interaction of this variable with a firm-specific indicator Distress$_{i,t}$ that equals one if firm i is in financial distress at time t and zero otherwise. We classify a firm as financially distressed if the average PD across all banks that lend to this firm, denoted by $\overline{PD}_{i,t}$, falls within the top decile of the unconditional distribution of $\overline{PD}_{i,t}$ across all firms within our sample. We choose this definition for the following three reasons. First, we use firms' PDs since those can be understood as *sufficient statistics* to measure firm financial distress and because they directly relate to our theory, which is concerned with firms' distance to default. We use a binary indicator variable, as opposed to the continuous variable $\overline{PD}_{i,t}$, since our theory shows that the relation between firm distress and lender's willingness to evergreen loans is inherently nonlinear (as visible in Appendix Fig. A.3), and the indicator Distress$_{i,t}$ is a simple approximation of this relation. Second, we average PDs across banks since banks differ in their assessments, and the average most likely represents a common view.

And third, we consider the top 10 percent as a reasonable cutoff to capture the part of the firm population that has some realistic chance of default. In the data, most firms have PDs that are close to zero as shown in Appendix Table C.1, and even the median firm has a relatively low PD of around 0.8 percent. The cutoff value for the top decile that we use to define a distressed firm is 3.89 percent. Within the top decile, the threat of default is common, with the median firm having a 7.8 percent likelihood of default which rises steeply at the very top of the distribution. As shown below, our results are robust to varying the cutoff value for Distress$_{i,t}$ around our chosen benchmark, and to excluding firms for which default seems unavoidable (like the ones with high legacy debt in Figs. 2.1 and A.3).

We interpret variation in Debt-Share$_{i,j,t}$ and Debt-Share$_{i,j,t}$ × Distress$_{i,t}$ as capturing credit supply effects, conditional on the fixed effects and other bank-specific controls that are collected in the vector $X_{j,t}$. However, two concerns may invalidate this interpretation. First, nondistressed firms may have a preference for diversifying their borrowing, shifting their demand away from banks at which they have borrowed more in the past, resulting in $\beta_1 < 0$. Second, conditional on finding itself in financial distress, a firm may turn to its concentrated lender from which it has borrowed more in the past, resulting in $\beta_2 > 0$. To exclude such possible demand shifts, we also consider interest rate responses in addition to changes in credit. To this end, we use $r_{i,j,t+2} - r_{i,j,t}$ as a dependent variable in regression (3.1), where $r_{i,j,t}$ denotes the interest rate associated with the credit agreement between firm i and bank j.[10] If our results represent demand shifts, the estimated coefficients from the interest rate regressions should have the same signs as the corresponding ones from the credit regressions. In contrast, if we capture credit supply effects, they should have the opposite sign.

Last, we exclude credit lines and focus on term loans only. That is because credit movements for credit lines largely represent demand changes. Such contracts provide borrowers with the possibility to flexibly draw and repay credit subject to a predetermined limit and at a fixed spread (Greenwald et al., 2021).[11] As shown below, our key results remain if we include credit lines, but the interest rate responses indicate that the findings may be driven by demand shifts.

The estimation results for regressions (3.1) are reported in Table 3.1.[12] Columns (i) and (iv) show our baseline estimates for credit and interest rates. For the credit regressions, we find that $\beta_1 < 0$ and $\beta_2 > 0$, and both are statistically different from zero at standard confidence levels based on two-way clustered standard errors by bank and firm. The negative coefficient associated with Debt-Share$_{i,j,t}$ shows that a nondistressed firm, that has borrowed more from one bank in the past, has relatively less credit growth going forward with that lender. The positive β_1 for the interest rate regressions indicates that these results represent supply effects, possibly indicating that lenders have a preference to reduce their exposure to firms for which they hold a large debt share.

The positive β_2 for the credit regression shows that these results change for distressed firms. Relative to a nondistressed firm, one with an elevated risk of default has more credit growth with a bank that holds a larger share of the firm's debt. The negative β_2 for the interest rate regressions shows that these findings represent supply effects. That is, more exposed lenders provide distressed firms with relatively better

[10] In case of multiple contracts for a bank-firm pair, we consider the weighted sum of the various interest rates using the used credit amounts relative to the aggregated credit as weights.

[11] Note that we exclude bank-firm pairs that cover both credit lines and term loans, though a firm may still have a credit line with another bank that is not part of the regression sample or outside of our data.

[12] Appendix Table C.2 shows summary statistics for the variables that are part of our main regressions.

credit conditions. The results are also quantitatively important. Relative to a nondistressed firm and a hypothetical lender with zero-exposure, a distressed firm has around 46 percent higher credit growth at close to one percentage point lower interest rates with a lender that holds all of a firm's debt.

The remaining columns in Table 3.1 consider alternative specifications of our baseline regression setup. Columns (ii) and (v) extend the firm-time fixed effects by different loan purposes. These regressions are intended to address the possibility that banks specialize in certain types of lending and that firm demand differs across lending types which may be correlated with our regressors of interest (Paravisini et al., 2021).[13] While the interest rate regressions already provide evidence against such a concern, the estimation results based on the extended fixed effects confirm that our findings reflect supply rather than demand effects. Finally, in columns (iii) and (vi), we include bank-time fixed effects. While the impact of other bank characteristics cannot be estimated separately in this case, our initial findings remain intact with estimated coefficients that are close to our benchmark estimates.

Before continuing, we note two possible reasons why PDs may not be good measures of firm distress. First, banks may misreport these statistics (a concern we address below). Second, they may reflect banks' expectations of future lending decisions. In particular, if a bank intends to save a firm whenever it experiences some distress so that the firm can repay its outstanding debt, the bank may assign a low PD to that firm today. If anything, such risk assessments would downward-bias our estimates in Table 3.1 and therefore make it harder for us to find evidence for our theory. In that sense, our quantitative findings thus far can be viewed as conservative. Taken together, the results provide empirical support for our theoretical mechanism, showing that concentrated lenders—that hold a larger share of a firm's debt—provide distressed firms with relatively better credit conditions.

In Appendix C, we explore extensions and consider the robustness of our empirical findings along the following dimensions. First, we investigate whether our results can be explained by an alternative channel such as theories of evergreening or zombie lending based on bank capital positions (e.g., gambling for resurrection or risk-shifting) or by a different mechanism of debt forgiveness or restructuring. Second, we test the sensitivity of our findings to the chosen cutoff value for $\overline{PD}_{i,t}$, to the potential misreporting of PDs by banks, to banks being poorly capitalized, and to the disagreement about PDs across banks. Third, we explore alternative regression specifications that extend the firm-time fixed effects by other contract terms, that consider firms that transition into financial distress, and that include credit lines into the analysis. By and large, our findings remain much the same across the various robustness tests and extensions.

