Evergreening

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Abstract

We develop a simple model of relationship lending where lenders have incentives for evergreening loans by offering better terms to less productive and more indebted firms. We detect such lending behavior using loan-level supervisory data for the United States. Low-capitalized banks systematically distort firms' risk assessments to window-dress their balance sheets. To avoid further reductions in their capital ratios, such banks extend relatively more credit to underreported borrowers. 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.

Keywords: evergreening, zombie firms, bank lending, misallocation

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"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, Hoshi and Kashyap, 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).

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 has market power and internalizes how the offered lending terms influence a firm's decision to default on existing liabilities. The presence of such relationship banking and market power 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 can raise 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.

Our theory generates two predictions that we aim to test empirically. When deciding on new credit conditions, (i) lenders take into account the outstanding debt that they have with a borrower, and (ii) they actively try to steer a firm's default decision. 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 loan and that banks have an incentive to assess similar loans differently due to the regulatory environment. Specifically, we show that low-capitalized banks systematically understate their credit risk exposure, confirming previous findings by Plosser and Santos (2018) and Behn, Haselmann and Vig (2022). Such "window-dressing" can arise because the loan risk assessments directly or indirectly affect bank capital positions. The differential risk assessments provide us with variation to identify whether banks take into account the legacy debt when choosing new loan terms. In the cross-section of banks, the less capitalized ones should have stronger incentives to lend relatively more to underreported borrowers to avoid further declines in their capital ratios and to reconcile their reporting. We confirm such differential evergreening behavior across banks using the approach by Khwaja and Mian (2008). As evidence that banks actively try to steer firm default, we show that these results are only present for low-productivity firms and when banks hold a large share of a firm's debt. We find these effects even outside of a recession, when U.S. banks were well-capitalized and operating with relatively high capital ratios but smaller capital buffers above regulatory requirements—illustrating the generality of the theoretical incentives.

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 model 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% 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% relative to an economy with competitive 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 also 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, Sette and Tabellini (2022) tend to correlate with our measure.

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, Hoshi and Kashyap (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, Lenzu and Wang, 2021), 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 or default.

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,

[1] Within the bank, loan officers may engage in evergreening if they face a lower likelihood of being exposed (Hertzberg, Liberti and Paravisini, 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, Andrews and Millot (2018), Acharya et al. (2019), Andrews and Petroulakis (2019), Acharya et al. (2020), Bittner, Fecht and Georg (2021), Schmidt et al. (2020), Acharya et al. (2021), Chari, Jain and Kulkarni (2021), Banerjee and Hofmann (2022), and Artavanis et al. (2022).

enabling them to borrow and invest relatively more — the opposite result. 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.

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, Lenzu and Wang (2021) 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—in contrast to prior studies that concentrated on European and Japanese institutions.[4,5] Related to our findings, Blattner, Farinha and Rebelo (2020) 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, Sette and Tabellini (2022) find that weakly capi-

[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, Sim and Zakrajšek, 2013; Liu, Mian and Sufi, 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, Ivanov and Rezende (2022), and Ma, Paligorova and Peydró (2021) have used the Y-14 data in this context to investigate the effects of bank capitalization and lender expectations.

[5]Behn, Haselmann and Vig (2022) provide related evidence, showing that German banks that implemented the internal ratings-based approach increased lending relatively more to firms for which the possible reduction in capital requirements was larger due to the underreporting of risk. Such underreporting has been found to be linked to bank capital positions in a number of circumstances (see, e.g., Begley, Purnanandam and Zheng, 2017; and Plosser and Santos, 2018).

talized 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 some preexisting liabilities and may choose to default on its outstanding debt. Given the firm's problem, we compare the equilibrium outcomes of two economies: (i) one with competitive lenders and (ii) an economy with relationship banking. The latter features a single lender that owns the firm's outstanding debt and internalizes how the offered lending terms affect the firm's decision to default on its legacy debt.

Environment. Time is discrete and finite with two periods $t = 0, 1$. The economy features two types of agents: firms, which are indexed by their pre-determined states (z, b), where z is productivity, and b are preexisting liabilities, and lenders, who are risk-neutral and have deep pockets. In the competitive lending economy, there is a continuum of lenders for each firm. In the relationship banking economy, each firm borrows from a single lender.

2.1 Firm Problem

At the beginning of the first period $t = 0$, the firm may choose to default. If the firm defaults, it obtains 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 $t = 1$.

If the firm does not default, it has to repay 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 $\theta > 0$.[6] 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.[7] We assume for now that the constraint is binding, which occurs if $Q \geq \beta^f$, and later impose restrictions on the model's parameters to ensure this is the case. With a binding constraint, the closed-form expressions for the optimal capital stock and the level of new debt are

$$k'(z; Q) = \left(\frac{\beta^f \alpha z}{1 - \theta(Q - \beta^f)} \right)^{\frac{1}{1-\alpha}} \quad , \quad b'(z; Q) = \theta k'(z; Q) \quad , \tag{2.2}$$

and the value function can be written in closed-form

$$V(z, b; Q) = -b + \left(\frac{1}{\alpha} - 1 \right) \frac{(\beta^f \alpha z)^{\frac{1}{1-\alpha}}}{[1 - \theta(Q - \beta^f)]^{\frac{\alpha}{1-\alpha}}} \quad . \tag{2.3}$$

This characterizes the firm's problem for an arbitrary price of debt Q, which is taken as given. We restrict $Q \leq \beta^f + 1/\theta$ to ensure that policy and value functions are well-defined and later confirm that this restriction is satisfied in equilibrium. Equations 2.2 and 2.3 show that the firm's policies and value are all strictly increasing in productivity z and the price of debt Q. Additionally, firm value is strictly decreasing in the amount of legacy debt b. We can use these facts to characterize the firm's optimal decision in the following proposition.

Proposition 1. *There exists a* $Q^{\min}(z, b)$ *such that the firm defaults if and only if* $Q <$

[6] Appendix A.1 discusses more general borrowing constraints of the type $b' \leq g(k')$, with g positive and increasing, for which we can still prove our main results.

[7] 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.

$Q^{\min}(z,b)$. The threshold is given by

$$Q^{\min}(z,b) = \beta^f + \frac{1}{\theta} - \frac{(\beta^f \alpha z)^{\frac{1}{\alpha}}}{\theta}\left(\frac{1-\alpha}{\alpha b}\right)^{\frac{1-\alpha}{\alpha}} \quad .$$

The threshold 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.