3.4. Comparison with zombie firm classifications

Next, we investigate how typical measures of zombie firms from the literature compare with our firm distress indicator and firms' PDs more generally.

To this end, we define zombie firms following the classifications by Caballero et al. (2008), Schivardi et al. (2022), and Favara et al. (2022a) since these three measures can be computed based on the available data.[14] In addition, we also define a zombie firm as one that has high leverage and low productivity.[15] This measure is intended to relate to the static model which predicts that such firms experience financial distress. As shown in Appendix Table C.1, the zombie definitions by Schivardi et al. (2022) and Favara et al. (2022a), as well as the model-based measure, are positively correlated with $\text{Distress}_{i,t}$. Firms that are considered to be zombies based on these measures also have higher PDs. However, the correlations are not perfect and many firms that are considered zombies appear financially sound with PDs close to zero.[16]

Thus, while hard firm characteristics such as leverage and productivity have some predictive power for firms' likelihood of default, many other idiosyncratic reasons also determine financial distress in practice. We therefore view the use of banks' reported PDs—as opposed to some distress definition based on firm characteristics—as the most direct way of relating to our theory, which is concerned with firms' distance to default.

3.5. Firm level effects

In a final exercise, we test whether the effects also persist at the firm level, affecting total debt and investment. To this end, we aggregate a firm's borrowing exposures across its lenders, using the debt shares as weights (as in Khwaja and Mian, 2008, for example). This aggregation leads to a regression specification with an intuitive interpretation. For firm i, we estimate

$$\begin{aligned}\frac{y_{i,t+4}-y_{i,t}}{0.5\cdot(y_{i,t+4}+y_{i,t})}\\ =\alpha_i+\tau_{m,k,t}+\beta_1 HHI_{i,t}\\ +\beta_2 HHI_{i,t}\cdot Distress_{i,t}+\beta_3 Distress_{i,t}+\gamma X_{i,t}+u_{i,t}\,,\end{aligned} \tag{3.2}$$

where $y_{i,t}$ denotes either total firm debt or tangible assets as an approximation for investment, α_i is a firm fixed effect, $\tau_{m,k,t}$ is an industry-state-time fixed effect, and $X_{i,t}$ is a vector of firm controls. $HHI_{i,t}$ are the aggregated debt exposures, defined as $\sum_j (L_{i,j,t}/Debt_{i,t})^2$ which lie in the range $[0,1]$, and can be interpreted as a Herfindahl-Hirschmann-Index for debt concentration.[17] $Distress_{i,t}$ is the same binary indicator variable that we used above, which equals one if $\overline{PD}_{i,t} \geq 3.89\%$.

We note that, unlike regression (3.1), we are unable to include firm-time fixed effects, as regression (3.2) covers only a single firm observation per period. As a result, the sample now also includes firms with only a single lender. We estimate regressions (3.2) at an annual frequency since firm financials are typically updated once per year. The estimation results are shown in Table 3.2.

Columns (i) and (iii) show the baseline results for total debt and investment, respectively, and columns (ii) and (iv) test the robustness of those initial results by including additional interaction terms between the various (demeaned) firm controls and the distress indicator. We find $\beta_1 > 0$ for both outcome variables, which are statistically different from zero at the one percent confidence level. These results can be explained by the fact that—relative to other nondistressed firms—the ones with more concentrated debt positions are potentially younger firms that are

[13] Specifically, we consider the categories "Mergers and Acquisition," "Working Capital (permanent or short-term)," "Real estate investment or acquisition," and "All other purposes" as separate types (see also Appendix Table B.3).

[14] Caballero et al. (2008) define a zombie firm as one that pays average interest rates on its debt below safe rates. We measure firm-specific safe rates using six-month and two-year government bond rates weighting those by firms' short- and long-term debt ratios. Schivardi et al. (2022) define a zombie as one with a return on assets below the safe rate (which we approximate using the federal funds rate) and a debt-to-asset ratio above 0.4. Favara et al. (2022a) define a zombie firm as one with negative sales growth over the previous three years, a leverage ratio above the median across all firms, and an interest coverage ratio below one.

[15] For leverage, we use the 90th percentile across all firms for a particular period as a cutoff. For productivity, we use the 10th percentile of firms' return on assets for a particular period as a cutoff.

[16] The mass of firms with low PDs is relatively large for zombies under all three measures, with more than half of the firms having a PD of 2.8 percent or less. That makes it unlikely that these are all firms that are saved whenever they experience some distress, so that their lenders assign low PDs with such expectations.

[17] Consistent with the previous regressions, we restrict the sample to term loans only. Since we do not cover all firm debt positions, we control for the ratio of observed credit to total firm debt.

Table 3.2
Credit supply to distressed firms - firm level.

	Δ Total Debt		Investment		Δ Ave. Interest Rate	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
HHI	33.71***	32.79***	11.82***	11.81***	-2.21***	-2.22***
	(8.27)	(8.30)	(3.88)	(3.92)	(0.42)	(0.42)
HHI × Distress	13.34***	19.49***	6.88**	7.55**	-0.78	-0.82
	(4.54)	(5.41)	(3.49)	(3.85)	(0.82)	(0.89)
Distress	-4.38***	-7.24***	-2.56***	-2.34***	0.04	-0.01
	(1.38)	(1.83)	(0.71)	(0.86)	(0.10)	(0.13)
Fixed Effects						
Firm	✓	✓	✓	✓	✓	✓
Time × Industry × State	✓	✓	✓	✓	✓	✓
Firm Controls × Distress		✓		✓		✓
Firm Controls	✓	✓	✓	✓	✓	✓
R-squared	0.56	0.56	0.58	0.58	0.44	0.44
Observations	60,636	60,636	71,854	71,854	55,222	55,222
w/ Distress = 1	5,211	5,211	6,195	6,195	4,896	4,896
Number of Firms	14,400	14,400	17,063	17,063	13,021	13,021
Number of Banks	37	37	37	37	37	37

Notes: Estimation results for regression (3.2) multiplied by 100, where $y_{i,t}$ is either total firm debt in columns (i) and (ii) or tangible assets in columns (iii) and (iv). Columns (v) and (vi) estimate regression (3.2) using the change in the average interest rate $r_{i,t+4} - r_{i,t}$ as a dependent variable. All specifications include firm fixed effects, time-industry-state fixed effects where an industry is classified using two-digit NAICS codes, the ratio of observed debt to total debt, and various firm controls: cash holdings, tangible assets, liabilities, debt, net income (all scaled by total assets), and firm size (natural logarithm of total assets). Columns (ii), (iv), and (vi) include interactions of each of the demeaned firm controls with the distress indicator. Standard errors in parentheses are two-way clustered by firm and the bank with the largest debt-share. Sample: 2014:Q4 - 2019:Q4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

growing relatively faster and therefore have a higher demand for additional debt. We further find $\beta_3 < 0$ for both debt and investment, which are again highly statistically significant. That is, relative to other firms with dispersed borrowing, distressed ones have less debt growth and investment over the next year, which can be due to supply restrictions by their lenders.