2.2 Competitive 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 unlimited resources, 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 imposes that the offered contract satisfies

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

The equilibrium allocation is then obtained by evaluating 2.2 and 2.3 at $Q = \beta^k$.[8] All non-defaulting firms borrow at the same interest rate, regardless of their initial states (z,b), which implies that marginal products of capital (MPK) are equalized. More productive firms invest more and therefore also borrow more, but credit quantities and prices are independent of the amount of legacy debt b.

2.3 Relationship Lending

We now analyze the equilibrium under a different institutional setting resembling relationship banking. Compared with the competitive lending economy, there are two key differences. First, the lender has market power and behaves like a Stackelberg leader, internalizing how its choice of Q affects the firm's policies and value. Second, lending is non-anonymous because the lender owns the preexisting debt

[8] Since $\beta^k = Q > \beta^f$, our conjecture that the borrowing constraint in (2.1) binds is confirmed.

b and understands that this debt is lost in the case of default. In the context of relationship lending, we use the terms "lender" and "bank" interchangeably. The lender's problem is given by

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

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. Otherwise, the lender recovers b, lends Qb', and obtains b' at $t = 1$, which is discounted with 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. Note that we can equivalently write the bank's problem as

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

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 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 the bank's 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*

$$W(z, b; Q^{\max}) = 0 \Leftrightarrow b + [\beta^k - Q^{\max}(z, b)]\theta \left(\frac{\beta^f \alpha z}{1 - \theta(Q^{\max}(z, b) - \beta^f)} \right)^{\frac{1}{1-\alpha}} = 0 \, ,$$

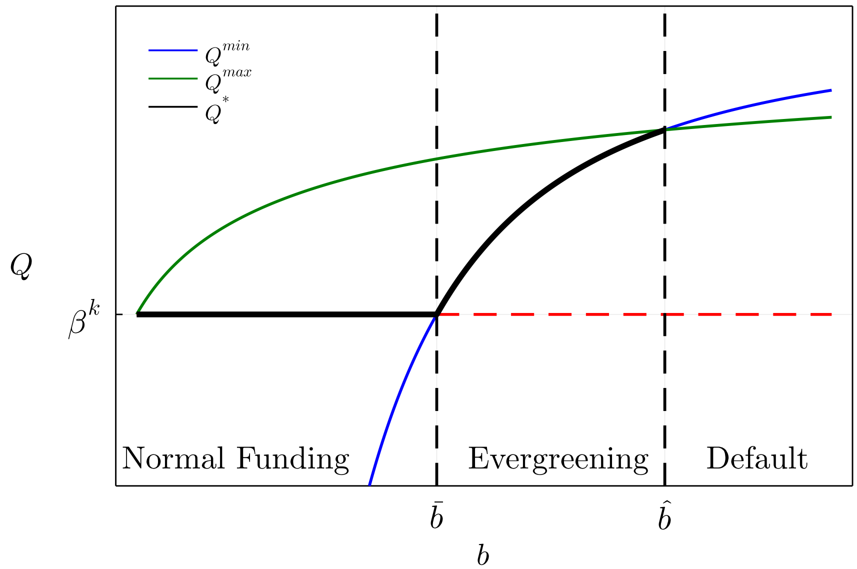
and satisfies the properties (i) $Q^{\max}(z, b) > \beta^k$ iff $b > 0$, (ii) it is increasing in b, (iii) it is decreasing in z.

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 $Q^{\min}(\hat{b}(z), z) = Q^{\max}(\hat{b}(z), z)$,

Figure 2.1: Relationship 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^*.

with closed-form expressions given by

$$\bar{b}(z) = \frac{1-\alpha}{\alpha}\left[\frac{\alpha\beta^f z}{(1-\theta(\beta^k-\beta^f))^\alpha}\right]^{\frac{1}{1-\alpha}} \quad , \quad \hat{b}(z) = (1-\alpha)\left[\frac{\beta^f z}{(1-\theta(\beta^k-\beta^f))^\alpha}\right]^{\frac{1}{1-\alpha}} \quad ,$$

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 $b \in [\bar{b}(z), \hat{b}(z)]$.

Proposition 3 states that, as long as the legacy debt is nonzero, $b > 0$, 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 Figure 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 relationship economy coincides with the competitive 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 competitive economy. In the relationship 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, $Q^{\min}(z, b)$ exceeds the maximum price the bank is willing to offer to break even, and the bank decides to liquidate the firm ("default").

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 relationship and competitive lending economies.

Before presenting the empirical analysis, we compare our mechanism to existing corporate finance theories, discuss some assumptions, and extend the model to include bank capital as a motivation for our empirical identification approach.

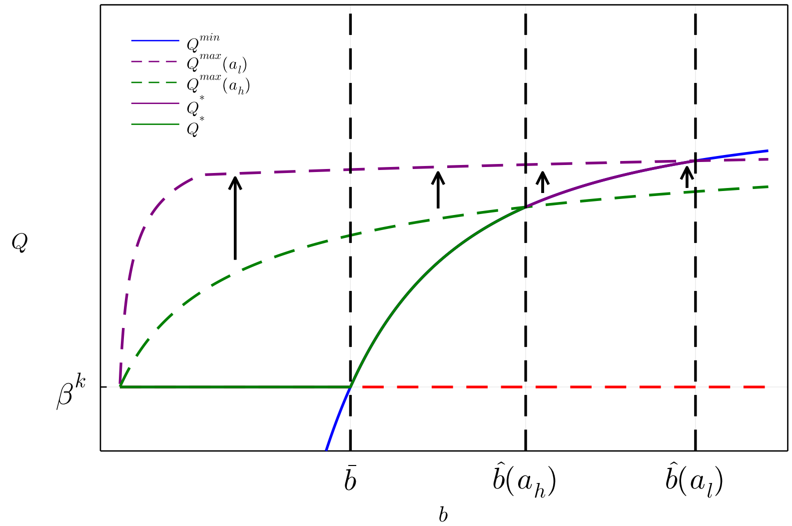
Relation to Existing Corporate Finance Theories. Our proposed mechanism is distinct from phenomena such as risk-shifting or debt overhang. Risk-shifting postulates that distressed borrowers have incentives to invest in risk-increasing negative NPV projects under limited liability (e.g., Jensen and Meckling, 1976). That is because they can reap the benefits if the investments go well, but creditors bear the costs otherwise. Bruche and Llobet (2013) and Acharya, Lenzu and Wang (2021) build on this idea to explain why banks engage in zombie-lending. In contrast, in our framework, banks do not borrow, firms do not default *following* their investments, and there is no uncertainty, preventing such risk-shifting from occurring.

According to the debt overhang theory, highly indebted borrowers underinvest since the potential profits would primarily accrue to the current creditors, hindering further borrowing (e.g., Myers, 1977). The debt overhang theory relies on the timing that the outstanding (long-term) debt matures *after* the investment decision takes place. In contrast, in our framework, the timing of these decisions is reversed, legacy debt is short-term, and highly indebted firms "overinvest," in the sense that their MPKs are lower than the ones of less indebted firms.

Contracting Protocol and Debt Forgiveness. Our benchmark model assumes a specific contracting protocol based on a Stackelberg game. The relationship lender is the leader (offering Q), and the firm is the follower (choosing b', k' based on Q). One could think of alternative arrangements where the lender sets the price Q and the quantity of debt b' in a take-it-or-leave-it offer. Appendix A.3 derives the solution to such a contracting protocol. In this case, the lender implicitly chooses the firm's investment while extracting maximum surplus by setting the firm's value to zero. This solution is equivalent to the lender owning the firm, who undertakes the project without investment distortions. Intuitively, the lender restricts the quantity of credit to less productive firms while offering a more favorable price of debt to raise those firms' values, just enough to prevent them from defaulting.

Alternatively, we could allow for debt forgiveness or restructuring. A lender may prefer to write off a fraction of the legacy debt to prevent the firm from defaulting. This enables the lender to charge a higher interest rate and obtain a larger surplus on new lending. In comparison, our benchmark model implies that the lender transfers surplus to the borrower by lowering the interest rate instead of writing off debt. The solution to a model with debt forgiveness is described in Appendix A.4. In practice, debt forgiveness could entail additional costs that we do not consider. In contrast to the predictions of these two contracting protocols, we show in the next section that evergreening is characterized by more favorable lending conditions both with respect to credit quantities and interest rates in the

Figure 2.2: Low vs. High Bank Capital



Notes: Equilibrium allocation as a function of b, for high-capital a_h (green) and low-capital a_l (purple) banks.

data. We therefore view our benchmark model as the empirically relevant case.

2.5 Bank Capital

While the incentives to evergreen loans are independent of a lender's capital position in our benchmark model, we next extend the model by including bank capital to motivate our empirical strategy. We leave the derivations to Appendix A.5 and illustrate the intuition of the results in Figure 2.2, which again shows the optimal pricing policies for a firm with a given productivity and various levels of legacy debt. The graph includes two $Q^{\max}$-curves, one for a bank with high capital and one for a bank with low capital. The $Q^{\max}$-curve of the low-capital bank lies strictly above the one of the high-capital bank. For low and intermediate levels of legacy debt, the optimal policies of the two banks coincide. However, after the point where the $Q^{\min}$-curve intersects the $Q^{\max}$-curve of the high-capital bank, the optimal policies diverge. The high-capital bank is unwilling to save the firm, while it is still beneficial for the low-capital bank to evergreen credit of a firm with such high legacy debt, and a similar result emerges for firm productivity. Thus, scarce bank capital leads to stronger evergreening incentives.

3 Empirical Analysis

3.1 Identification Approach

Our theory has two key predictions that we aim to test empirically. When deciding on new lending terms, (i) lenders take into account the legacy debt, and (ii) they actively try to steer a firm's default decision. To identify such credit supply effects, 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.

We rely on cross-sectional variation in bank capital positions to test the first prediction. As illustrated in Figure 2.2, all else equal, banks that are less capitalized should have stronger incentives to evergreen loans as they value the legacy debt more. However, in the data, credit supply may also vary with bank capital for several other reasons unrelated to our mechanism. For example, low-capitalized banks may generally aim to lower asset growth or face creditor scrutiny about their asset allocation. We, therefore, further identify certain loans that low-capitalized banks value differently. Specifically, loans with underreported credit risk are particularly valuable for low-capitalized banks to keep on their books, and we provide evidence that low-capitalized banks systematically understate their credit risk exposure. We find that the differential risk assessments—of otherwise similar loans—influence lending decisions. Low-capitalized banks extend relatively more credit to underreported borrowers at lower rates, providing evidence that banks actively take into account the legacy debt when deciding on new lending terms. To test whether banks also try to steer a firm's default decision in this way, we further split the sample according to indicators of firm distress and a bank's engagement in a firm, measured by the share of the total debt a bank holds. In support of our mechanism, we find that our results are driven by the samples of distressed firms and if banks are large debt-holders.

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).[9] 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. Important for our analysis, the data cover risk assessments for each loan, allowing us to compare evaluations for the same borrower across banks, as explained in the next section.

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 restrict the start of the sample to 2012:Q3 to allow for a short phase-in period for the structure of the collection and variables to stabilize, though most of our analysis is constrained to begin in 2014:Q4 when loan risk assessments were required for all banks. We include information up until 2020:Q4. Over this sample, we cover 4,904,321 loan facility observations and 216,661 distinct firms. We identify 3,217 of those firms as public since they can be matched to Compustat. Last, we apply a number of filtering steps that are described in Appendix B, which also includes an overview of the variables that are used.

3.3 Risk-Reporting and Bank Capital

For each loan, banks have to report several risk measures: the probability of default (PD), a loan rating, the loss given default, and the exposure at default. Among those, we use the PD for 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 the borrower is sufficiently late on payments, and it should therefore not be understood as a measure of firm bankruptcy. In

[9] 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.

contrast to the other risk measures, the PD has the advantage that it is a continuous measure, and banks are supposed to assess the PD at the borrower rather than loan level, which makes it comparable when multiple banks lend to the same firm.[10]

To understand the origin of this dispersion across banks, we conduct a similar analysis as Plosser and Santos (2018) and Behn, Haselmann and Vig (2022). Weighted by all outstanding loans, we denote the probability of default that bank j reports for firm i at time t by $PD_{i,j,t}$. To compare risk-reporting across banks, we further define the difference between this variable and the average reported PD by all other banks as PD-Gap$_{i,j,t} = PD_{i,j,t} - \overline{PD}_{i,t}$ where $\overline{PD}_{i,t} = (1/M)\sum_m^M PD_{i,m,t}$ for all $m \neq j$. In practice, there are many reasons why banks differ in their risk assessments, reflected in the fact that PD-Gap$_{i,j,t}$ has a relatively large standard deviation of around 7.5 percentage points. For example, some banks may possess private information about a borrower, resulting in a more accurate and potentially different forecast relative to other banks. To assess whether bank capital positions can explain the dispersion, we estimate different versions of the regression

$$\text{PD-Gap}_{i,j,t} = \beta Capital_{j,t-1} + \gamma X_{j,t-1} + \alpha_{i,t} + \kappa_j + u_{i,j,t} \quad , \tag{3.1}$$

where $X_{j,t-1}$ is a vector of bank characteristics, $\alpha_{i,t}$ is a firm-time fixed effect, and κ_j is a bank fixed effect.[11] The variable of interest is $Capital_{j,t-1}$, and we use the buffer over the common equity Tier 1 (CET1) requirement to measure bank capital.[12]