Interestingly, we find $\beta_2 > 0$ for both debt and investment. Relative to nondistressed firms with dispersed borrowing, a firm that finds itself in distress with concentrated borrowing has relatively more debt growth and investment, in addition to the effect stemming from $\beta_1 + \beta_3 > 0$. The estimates are again strongly statistically significant and quantitatively important, with around 13 percent for debt growth and 7 percent for investment for a firm with a single lender versus a firm with extremely dispersed borrowing ($HHI \approx 0$).

Columns (v) and (vi) repeat the estimation of regression (3.2) using the change in the average interest rate $r_{i,t+4} - r_{i,t}$ that a firm pays on all its debt as a dependent variable. While we do not observe the average interest rate directly, we obtain an approximation using a firm's reported interest expenses divided by its total debt. We note that this imputation likely adds some noise since interest expenses are a flow over a 12-month period in our data, whereas a firm's total debt is a stock at a particular point in time. Nonetheless, we estimate coefficients β_1 and β_2 that are consistent with our previous findings. However, they are also less precisely estimated compared with the regressions for debt and investment, possibly explained by the imputation of the average interest rate.[18]

These findings are consistent with our theoretical mechanism. A concentrated lender subsidizes a firm in financial distress relative to dispersed lenders. Building on this empirical validation of our theory, we embed the mechanism into a dynamic model to study whether such lending behavior can affect aggregate outcomes like capital, productivity, and output.

4. Dynamic model

We first present the model setup and the decision problem of a firm. We describe two potential institutional arrangements, as in the static model, that give rise to different debt price functions and therefore to different equilibria. In Section 5, we calibrate the model and compare equilibria under the two arrangements.

4.1. Setup

Environment Time is discrete and infinite, $t = 0, 1, 2, \ldots$. The economy is populated by a continuum of firms. The distribution of firms is denoted by $\lambda(z, b, k)$, where z denotes productivity, b is debt, and k is capital. Firms endogenously enter and exit the economy, with the mass of entrants denoted by m. For now, we assume that the price of debt is described by some arbitrary function $Q(z, b, k)$ that firms take as given. In the following sections, we present alternative institutional arrangements that provide microfoundations for this function.

Timing The timing within each period is as follows: (1) firm productivity z is realized, (2) a lending contract Q is offered and depends only on the firm's current state (z, b, k), (3) firms draw additive shocks $(\varepsilon^P, \varepsilon^D)$ to the value of repayment and default, (4) firms decide to default, nondefaulting firms repay their debt, and new firms enter, (5) firms invest, produce, repay, borrow, and pay dividends.

Besides entry, another new feature relative to the static model is the introduction of i.i.d. additive shocks for the firm. This feature is primarily introduced for computational tractability as it smooths the expectation and probability functions for the firm and the lenders (see Dvorkin et al., 2021).

[18] Alternatively, these results can speak to a mechanism whereby concentrated lenders extend relatively more credit at roughly similar rates to a firm in financial distress compared with dispersed lenders. While our mechanism works via interest rates, it could also occur via credit rationing as in, e.g., Stiglitz and Weiss (1981), with a smaller reduction or no change in rates due to information frictions not present in our model.

4.2. Firm problem

Firms have access to a decreasing returns-to-scale production technology with the production function given by $zk^\alpha n^\eta$, where z is current productivity, k is current capital, and n is labor. The capital share is α, and the labor share is η. The firm hires labor at wage w and invests in new capital k' at a constant unit cost. Capital depreciates at rate δ. Additionally, the firm pays a fixed cost of operation equal to $\mathbf{c}$. The value of repaying conditional on today's state $s = (z, b, k)$ and the offered contract Q is given by

$$V^P(z,b,k;Q) = \max_{b',k',n\geq 0} div - \mathbb{I}[div<0][e_{con} + e_{slo}|div|] + \beta^f \mathbb{E}_{z'}[\mathcal{V}(z',b',k')|z] \quad (4.1)$$

$$\text{s.t.} \quad div = zk^\alpha n^\eta - wn - k' + (1-\delta)k + Qb' - b - \mathbf{c} \quad , \quad (4.2)$$

$$b' \leq \theta k' \quad . \quad (4.3)$$

The value of repayment is equal to current dividends div plus the continuation value, which is explained below. The firm is also subject to equity issuance costs, with a fixed cost component e_{con} and a linear cost scaled by e_{slo}. Equation (4.2) defines the firm dividend: the value of production, minus the wage bill, minus the new investment net of undepreciated capital, plus new borrowings, minus debt repayments, and minus the fixed cost. Equation (4.3) is a borrowing constraint as in the static model. We refer to the policy functions that solve this problem as $\mathcal{B}(z,b,k;Q)$ and $\mathcal{K}(z,b,k;Q)$, and the optimal labor choice results from a simple static problem.

The firm chooses how much to borrow b' for an offered price of debt Q that is taken as given. In this sort of environment with defaultable debt, a borrowing constraint is required for an equilibrium to be well-defined (see, for example, Ayres et al., 2018). However, due to precautionary behavior arising from the interaction between the expectation of future shocks and equity issuance costs, the borrowing constraint may not necessarily bind.

The firm's value before deciding repayment, after receiving an offer Q, and upon realizing the additive shocks ε^P and ε^D can be written as $V_0(z,b,k,\varepsilon^P,\varepsilon^D;Q) = \max\left\{V^P(z,b,k;Q)+\varepsilon^P, 0+\varepsilon^D\right\}$, where $V^P(z,b,k;Q)$ is defined in (4.1), and we normalize the value of default to zero.[19] The shocks ε^P and ε^D represent a stochastic outside option for the entrepreneur who runs the firm, and we assume that they follow a type I extreme value distribution (Gumbel), which implies that the difference between the two random variables $\varepsilon = \varepsilon^P - \varepsilon^D$ follows a logistic distribution with scale parameter κ. Given these assumptions, the probability of repayment today given Q is

$$\mathcal{P}(z,b,k;Q) = \frac{\exp\left[\frac{V^P(z,b,k;Q)}{\kappa}\right]}{1+\exp\left[\frac{V^P(z,b,k;Q)}{\kappa}\right]} \quad . \quad (4.4)$$