Before estimating the regression, it is useful to consider various explanations for different values of β. First, assume that some banks possess private information and therefore have more accurate forecasts than others. All else being equal, such an explanation should not result in a systematic relation between bank capital and reported PDs but rather yield $\beta \approx 0$. Second, assume that a bank has downward-

[10] 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

[11] Despite the normalization of the dependent variable, we include a firm-time fixed effect since such a fixed effect normalizes the regressors by their firm-time specific averages to compute their relation with the dependent variable (see, e.g., Hansen, 2019, Chapter 17.8).

[12] Throughout our analysis, we use the CET1 buffer since CET1 is the most "costly" type of capital for banks. It covers common stock, stock surplus, retained earnings, minority interest, and accumulated other comprehensive income. We define the capital buffer as the difference between the capital ratio and the required capital, consisting of a minimum and a capital conservation buffer requirement (GSIB surcharge + stress capital buffer + countercyclical capital buffer).

biased PDs or learns its portfolio is less risky. If that bank's risk-weighted assets (RWAs) are computed according to the internal ratings-based approach (IRB), then such a bank would assign relatively lower risk-weights and thus lower RWAs. The ratio of capital-to-RWAs should therefore be higher, resulting in $\beta < 0$. And third, two relevant explanations can instead result in $\beta > 0$. Assume that a bank's overall risk-perception is low or its risk-taking is high. Such a bank may assign low PDs but also operate with high leverage (or low capital buffers). Similarly, if banks specialize in risky lending, they may assign high PDs but also operate with high capital buffers to support potential losses. To account for this "business-model" explanation, we include bank fixed effects and total portfolio risk variables into our regressions, controlling for time-invariant and time-varying factors, respectively.

The final explanation for why we should find $\beta > 0$ is that low-capitalized banks systematically underreport their credit risk exposure due to regulatory incentives. In the U.S., banks may have such incentives for the following three reasons. First, around half of the banks in our sample were subject to the IRB approach, which allows banks to use their own risk measures to compute loan-specific risk weights.[13] The PDs that we use directly enter those calculations, and banks with low capital buffers may underreport PDs to avoid further declines in their capital ratios and potential penalties for violating capital requirements.[14] Second, the Federal Reserve's stress tests also make use of the banks' own risk measures.[15] Institutions with low capital buffers may therefore have an incentive to

[13] According to the advanced IRB approach, banks' own risk measures determine risk weights (PD, exposure at default, loss given default, expected credit loss, and loan maturities). In the U.S., banks subject to the advanced IRB approach must also compute their capital ratios based on the standardized approach and must comply with the capital requirements under both approaches. Source: https://www.federalreserve.gov/aboutthefed/boardmeetings/files/board-memo-20181031.pdf

[14] When bridging the capital conservation buffer requirement, banks may face limitations such as restrictions on dividend payouts, retained earnings, and share buybacks. When violating the minimum requirement, regulators may, for example, force a bank to issue capital or restrict asset growth ("prompt corrective action"). Sources: https://www.bis.org/basel_framework/chapter/RBC/30.htm and https://www.occ.gov/news-issuances/bulletins/2018/bulletin-2018-33.html

[15] Specifically, banks' corporate loan ratings are one of the inputs that are used to compute potential losses under various scenarios. These ratings are directly related to the PDs (see the Y14 data description, Appendix Table B.3). Starting in 2020:Q4, the bank-specific stress capital buffer requirement is also based on the outcome of the stress tests, providing an additional incentive for low-capitalized banks to underreport their credit risk exposures. Source: https://www.federalreserve.gov/publications/files/2019-march-supervisory-stress-test-methodology.pdf

Table 3.1: Reported PDs and Bank Capital.

	(i)	(ii)	(iii)
Capital	0.14***	0.10**	0.18***
	(0.05)	(0.04)	(0.04)
Fixed Effects			
Firm × Time	✓	✓	
Syndicate × Time			✓
Bank		✓	✓
Portfolio Risk Controls		✓	✓
Bank Controls	✓	✓	✓
R-squared	0.01	0.01	0.02
Observations	412,537	401,790	57,186
Number of Firms	12,189	12,065	2,844
Number of Banks	32	32	31

Notes: Estimation results for regression (3.1), where the dependent variable is PD-Gap$_{i,j,t}$. Column (iii) restricts the sample to loans within the same syndicate. Portfolio Risk Controls: RWA/assets, weighted portfolio PD. Bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (deposits/assets), and banks' income gap. Standard errors in parentheses are clustered by bank. Sample: 2014:Q4-2020:Q4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

underreport their credit risk exposure to increase the chance of passing the tests. Similarly, low-capitalized banks attract supervisory attention and may therefore window-dress their balance sheets to circumvent further regulatory scrutiny (e.g., through on-site inspections). And third, low-capitalized banks may try to avoid loan write-offs and loan loss provisions (LLPs), since both reduce the book value of loans and therefore decrease capital ratios. If the financial situation of a borrower deteriorates, a low-capitalized bank may either try to delay the recognition of loan losses and PD changes, or continue lending, so that the firm can make its payments to the bank. As long as the additional funds are not equally used to meet outstanding payments with another (high-capital) bank, the write-offs, LLPs, and PDs may differ across banks depending on their capital position. Thus, a positive relation between PDs and bank capital may already indicate evergreening or the delayed recognition of changes in borrower health.

With these explanations in mind, we expect to find $\beta \leq 0$ when accounting for the business-model explanation and absent any regulatory incentives to distort PDs. Table 3.1 reports the estimation results for various setups of regression (3.1). All specifications include a standard set of bank controls. To account for the business-model explanation, we add bank fixed effects and total portfolio risk controls into the regressions reported in columns (ii) and (iii).[16] To relate our findings to the ones by Plosser and Santos (2018), we conduct the same analysis at the level of a loan syndicate in column (iii).[17] Across the various specifications, we find that β is positive and statistically significant at either the 1 percent or the 5 percent confidence level. These results are also economically sizable. A 1 percentage point higher capital buffer is related to a 10-18 basis points higher PD of a bank's entire loan portfolio. A one-standard-deviation higher capital buffer implies a 41-74 basis points increase. These are substantial effects, given that the average PD across all loans is around 2.5 percent. The magnitude of the effects is also comparable to the ones by Plosser and Santos (2018)—at both the firm and the syndicate level.[18]

We interpret these findings as evidence that low-capitalized banks systematically underreport their credit risk exposure. The quantitative magnitude of our results are likely a lower bound for two reasons. First, the described alternative explanations may push β in the opposite direction, so the effect originating from regulatory incentives may be even larger. Second, our findings are conservative if all banks are misreporting, even the ones with the largest capital buffers.

3.4 PDs, Bank Capital, and Credit Supply

Next, we exploit these differential risk assessments and test whether they result in lending distortions. Specifically, we are interested in whether low-capitalized banks not only understate their credit risk exposure but also lend relatively more to underreported borrowers. Based on the previous explanations, low-capitalized banks have such incentives since the continued lending to underreported borrowers allows them keep the associated PDs, risk-weights, LLPs, and write-offs low, thereby benefiting their capital position, while also reconciling their reporting towards regulators. At a first pass, we analyze credit movements following the out-

[16]Following Plosser and Santos (2018), we use the ratio of risk-weighted assets to total assets and the PD of the total loan portfolio based on the average reported PDs of other banks, given by $PD_{j,t} = \sum_i \overline{PD}_{i,t} Loan_{i,j,t} / \sum_i Loan_{i,j,t}$ where $\overline{PD}_{i,t} = (1/K) \sum_k PD_{i,k,t}$ where $k \neq j$.

[17]While the Y14 data do not identify loan syndicates exactly, they do include information on the shares of the total commitments held if a loan is syndicated. This information allows us to match loans belonging to the same syndicate at any point in time if the dollar amounts of total loan commitments exactly match.

[18]Appendix Table C.1 shows that our results also extend to local projections that consider how PDs adjust following changes in bank capital buffers.

break of COVID-19 in 2020:Q1, an adverse macroeconomic shock that was largely unexpected. For firm i, bank j, and loan type k, we estimate

$$\begin{aligned}\frac{L^k_{i,j,t+2} - L^k_{i,j,t}}{0.5 \cdot (L^k_{i,j,t+2} + L^k_{i,j,t})} =& \alpha^k_{i,t} + \beta_1 \text{Capital}_{j,t} + \beta_2 \text{Low-PD}^k_{i,j,t} \\ &+ \beta_3 \text{Low-PD}^k_{i,j,t} \times \text{Capital}_{j,t} + \gamma X_{j,t} + u^k_{i,j,t}\end{aligned} \tag{3.2}$$

where t denotes 2019:Q4 and we consider movements in credit $L^k_{i,j,t}$ over two quarters. As a dependent variable, we use the symmetric growth rate as an approximation of a percentage change in credit. Following Khwaja and Mian (2008), we include firm-time fixed effects $\alpha^k_{i,t}$ into our regressions, which restricts the sample to firms that borrow from multiple banks. This approach accounts for potential links between bank-firm selection and firm demand. The fixed effects control for credit demand if firms have a common demand across their lenders.

The coefficients of interest β_1, β_2, and β_3 therefore capture credit supply effects, conditional on other bank-specific controls that are collected in the vector $X_{j,t}$. The variable $\text{Capital}_{j,t}$ again denotes bank j's CET1 capital buffer in period t. $\text{Low-PD}^k_{i,j,t}$ is a binary indicator variable that takes the value of one if $\text{PD-Gap}_{i,j,t}$ is negative, that is, $PD^k_{i,j,t}$ is lower than the average reported PDs by other banks for the same firm and zero otherwise.[19] Appendix Table D.1 shows that loans, whether they are classified as $\text{Low-PD}^k_{i,j,t}$ or not, are ex-ante similar along various characteristics. Thus, the following results arise due to differential risk assessments of otherwise similar loans—providing evidence against various potential identification concerns.

We restrict the sample in three additional ways. First, we exclude loans guaranteed by a third party since the associated PD may not be representative of the firm itself. Second, we consider only term loans and omit credit lines, which were largely demand-driven after the COVID outbreak (Greenwald, Krainer and Paul, 2021). To account for the variation of credit line drawdowns across banks at the time, we also include the bank-specific ratio of unused credit lines to total assets before the outbreak into $X_{j,t}$. Third, we consider adjustable- and fixed-rate loans

[19] That is, $\text{Low-PD}^k_{i,j,t}$ is one if $PD^k_{i,j,t} < \overline{PD}_{i,t}$. After excluding credit lines as described in the text, $\overline{PD}_{i,t} = (1/M)(1/K)\sum_m^M \sum_k^K PD^k_{i,m,t}$ is the average PD for firm i at time t across all non-j lenders and loan types.

as separate types k since the demand for these loans may differ when short-term rates adjust suddenly and may be correlated with the bank-specific variables.[20]

The estimation results for regression (3.2) are shown in Table 3.2. The first three columns introduce the regressors of interest sequentially. In column (iii), β_1 and β_2 are estimated to be positive, while β_3 is negative, and the three coefficients are statistically different from zero at either the 5 percent or the 10 percent level. Their magnitudes also imply that the effects are economically important with the following interpretation of the coefficients. Considering two banks that assign high PDs to the same firm, an additional unit of capital at one bank implies a 1.8 percent relative increase in credit—a sizable effect given that the standard deviation of bank capital is around 2.3 percentage points. In comparison with columns (i) and (ii), β_1 increases in magnitude and statistical significance in column (iii), highlighting the importance of the interaction term. The coefficient β_2 shows that at two banks with zero capital buffers, the one assigning a relatively low PD extends around 6.5 percent more credit to a firm. The coefficient β_3 implies that lowering banks' capital by one unit predicts a 1.2 percent relative increase in lending from low-PD banks compared to high-PD banks. The estimates imply that low-capitalized banks lend relatively more to borrowers with low-risk reporting. Appendix Figure D.1 provides a graphical illustration of the estimates in Table 3.2.