We assume that lenders cannot commit to future prices Q. This means that firms take a price function $Q(z,b,k)$ as given in the next period, which allows us to write the expected value of the firm with respect to the shocks $(\varepsilon^{P\prime}, \varepsilon^{D\prime})$ given future states (z',b',k') as

$$\mathcal{V}(z',b',k') = \mathbb{E}_{\varepsilon^{P\prime},\varepsilon^{D\prime}} V_0(z',b',k',\varepsilon^{P\prime},\varepsilon^{D\prime}) = \kappa \log\left\{1+\exp\left[\frac{V^P(z',b',k')}{\kappa}\right]\right\}. \quad (4.5)$$

4.3. Alternative lending arrangements

Dispersed lending economy (DLE) The first institutional arrangement consists of a purely competitive credit market. It can be thought of as a bond market with a large mass of atomistic lenders. In this case, the price of debt Q is determined by a free-entry condition for lenders. Given $s = (z, b, k)$, we use the notation $Q^c(s)$ to refer to the dispersed lending equilibrium price, which is the price that satisfies the following zero expected-discounted profit condition

$$0 = -Q^c\mathcal{B}(s;Q^c) + \beta^k \mathbb{E}_{z'}\{\mathcal{P}(z',\mathcal{B}(s;Q^c),\mathcal{K}(s;Q^c))\mathcal{B}(s;Q^c) + [1-\mathcal{P}(z',\mathcal{B}(s;Q^c),\mathcal{K}(s;Q^c))]\psi(z',\mathcal{B}(s;Q^c),\mathcal{K}(s;Q^c))\} \quad , \quad (4.6)$$

where ψ is the recovery value in case of default. This value is given by a fraction ψ_1 of the revenue generated by producing one last period and liquidating the undepreciated stock of capital, i.e. $\psi(z,b,k) \equiv \psi_1\left[\max_n zk^\alpha n^\eta - wn + (1-\delta)k - \mathbf{c}\right]$. The expression for the price resembles the one used in models of sovereign default, with the difference that we have to take into account the firm choices for capital and debt, $\mathcal{K}(s;Q)$ and $\mathcal{B}(s;Q)$, which are determined after Q^c is offered. Note that we assume that lenders have a discount factor larger than that of the firm, $\beta^k > \beta^f$. This assumption ensures that firms never fully escape their constraints, even in the long run (Rampini and Viswanathan, 2013). It is also similar to the existence of a tax advantage of debt as it distorts firms' choice of capital structure towards debt (Kiyotaki and Moore, 1997; Li et al., 2016).

Concentrated lending economy (CLE) The second type of credit market we study is one where lenders internalize the firm choices and the possibility of default on current claims b when choosing lending terms. Consequently, such concentrated lenders may offer a different Q that we denote by $Q^r(s)$. The market power that an existing lender can exercise is limited since a large mass of potential lenders stands ready to start a new relationship with a firm.[20] The problem of a lender that has lent b in the previous period to a firm with current capital k and productivity z is

$$W(s) = \max_{Q^r \geq Q^n(s)} \mathcal{P}(s;Q^r)\big[b - \mathcal{B}(s;Q^r)Q^r + \beta^k\mathbb{E}_{z'}[W(z',\mathcal{B}(s;Q^r),\mathcal{K}(s;Q^r))|z]\big] + [1-\mathcal{P}(s;Q^r)]\psi(s) \quad , \quad (4.7)$$

where $Q^n(s)$ is the price offered by new lenders. Given the free-entry assumption, $Q^n(s)$ is determined by the zero expected-discounted profit condition

$$-Q^n\mathcal{B}(s;Q^n) + \beta^k\mathbb{E}_{z'}[W(z',\mathcal{B}(s;Q^n),\mathcal{K}(s;Q^n))|z] = 0 \quad . \quad (4.8)$$

Thus, a concentrated lender would like to extract as much surplus as it can, but is constrained by the outside option of the firm to start a new relationship. In addition, the concentrated lender also understands that Q^r affects the probability of survival today $\mathcal{P}(s;Q^r)$ and hence the likelihood of b being repaid. The lender may therefore offer a Q^r that is strictly higher than Q^n. We say that the firm benefits from subsidized lending whenever the prevailing price of debt offered by a concentrated lender is strictly larger than the counterfactual price of debt that the firm would obtain were it to match with a new lender, $Q^r > Q^n$.

4.4. Closing the economy

New entrants have to pay a fixed cost ω to take a productivity draw $z \sim \Gamma(z)$ and start operating. We assume that new entrants are endowed with a certain amount of capital equal to $\underline{k}$. Firms are willing to enter as long as

$$\mathbb{E}_\Gamma[\mathcal{V}(z',0,\underline{k})] \geq \omega + \underline{k} \quad . \quad (4.9)$$

[19] Note that we focus on solvency default, not liquidity default as in Ivanov et al. (2021), for example.

[20] In fact, the model is perfectly competitive due to the assumption of free-entry of lenders and no costs of switching lenders. Adding switching costs would generate ex-post market power for lenders. Lender free-entry would still ensure that contracts are ex-ante competitive.

Let $\lambda(z,b,k)$ be the measure of firms after entry and exit have taken place. In a stationary equilibrium, the measure λ is the same across periods, and consistent with a law of motion

$$\lambda(z',b',k') = \int_{z,b,k} \Pr(z'|z)\mathbb{I}[\mathcal{B}(z,b,k)=b']\mathbb{I}[\mathcal{K}(z,b,k)=k']\mathcal{P}(z,b,k)\mathrm{d}\lambda(z,b,k) + \mathrm{m}\int_{z} \Gamma(z)\Pr(z'|z)\mathbb{I}[\mathcal{B}(z,0,\underline{k})=b']\mathbb{I}[\mathcal{K}(z,0,\underline{k})=k']\mathcal{P}(z,0,\underline{k})\mathrm{d}z\ , \tag{4.10}$$

where $\mathbb{I}$ is the indicator function, equal to 1 if the condition in brackets is satisfied and 0 otherwise, m is the mass of new entrants, and $\Gamma(z) \equiv \mathcal{U}(z;\underline{z},\tilde{z})$ is the distribution of productivity for entrants, which is a uniform distribution between the minimum value of productivity, $\underline{z}$, which is set at two standard deviations below the mean, and an intermediate value $\tilde{z}$, which is internally calibrated.

With the measure of firms, we can compute labor demand as

$$N^d = \int_{z,b,k} n(z,b,k)\mathrm{d}\lambda(z,b,k)\quad . \tag{4.11}$$

In what follows, we make two alternative assumptions about how to close the economy, which is defined for some function $Q(z,b,k)$ that firms take as given. The key difference between the two equilibrium concepts is whether wages adjust. Under "constant entry," wages do not adjust, and one can therefore interpret the economy as a single industry that is relatively small in terms of the aggregate labor market. Under "constant labor," wages adjust, and the economy rather represents the general equilibrium of an entire economy.

Constant entry First, we consider an economy with constant entry by making the assumptions that (i) the measure of entrants is perfectly inelastic, $\mathrm{m} = \bar{\mathrm{m}}$ and (ii) labor supply is perfectly elastic, so it adjusts to be equal to the labor demand as in (4.11). An equilibrium with constant entry is a collection of policy and value functions $(\mathcal{K},\mathcal{B},V^p)$, a constant wage $w=1$, a measure $\lambda(z,b,k)$, and a constant mass of entrants $\bar{\mathrm{m}}$ such that (a) the policy and value functions solve the firm's problem in (4.1) given the function Q and $w=1$, (b) a wage $w=1$ that ensures that the free-entry condition (4.9) is satisfied (possibly with a strict inequality), and (c) the distribution of firms is given by a measure λ that satisfies (4.10).

Constant labor Second, we consider an economy with constant labor by assuming that (i) the measure of entrants is perfectly elastic and new firms make zero expected-discounted profits, and (ii) labor supply is constant at $\bar{N}$. An equilibrium with constant labor is a collection of policy and value functions $(\mathcal{K},\mathcal{B},V^p)$, an equilibrium wage w, a measure of firms $\lambda(z,b,k)$, and a mass of entrants m such that (a) the policy and value functions solve the firm's problem (4.1) given Q and the wage rate w, (b) a wage rate w that ensures that the free-entry condition (4.9) is satisfied with *equality*, (c) the measure of firms λ satisfies (4.10), and (d) the mass of entrants m is such that the demand for labor (4.11) is equal to $\bar{N}$. This definition resembles the one in Hopenhayn (1992).

5. Quantitative evaluation

5.1. Calibration

We calibrate the model to an annual frequency, and the parameters we pick are summarized in Table 5.1. We use a combination of external and internal calibration. As our benchmark economy, we choose the model under concentrated lending and the equilibrium with constant labor. Our calibration strategy is based on matching a series of general moments from the literature and the Y-14 data that are typically used as targets in the literature but that are not directly related to the evergreening mechanism. We then show that even our agnostic calibration is able to generate evergreening in equilibrium, and generate patterns that are consistent with the empirical evidence that we document in Section 3, which we take as an external validation of the model.

We pick the entry cost ω such that condition (4.9) is satisfied with *equality* for $w=1$ and normalize $\bar{N}=100$. We assume that firm productivity follows an AR(1) process in logs, $\log z' = \mu_z + \rho_z \log z + \sigma_z\epsilon_z$. The associated parameters are taken from Gomes (2001) and Gourio and Miao (2010), with $\mu_z = 0$. The two references report similar values for the persistence of the AR(1) process, which we adopt, but relatively different values for the standard deviation of the innovations. We choose $\sigma_z = 0.11$, an intermediate value within the range of reported values (0.035 and 0.22). The slope parameter for the linear component of the equity issuance cost is set to a standard value of 0.2, consistent with the estimates in Hennessy and Whited (2007). The depreciation rate is calibrated to $\delta = 0.1$, which is in line with standard values for physical capital depreciation in models calibrated at the annual frequency and helps us match an aggregate investment rate of 10.4%. The production function parameters α and η are set to 0.32 and 0.48, respectively. This is consistent with a capital share equal to 0.4 and a degree of returns to scale of 0.8. This helps us match an aggregate profit share, net of fixed costs, of 17.6%, close to the 16% that we measure in the Y-14 data. The discount factor of lenders is set to target a risk-free rate of around 3 percent, a standard value. The recovery rate is calibrated to $\psi_1 = 0.35$, consistent with the recent evidence in Kermani and Ma (2020). The firm discount factor, the fixed cost of operation, the scale for the logistic distribution, the TFP distribution for entering firms, their initial capital, the collateral constraint parameter, and the cost of issuing equity are internally calibrated and jointly chosen to match a series of moments from the data, presented in Table 5.2.

The model does a relatively good job at matching key moments for the distribution of firm financials, such as median market leverage and debt relative to fixed assets (capital), as well as the aggregate investment rate. For these moments, we report two numbers, one computed based on firm financials reported in the Y-14 data and another based on Compustat data. Both moments refer to the main sample period of our empirical results, 2014:Q4 through 2019:Q4. The model can generate an exit rate in line with the average value for the last 40 years, as documented by Hopenhayn et al. (2022), as well as a reasonable value for the median interest rate spreads reported on the Y-14 loans.[21] Finally, the model does a relatively good job of matching a series of moments on size and productivity of firms at entry and exit, following Lee and Mukoyama (2015): size is measured as employment, and all of these moments are relative to the unconditional average over the entire distribution. The model can replicate the fact that firms tend to be smaller and less productive than average both at entry and exit.

5.2. Lending prices and firm choices

Fig. 5.1 plots policy functions, continuation values, and debt prices for a firm with the same (z,k) in the two economies, as a function of preexisting debt b. We begin by describing the dispersed lending case illustrated by the blue dashed lines, where results are perhaps more standard and intuitive. The firm's value is strictly decreasing in b, which implies the same relation for the probability of repayment (panel a). Similarly, k' is strictly decreasing in b as visible in panel (d). That is because firms with more debt are more likely to realize negative profits, forcing them to issue costly equity. When the marginal value of equity is high, investment is lower, which implies less borrowing due to the borrowing constraint, as shown in panel (c). Finally, panel (b) plots the

[21] The median spread from the Y-14 is likely a lower bound as the data covers larger loans of at least $1M (committed amount) issued by relatively large banks.

Table 5.1
Model parameters and values.

Parameter	Description	Value	Source/Reason
ω	Cost of entry	1.184	Normalize $w = 1$
ρ_z	TFP persistence	0.767	Gomes (2001), Gourio and Miao (2010)
σ_u	TFP volatility	0.110	Gomes (2001), Gourio and Miao (2010)
e_{slope}	Equity issuance cost	0.200	Hennessy and Whited (2007)
δ	Depreciation rate	0.100	Aggregate investment/capital of 10%
α	Production, capital share	0.320	Profit share of 16%
η	Production, labor share	0.480	Profit share of 16%
β^k	Lender discount rate	0.970	Real rate of 3%
ψ_1	Recovery value	0.350	Kermani and Ma (2020)
β^f	Borrower discount factor	0.884	Internally calibrated
$\mathbf{c}$	Fixed cost	0.055	Internally calibrated
κ	Logistic distr., scale	0.225	Internally calibrated
$\bar{z}$	TFP distr. for entrants	1.147	Internally calibrated
$\underline{k}$	Initial capital	0.805	Internally calibrated
θ	Constraint parameter	1.040	Internally calibrated
e_{con}	Fixed cost of issuing equity	0.010	Internally calibrated

Table 5.2
Data moments and model fit.