Columns (iv)-(vi) consider alternative specifications that address several identification concerns. First, the demand for syndicated and non-syndicated loans may have changed during the COVID crisis as some firms may have chosen to borrow from their main relationship lender. In turn, the supply of these different types of credit may depend on bank capitalization and potentially relative risk assessments, leading us to interpret shifts in credit demand as supply effects. To account for this possibility, we extend $\alpha^k_{i,t}$ by a loan's syndication type in column (iv). Similarly, if banks specialize in certain types of lending and firm demand across the lending types differs, then β_1, β_2, and β_3 may again capture demand rather than supply effects if such bank specialization is correlated with $\text{Capital}_{j,t}$ or $\text{Low-PD}^k_{i,j,t}$ (Paravisini, Rappoport and Schnabl, 2021). To address this possibility, we extend

[20] To avoid the possibility that our results are explained by a switching effect between credit lines and term loans, as well as between loans that differ in the flexibility of interest rates, we exclude bank-firm pairs that cover multiple types. If a bank issues multiple loans of a single type to the same firm, we aggregate these loans at each date.

Table 3.2: COVID-19 − Credit Supply.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Capital	0.78	0.96	1.77*	2.27**	3.80***	
	(0.59)	(0.70)	(0.86)	(0.92)	(1.04)	
Low-PD		2.63*	6.51**	9.86***	11.56***	8.29**
		(1.51)	(2.74)	(2.93)	(2.70)	(3.44)
Capital × Low-PD			-1.23*	-2.16***	-2.19**	-1.43**
			(0.63)	(0.68)	(0.78)	(0.68)
Fixed Effects						
Firm × Rate	✓	✓	✓			✓
Firm × Rate × Syn.				✓		
Firm × Rate × Pur.					✓	
Bank						✓
Bank Controls	✓	✓	✓	✓	✓	
R-squared	0.53	0.53	0.53	0.53	0.55	0.55
Observations	892	667	667	612	510	663
Number of Firms	412	309	309	286	240	307
Number of Banks	24	23	23	21	23	21

Notes: Estimation results for regression (3.2). All specifications include firm fixed effects that additionally vary by rate type (adjustable- or fixed-rate) and whether the loan is syndicated (column iv) or the loan purpose (column v). Columns (i)-(v) include various bank controls for 2019:Q4: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), banks' income gap, and the ratio of unused credit lines to assets. Column (vi) includes bank fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2019:Q4 - 2020:Q2. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

$\alpha^k_{i,t}$ by categories of loan purposes that firms report in column (v).[21] The estimation results show that the findings strengthen in magnitude and statistical significance with the more granular fixed effects. Last, in column (vi), we include a bank fixed effect. While the impact of other bank characteristics cannot be estimated separately in this case, our findings regarding β_2 and β_3 remain intact. Taken together, our results show that bank capitalization and risk assessments jointly determine credit availability. Low-capitalized banks not only underreport their credit risk exposure but also lend relatively more to underreported borrowers.

[21]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).

3.5 Extensions & Robustness

Bank Capital Buffers. While the outbreak of COVID-19 represents a unique setting with a sharp adverse macroeconomic shock, the mechanism we identify may not be specific to this episode but can also be present during other periods. To explore this possibility, we exploit the historical evolution of bank capital buffers throughout our sample. As shown in Appendix Figure D.2, the typical bank in our sample operates with a capital buffer of 3 percent or more in "normal times," such as during the early 2000s until the financial crisis of 2007-09, when bank capital buffers sharply increased. In the following years, capital buffers remained elevated, possibly in anticipation of the higher capital requirements, which increased step-by-step from 2013:Q1 until the end of our sample, while bank capital ratios stayed high (see Appendix Figures D.3 and D.4). This allows us to split our sample into two parts: one running from 2014:Q4 to 2017:Q4 when typical capital buffers were relatively high (marked by the two vertical lines in Figure D.2), and one starting in 2018:Q1 with typical capital buffers close to the ones in the early 2000s.[22]

For these two subsamples, we reestimate regression (3.2). For the earlier sample with high capital buffers—left to Appendix Table D.2—the estimated coefficients are relatively small compared with the ones in Table 3.2, sometimes with opposite signs, and largely statistically insignificant. In contrast, for the later sample with low capital buffers—shown in Appendix Table D.3—the estimated coefficients are slightly smaller in absolute magnitude but close to the ones in Table 3.2 and highly statistically significant. In comparison, the estimations cover a substantially larger sample with close to 7,000 observation and we further find that do not depend on the inclusion of the COVID episode. Overall, these findings suggest that economies may be more prone to the documented lending distortions when the banking sector has relatively low *capital buffers* but may be present even when banks have high *capital ratios*, such as the banks in our sample that were generally perceived to be "well-capitalized" around the onset of the COVID crisis.

Robustness. Appendix D.2 collects additional evidence and robustness checks of our findings for the extended "low-capital-buffer" sample. First, Table D.4 shows

[22] We end the low capital buffer sample in 2020:Q2, such that the latest capital ratios that enter the estimations are the ones in 2019:Q4. This avoids adding to our analysis the capital ratios during the COVID crisis, which were subject to a number of regulatory changes.

that the effects are not only present for loan quantities but also for interest rates. This additional finding is in accordance with our static model, which predicts that evergreening leads to lower interest rates and larger quantities of credit, providing support for the contracting protocol we assume. Second, we test whether our findings depend on the inclusion of the firm fixed effects. Table D.5 omits the firm-specific component of the fixed effect and Table D.6 uses time, location, industry, and firm-size fixed effects instead. Across the various alternative specifications, our results remain largely unchanged.[23] Third, we investigate whether our findings can be explained by an alternative channel, as opposed to the mechanism working through underreporting and lending distortions. For example, low-capitalized banks may disproportionally favor safer borrowers. To test for this hypothesis, we replace Low-$\text{PD}^k_{i,j,t}$ with $\text{PD}^k_{i,j,t}$ itself in regression (3.2). As shown in Table D.7, we do not find evidence that low-capitalized banks favor safer borrowers since the coefficient β_3 is statistically not distinguishable from zero across the various regressions. Alternatively, lending supply may be jointly determined by Low-$\text{PD}^k_{i,j,t}$ and another bank characteristic. To account for this possibility, we include various interaction terms between Low-$\text{PD}^k_{i,j,t}$ and the bank controls into regression (3.2). The estimation results in Table D.8 show that the original size and significance of the coefficient β_3 remain much the same.

Firm Level Effects & Alternative Identification Approach. In Appendix D.3, we test whether the lending distortions persist at the firm level, as firms may substitute across banks or towards nonbank lenders. The results show that such substitution is insufficient in that firm debt and investment are affected. Last, in Appendix D.4, we present the results of an alternative identification approach that differentiates banks by the share of a firm's total debt that they hold, building on the idea that banks with a larger debt-share have stronger incentives to evergreen loans. While the results based on this approach further support our theory, it is subject to some identification concerns and therefore highlights the virtues of our main empirical strategy.