Moment	Source	Data	Model
Market leverage (median)	Y-14/Compustat	0.63/0.57	0.59
Debt over fixed assets (median)	Y-14/Compustat	1.09/1.20	1.04
Investment rate (aggregate)	Y-14/Compustat	0.104/0.14	0.117
Profit share (aggregate)	Y-14	0.16	0.176
Interest rate spread (median)	Y-14	3.46%	4.47%
Exit rate	Hopenhayn et al. (2022)	9.0%	8.8%
Size at entry (relative to mean)	Lee and Mukoyama (2015)	0.60	0.58
Size at exit (relative to mean)	Lee and Mukoyama (2015)	0.49	0.38
TFP at entry (relative to mean)	Lee and Mukoyama (2015)	0.75	0.88
TFP at exit (relative to mean)	Lee and Mukoyama (2015)	0.64	0.86

Notes: Y-14/Compustat moments correspond to unconditional moments between 2014:Q4 and 2019:Q4. Size and productivity at entry and exit are measured in % of average values for incumbent firms, where size is defined as total employment. Investment rate is equal to net investment divided by capital/fixed assets. The profit share is measured as operating profits net of fixed costs divided by output in the model, and as operating surplus divided by sales in the data. The median interest rate spread is computed with respect to a weighted average over contemporary yields on 6-month and 2-year treasury notes, where the weights are given by each firm's short- and long-term debt shares relative to total debt.

equilibrium price $Q^c(z, b, k)$. As legacy debt increases, the probability of default in the following period rises, leading to a fall in the dispersed lending price. For high levels of legacy debt, the equilibrium price rises slightly as the firm strongly cuts down on its borrowing but still invests. The red lines correspond to the same policy functions under concentrated lending. For low enough debt, the policies are much the same. However, after a certain point, they begin to diverge. Specifically, panel (b) shows that the price of debt rises earlier with more legacy debt. The higher price of debt reflects the subsidy from the concentrated lender who attempts to prevent firm default. As panels (a), (c), and (d) show, the subsidy affects the probability of repayment, as well as firm choices of capital and debt, which are all larger compared with the dispersed lending case. Note that this plot refers to a particular combination of firm states (k, z) that we keep fixed throughout: in other regions of the state space, the probability of repayment may not be sufficiently sensitive to the price of debt such that the policies look more similar across the two economies.

5.3. Aggregate effects: dispersed vs. concentrated lending

We assess the impact of introducing concentrated lending in Table 5.3 for the two equilibria mentioned before; one with constant entry and one with constant labor. In each of the columns, we compare moments for the stationary equilibrium under concentrated lending to those same moments for the stationary equilibrium under dispersed lending. The top part of the table corresponds to averages across firms, and the bottom part presents aggregates. By steering a firm's default decision through the offered lending terms, a concentrated lender can recover its previous investment more often, benefiting the lender, all else being equal. However, assuming lenders make zero profits in expectation, incumbent firms reap these benefits by borrowing at lower rates that decrease by 1.24% in the equilibrium with constant entry and by 1.13% with constant labor. The average firm in the CLE is, therefore, more indebted, with market leverage rising by 0.60% with constant entry and 0.54% with constant labor. Firms also become larger by nearly 2.34% with constant entry and 2% with constant labor. The average firm in the CLE is also slightly less productive, and firms exit less often.

Regarding aggregates, both debt and capital increase by over 3% with constant entry and by over 1% with constant labor. The more frequent survival of low-productive firms that invest relatively more impedes the entry of other firms and leads to a shift in the distribution of firm productivity. As a result, measured TFP falls by 0.32% with constant entry and 0.23% with constant labor. While measured TFP is lower, the fact that the CLE uses significantly more capital and labor results in 2.14% more output with constant entry. However, in the equilibrium with constant labor, total labor is fixed, and output is roughly the same in the two economies (0.10% larger).

Table 5.3 also shows the importance of the market-clearing wage assumption. Under constant entry, the CLE features larger increases in aggregate capital, labor, output, and debt. Note also that the equilib-

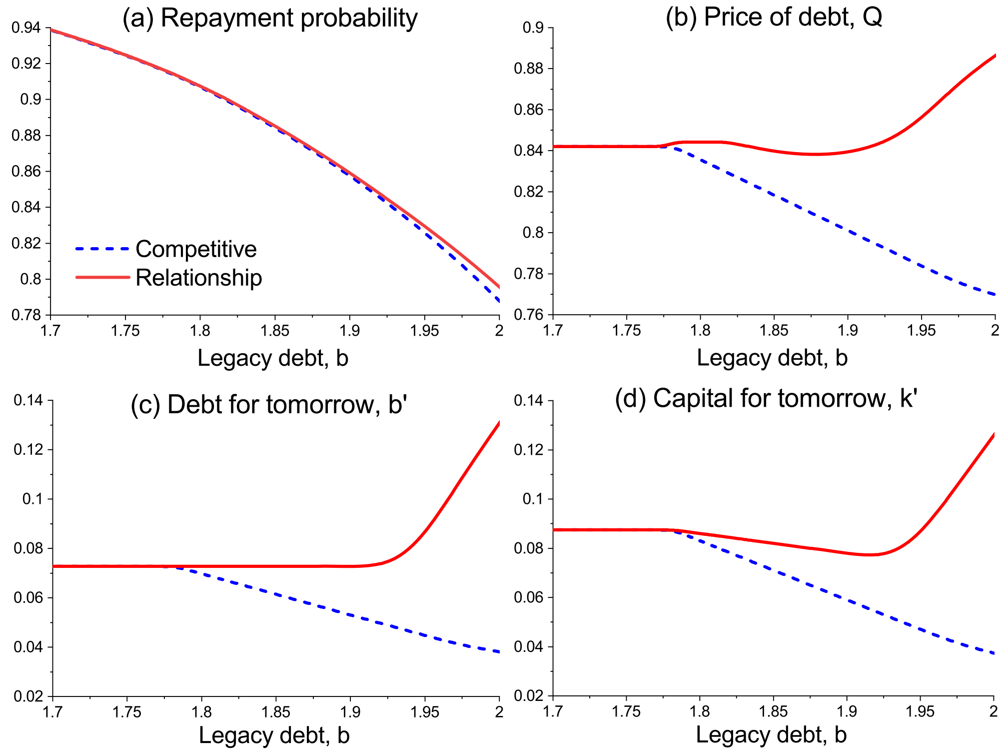

Fig. 5.1. Comparison of policy functions. **Notes:** Policy functions and values for a firm with the same set of $(z = 0.6, k = 2)$, as a function of b, dispersed lending (blue, dashed) vs. concentrated lending (red, solid) economies.

Table 5.3
Impact of introducing concentrated lending.