[23] Even though these regressions increase the sample size in comparison with Table D.3, they do not include firms that borrow from a single lender in our data. That is because we require a multi-bank sample to compute relative risk assessments and the variable Low-$\text{PD}^k_{i,j,t}$.

PDs and Lending Decisions. A final concern may be that PDs and credit supply are jointly determined. For example, if a bank expects to increase lending to a firm in the near future which may improve borrower health, the PD may already reflect this lending decision in the current period, likely resulting in a positive relation between Low-PD$^k_{i,j,t}$ and credit supply. Several arguments speak against this identification concern in the context of our analysis. First, if the PDs do not incorporate decisions about *future* lending, they can be taken as given and used as valid regressors. Second, the interpretation of our results is unaffected even if the PDs reflect a bank's willingness to lend to a firm whenever the firm's creditworthiness deteriorates, as such behavior can be understood as evergreening. And third, we find that the relation between Low-PD$^k_{i,j,t}$ and credit supply varies with bank capital and across samples, and it is unclear why this relationship would change along those dimensions if the PD depends on decisions about future lending.

Sample Splits. The results so far provide evidence that banks take into account the legacy debt with a firm when deciding on new lending terms, as predicted by our theory. To assess whether banks also try to manipulate a firm's default decision, we further split the previous sample according to measures of firm distress and the share of a firm's debt that a bank owns—proxying for the bank's influence on the firm's decisions. As measures of firm distress, we consider firm productivity and firm payouts. We use firm net income relative to assets as a productivity indicator but note that our results are robust to using operating income or dividing by firm sales. The separation by firm payouts is motivated by a prediction from the dynamic model.[24] Firms with low payouts or that raise equity (negative payouts) are close to the default boundary and are more likely to receive evergreening subsidies from their relationship lenders.

The results are shown in Table 3.3 for the extended when banks had relatively low capital buffers. Our previous findings were driven by the subsamples of distressed firms with low productivity and low payouts, and by banks owning a large share of a firm's debt. In contrast, the regression estimates for non-distressed firms and small debt shares are largely statistically insignificant. Thus, these results are consistent with the prediction that banks try to steer firm default with their lend-

[24]We measure payouts in the data as net income minus the change in retained earnings over the reporting period and again scale them by total assets.

Table 3.3: Low Capital Buffers − Sample Splits.

	(i) Low Prod.	(ii) High Prod.	(iii) Large Loans	(iv) Small Loans	(v) Low Payout	(vi) High Payout
Capital	3.39***	0.54	1.77	1.22	2.91***	0.85
	(1.06)	(0.73)	(1.08)	(0.96)	(0.71)	(1.14)
Low-PD	15.23**	8.83*	13.61***	8.49	15.22***	6.92
	(6.57)	(4.46)	(4.30)	(8.31)	(4.00)	(4.82)
Capital $\times$ Low-PD	-3.20***	-0.81	-2.77***	-1.02	-2.26***	-1.29
	(1.02)	(1.06)	(0.85)	(1.22)	(0.68)	(0.80)
Fixed Effects						
Firm $\times$ Rate $\times$ Time	✓	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓	✓
R-squared	0.56	0.64	0.51	0.69	0.67	0.52
Observations	632	618	549	547	520	500
Number of Firms	116	103	104	88	103	106
Number of Banks	24	20	22	20	24	23

Notes: Estimation results for regression (3.2). The samples are split at the median at time t according to net income relative to assets in columns (i) & (ii), the size of the loan relative to total firm debt in columns (iii) & (iv), and payouts relative to assets (v) & (vi). All specifications include firm-time fixed effects that additionally vary by rate type (adjustable- or fixed-rate) and various bank controls. Standard errors in parentheses are clustered by bank. Sample: 2018:Q1 - 2020:Q2. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

ing decisions. A potential concern is the reduced sample sizes in Table 3.3, which stem from the need to include data on firm financials that have lower coverage than the credit data. To address this concern, we extend the sample in two ways. First, we split loans according to their absolute size instead of the share of a firm's debt, which side-steps the need to include firm financials. As opposed to proxying for the bank's influence on the firm's decisions, the absolute loan size rather constitutes a good indicator of the importance of the loan for the bank, and we note that the following results remain when scaling the loan size additionally by total bank assets. Second, for the productivity- and payout-splits, we incorporate credit lines in addition to term loans. We consider changes in committed credit as a dependent variable in regression to reduce the possibility of picking up demand rather than credit supply effects (3.2). The results for these extensions, which now cover up to around 4,300 observations for a single regression sample, are shown in Appendix Table D.9 and confirm our original findings.

Taken together, our empirical results show that large U.S. banks with low capital buffers systematically underreport their credit risk exposure. To avoid further decreases in their capital ratios and to reconcile their reporting, such banks favor underreported borrowers in their credit decisions, affecting real firm outcomes like investment. Consistent with the theoretical mechanism in Section 2, the results show that banks take into account their legacy debt when making new lending decisions and actively try to steer firm default. Building on this empirical validation, we embed the mechanism into a dynamic model to study whether such lending incentives affect aggregate capital allocation, 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, non-defaulting 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).

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

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

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

$$b' \leq \theta k' \quad . \tag{4.3}$$

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'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. 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

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

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

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

4.3 Alternative Lending Arrangements

Competitive Lending Economy (CLE). 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 competitive lending equilibrium price, which is the price that satisfies the following zero expected-discounted profit condition

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

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.

Relationship Lending Economy (RLE). 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 relationship lenders may offer a different Q that we denote by $Q^r(s)$. However, the degree of 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. The problem of a lender that has lent b in the previous period to a firm with current capital k and productivity z is

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

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

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

Thus, a relationship 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 relationship 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. For clarity, we consider the basic problem of a relationship lender without bank capital.[25]

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

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

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

[25]Bank capital can be added via a simple extension that is described in Appendix E.2 and our quantitative experiments produce results that are similar to those of the baseline model.

with a law of motion

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

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, $\underline{z}$, and an intermediate value $\tilde{z}$.[26]

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

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

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

[26] $\underline{z}$ is set at two standard deviations below the mean, and $\tilde{z}$ is calibrated.

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 relationship lending and the equilibrium with constant labor. 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 $\sigma_z = 0.110$, 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 a standard annual value $\delta = 0.1$. 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 span of control parameter equal to 0.8 as in Clementi and Palazzo (2016). 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 collat-

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	Standard
α	Production, capital share	0.320	Standard
η	Production, labor share	0.480	Standard
β^k	Lender discount rate	0.970	Standard, real rate of 3%
ψ_1	Recovery value	0.350	Kermani and Ma (2020)
β^f	Borrower discount factor	0.884	Internally calibrated
c	Fixed cost	0.055	Internally calibrated
κ	Logistic distr., scale	0.225	Internally calibrated
$\tilde{z}$	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

eral constraint parameter, as well as the cost of issuing equity are jointly chosen to match a series of moments from the data, presented in Table 5.2.