	Δ % with const. entry	Δ % with const. labor
Firm level (Averages)		
Market Leverage	0.60	0.54
Interest rate	-1.24	-1.13
Size	2.34	1.99
Productivity	-0.04	-0.02
Exit rate	-0.70	-0.17
Aggregates		
Debt	3.13	1.04
Capital	3.13	1.04
Labor	2.14	0.00
Output	2.14	0.10
Wage	0.00	0.10
Measured TFP	-0.31	-0.23
Number of firms	0.77	-0.94

Notes: Size is measured in terms of capital. Measured TFP is given by $Y/(K^{\alpha}N^{1-\alpha})$.

rium concepts differ with respect to the number of firms. With constant entry, the number of firms increases as more firms survive, and the measure of entrants is constant. In contrast, with constant labor, the number of firms declines slightly because firms are larger, which implies that fewer resources are available for new entrants, leading to a drop in firm entry.

5.4. Aggregate productivity in the CLE and the DLE

Our results suggest that the lending regime affects the average size and profitability of incumbent firms, both of which could affect aggregate productivity. We decompose aggregate productivity under each lending regime into three separate terms: static misallocation in the spirit of Hsieh and Klenow (2009), selection (or dynamic misallocation), and average firm size. First, we explicitly define aggregate output in each economy as $Y = \int_s zk^{\alpha}n(s)^{\eta}\mathrm{d}\lambda(s)$. The following result describes the maximum level of output that a planner could achieve by reallocating fixed quantities of factors across a fixed mass of firms.

Proposition 4. *In an economy where a planner can freely reallocate capital and labor across firms to maximize production, for a given mass of firms, aggregate production is given by* $Y^* = M^{1-\alpha-\eta}\mathbb{E}[z^{\frac{1}{1-\alpha-\eta}}]^{1-\alpha-\eta}K^{\alpha}N^{\eta}$, *where* $K \equiv \int_s k(s)\mathrm{d}\lambda(s)$, $N \equiv \int_s n(s)\mathrm{d}\lambda(s)$ *are the aggregate stocks of capital and labor, respectively. Proof: See Appendix D.1.*

As a direct corollary we can write output in the decentralized economy as

$$Y = \underbrace{\left(\frac{1}{S}\right)^{1-\alpha-\eta}}_{\text{avg. firm size}} \times \overbrace{\mathbb{E}[z^{\frac{1}{1-\alpha-\nu}}]^{1-\alpha-\eta}}^{\text{selection}} \times \underbrace{\frac{Y}{Y^*}}_{\text{static misallocation}} \times \overbrace{K^{\alpha}N^{1-\alpha}}^{\text{factor qtys.}},$$

where $S \equiv N/M$ is the average firm size. The first three terms correspond to measured TFP, $MTFP \equiv Y/K^{\alpha}N^{1-\alpha}$. MTFP depends on three components: the first term is average firm size. This term appears since firms operate with decreasing returns to scale technology: an economy with more and/or smaller firms has higher MTFP, everything else constant. The second term represents selection, or dynamic misallocation: an economy with more productive incumbents on average has higher MTFP, everything else constant. The final term represents static misallocation in the sense of Hsieh and Klenow (2009). It is equal to 1 in an economy where a constant amount of factor inputs are distributed to equalize marginal products of inputs across firms.

This expression is useful to compare aggregate productivity across different economies: for two economies indexed by i, j, we can decompose the ratio

Table 5.4
MTFP decomposition: CLE vs. DLE.

Ratio	% Δ DLE constant entry to CLE	% Δ DLE constant labor to CLE
MTFP	-0.309	-0.227
Size	-0.270	-0.188
Selection	-0.008	-0.004
Static Misallocation	-0.032	-0.035

Table 5.5
Subsidized vs. non-subsidized Firms in the CLE (medians).

	Non-subsidized	Subsidized	Δ %
Capital	0.75	1.72	128.5
Productivity	1.02	0.94	-8.0
Output	0.41	0.60	46.1
Payouts/assets	0.05	-0.01	-114.4
Market leverage	0.53	0.80	50.6
Interest rate	7.75	10.02	29.2
Probability of survival	0.96	0.89	-7.6
Interest-coverage ratio	1.67	0.45	-73.1
Age	7.87	10.17	29.2

$$\frac{Y_i}{Y_j} = \left(\frac{1/S_i}{1/S_j}\right)^{1-\alpha-\eta} \times \left(\frac{\mathbb{E}_i[z^{\frac{1}{1-\alpha-\nu}}]}{\mathbb{E}_j[z^{\frac{1}{1-\alpha-\nu}}]}\right)^{1-\alpha-\eta} \times \left(\frac{Y_i/Y_i^*}{Y_j/Y_j^*}\right) \times \left(\frac{K_i^\alpha N_i^{1-\alpha}}{K_j^\alpha N_j^{1-\alpha}}\right). \tag{5.1}$$

Table 5.4 reports the results of the decomposition of MTFP for the CLE vs. the DLE with constant entry or constant labor. MTFP is lower in the CLE in both cases: the decomposition attributes most of this drop to the size component, as firms are on average larger in the CLE. There is also a small negative contribution from selection, as firm productivity is also lower on average in the CLE. Finally, static misallocation is worse in the CLE, suggesting that subsidized lending also worsens static efficiency. However, it accounts for only around 10% of MTFP losses, with the bulk arising from firm size. This suggests that traditional measures of static misallocation, such as the standard deviation of MPK, may not be informative regarding productivity losses generated by lending arrangements.

5.5. Subsidized vs. non-subsidized firms

How do subsidized and non-subsidized firms differ in the CLE? Table 5.5 explores this question, reporting medians for different individual firm characteristics, depending on whether those firms are subsidized. Recall that a firm is subsidized when it pays an interest rate to a concentrated lender that is below the rate that it would pay if it were to match with a new lender (regardless of the rate that a firm with the same states would pay in the dispersed lending economy, where no firms are subsidized). The table shows that subsidized firms are around 130% larger than non-subsidized firms. However, they are also around 8% less productive. Still, the size effect outweighs the lower productivity, and the median subsidized firm has around 46% larger output. Subsidized firms are also more leveraged and pay higher interest rates despite the subsidy, because they are riskier compared with non-subsidized firms.

Note that the subsidized firms have most of the characteristics that the literature typically associates with “zombie firms”: they are large, unproductive, indebted, unprofitable, and older. Interestingly, however, and despite the subsidy, these firms pay higher interest rates as they tend to be closer to default (the probability of survival is almost 8 pp lower). This puts in question empirical classifications of zombie firms that are based on costs of borrowing being below market or below average for a given peer group (as in Caballero et al., 2008). Subsidized firms in our model are ultimately risky firms, and thus they pay relatively higher interest rates. However, these interest rates are not as high as those offered by a new lender without evergreening incentives—a counterfactual that cannot be observed in the data.

Subsidized vs. zombie firms While there is a large empirical literature that attempts to classify zombie firms, there is no single definition of what constitutes one, and a wide range of classification methodologies have been proposed in the literature. We focus on the measure by Favara et al. (2022a) (FMP), who quantify the number of zombie firms in the U.S. using a similar dataset to ours. They classify a firm as a zombie if it satisfies the following three conditions: (i) leverage above the median, (ii) an interest coverage ratio below 1, and (iii) average negative sales growth over the past 3 years. Given our calibration, we find that 5.7% of firms satisfy this definition in the stationary equilibrium with concentrated lending. This is consistent with the estimates of FMP, who find a zombie firm share of 5.6%-5.7% between 2017 and 2019. This is a completely untargeted and relevant moment; thus, we take it as a measure of external validation of the model calibration.

Given the differences between subsidized and non-subsidized firms reported in Table 5.5, we also assess how various zombie definitions from the literature correlate with whether a firm receives a subsidy or not in our model (our precise definition of a zombie). Details of this exercise are left to Appendix D.2. We find a high correlation with the measure proposed by Schivardi et al. (2022), who classify a firm as a zombie if it has (i) a return on assets below the risk-free rate and (ii) leverage above 40%. Overall, classification measures that put more emphasis on profitability and leverage perform better.

5.6. Discussion: model vs. data

Our model analysis focuses on two extreme cases: all firms in the economy either borrow from concentrated or from perfectly dispersed lenders. In practice, however, there is substantial variation of lender concentration across firms in the data.

If firms were able to choose the lending regime in our setup, concentrated lending would become dominant. To see this, consider first the case where firms can choose the regime upon entry, and commit to it thereafter. As Table 5.3 shows, the wage rate is higher in the concentrated lending economy vs. the dispersed lending economy, which reflects a higher ex-ante value of entry in the concentrated lending economy for a given wage rate. The higher value of entry is due to differences in lending technology that allow for implicit restructuring in the concentrated lending economy. Second, if we allow firms to choose the regime period-by-period, we find in our calibration that the value function is weakly larger in the concentrated lending economy given a wage rate for any combination of state variables.

The fact that there is variation of lending regimes in the data suggests that other factors govern this choice that are not fully captured by our model; or some firms may not even be able to make this choice at all. To account for such factors, we set up a version of the model where a fraction ϕ of entrant firms is exogenously assigned to dispersed lenders, while all other entrants are exogenously assigned to concentrated lenders. While this version of the model still considers two extreme lending regimes, it generates regime variety in equilibrium by mixing the two.[22] We calibrate ϕ to match the average within-firm HHI

[22] For computational tractability, we set up this economy under constant entry, with $w = 1$.

of lending in the Y-14 data, the same measure we employ in Section 3.5. Our baseline estimate for this measure is 0.91 which implies $\phi = 0.09$.[23]

Based on this calibration, we investigate whether the model generates cross-sectional predictions that are in line with the patterns we find in the data. To this end, we simulate a large number of panels and replicate the empirical specification in Section 3.2 for each. In particular, we regress the (symmetric) growth rates of capital and debt on a measure of lender concentration, a measure of distress, and the interaction between the two. Firms with dispersed borrowing are assigned $HHI_{i,t} = 0$, while firms with concentrated borrowing are assigned $HHI_{i,t} = 1$. We define $Distress_{i,t} = 1$ if a firm borrowing from concentrated lenders receives subsidized credit or if a firm borrowing from dispersed lenders would have been subsidized by concentrated lenders given its current states, and zero otherwise.

The results are reported in Appendix Table D.2, which we compare to the ones in Table 3.2. The model generates the same qualitative predictions we find in the data: more concentrated borrowing is associated with higher capital and debt growth. At the same time, distress is related to lower capital and debt growth, everything else constant.[24] Importantly, the coefficient on the interaction between lender concentration and distress is positive; that is, distressed firms show additional debt and capital growth due to the subsidized borrowing they receive. The coefficient for the investment regression is close to its empirical counterpart, providing evidence that the model mechanism generates comparable real effects. If anything, the model slightly understates the importance of the mechanism. It should be noted that no moment that is directly related to the mechanism is explicitly targeted as part of our calibration strategy, and yet the model produces similar results that we find in Section 3. We also find that these regression results are largely insensitive to the choice of ϕ, which merely changes the fraction of firms with dispersed borrowing.

6. Conclusion

Up to this point, the literature has largely associated zombie lending or evergreening with economies that are in a depression and have severely undercapitalized banks. The main empirical contributions focus on cases that fit these descriptions—Japan in the 1990s and periphery countries during the Eurozone crisis more recently. In this paper, we take a different perspective. We theoretically and empirically argue that evergreening is a general feature of financial intermediation—taking place even outside of depressions and within economies that have well-capitalized banks.

Our proposed theoretical mechanism builds on an intuitive idea. To recover its past investment, a lender has incentives to offer more favorable lending terms to a firm close to default to keep the firm alive. We then explore the empirical relevance and macroeconomic consequences of this general theory of evergreening. We find empirical support for the mechanism in the context of large U.S. banks, at a time when those were thought to be relatively well-capitalized. Using a calibrated dynamic model, we find that evergreening has negative aggregate effects for TFP, mainly due to its role in increasing average firm size. Exploring how similar versions of our proposed mechanism may apply to other settings, such as the mortgage market as in Gupta (2022), is a salient path for future research.

[23] This is the average HHI for firms for which we observe at least 90% of total debt and is computed under the assumption that all unobserved debt is as dispersed as observed debt. This is likely to be a conservative estimate as the Y-14 data is tilted towards larger firms with more dispersed borrowing: average fixed assets of such firms in our sample is \$10.7 M, versus \$3.9 M for the entire economy (aggregate fixed assets from the BEA divided by total number of firms from County Business Patterns). Alternatively, we could pick ϕ to match other aggregate moments. Appendix Fig. D.1 shows that the zombie measure by Favara et al. (2022a) is strictly decreasing in ϕ and targeting it by choosing ϕ would imply an even lower choice of ϕ close to zero to match the share of zombie firms measured in the data.

[24] The quantitative results between model and data differ for those coefficients, possibly because firms with concentrated borrowing are younger ones that are still growing in practice leading to a more positive coefficient on $HHI_{i,t}$ in the data. Distressed firms may be slower to adjust their capital and debt in practice as they face capital adjustment costs and various other frictions that are absent from the model, leading to a less negative coefficient on $Distress_{i,t}$ in the data.

CRediT authorship contribution statement

Miguel Faria-e-Castro: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Pascal Paul:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Juan M. Sánchez:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Appendix A. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfineco.2024.103778.

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