We jointly set the values of the seven internally calibrated parameters to match a series of targets from the literature and the data. We present the nine targets 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, Neira and Singhania (2022), as well as a reasonable value for the median interest rate spreads reported on the Y-14 loans.[27] 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

[27]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 5.2: 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	0.098
Interest rate spread (median)	Y-14	3.46%	4.74%
Exit rate	Hopenhayn, Neira and Singhania (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

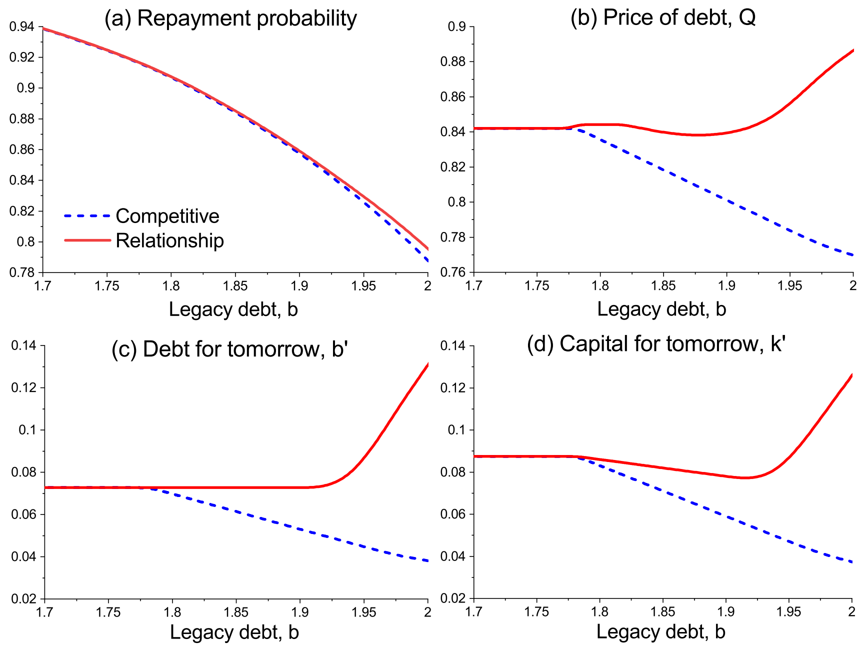
Notes: Y-14/Compustat moments correspond to unconditional moments between 2014:Q4 and 2019:Q4. Size and productivity at entry and exit are measured in % of average values for incumbent firms, where size is defined as total employment. Investment rate is equal to net investment divided by capital/fixed assets. The 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.

firms tend to be smaller and less productive than average both at entry and exit.

5.2 Lending Prices and Firm Choices

Figure 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 competitive 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 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 competitive 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 relationship 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

Figure 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, competitive lending (blue, dashed) vs. relationship lending (red, solid) economies.

with more legacy debt. The higher price of debt reflects the subsidy from the relationship 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 competitive case.

5.3 Aggregate Effects: Competitive vs. Relationship Lending

We assess the impact of introducing relationship 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 relationship lending to those same moments for the stationary equilibrium under competitive 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 relationship 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 RLE 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 RLE is also slightly less productive, and firms exit less often.

Table 5.3: Impact of introducing relationship 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 $Y/(K^{\alpha}N^{1-\alpha})$.

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 RLE 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 RLE features larger increases in aggregate capital, labor, output, and debt. Note also that the equilibrium 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 RLE and the CLE

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* $Y^* = M^{1-\alpha-\eta}\mathbb{E}[z^{\frac{1}{1-\alpha-\nu}}]^{1-\alpha-\eta}K^\alpha N^\eta$*, 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 E.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

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

Table 5.4: MTFP decomposition: CLE vs. RLE

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

Table 5.4 reports the results of the decomposition of MTFP for the RLE vs. the CLE with constant entry or constant labor. MTFP is lower in the RLE in both cases: the decomposition attributes most of this drop to the size component, as firms are on average larger in the RLE. There is also a small negative contribution from selection, as firm productivity is also lower on average in the RLE. Finally, static misallocation is worse in the RLE, 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 in the RLE

How do subsidized and non-subsidized firms differ in the RLE? Table 5.5 explores this question, reporting medians for different individual firm characteristics, depending on whether those 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 (by around 29%).

Table 5.5: Subsidized vs. non-subsidized Firms in the RLE (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

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, Hoshi and Kashyap, 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, Minoiu and Perez-Orive (2022) (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 relationship 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 E.3. We find a high correlation with the measure proposed by Schivardi, Sette and Tabellini (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. Firms that receive relatively larger lending subsidies conform to standard classifications of zombies. However, these tend to miss a significant share of firms that receive smaller lending subsidies.

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 evergreening interacts with other phenomena such as risk-shifting and existing regulation, and further investigating its macroeconomic effects are salient paths for future research.

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ONLINE APPENDIX

A Static Model

A.1 General Form of Borrowing Constraint

In this appendix, we show that several results of the static model hold for the case where the firm faces a general constraint of the type $b' \leq g(k')$, with $g, g' \geq 0$ and $g'' \leq 0$. Note that many types of borrowing constraints, such as no default constraints, are special cases of this general form. With such a general constraint, the choice of capital cannot be solved in closed form, and is implicitly given by

$$\beta^f z\alpha(k')^{\alpha-1} - 1 + (Q - \beta^f)g'(k') = 0 \quad .$$

Note that as long as the constraint binds, all the comparative statics for k' extend to b' due to monotonicity of g, i.e. $\frac{\partial b'(z;Q)}{\partial Q} = g'(k)\frac{\partial k'(z;Q)}{\partial Q}$. We can use the above expression to obtain the implicit derivatives

$$\frac{\partial k'(z;Q)}{\partial Q} = \frac{g'(k')}{\beta^f z\alpha(1-\alpha)(k')^{\alpha-2} - Qg''(k')} \geq 0 \quad ,$$
$$\frac{\partial k'(z;Q)}{\partial z} = \frac{\beta^f \alpha(k')^{\alpha-1}}{\beta^f z\alpha(1-\alpha)(k')^{\alpha-2} - Qg''(k')} > 0 \quad .$$

It is also straightforward to show that

$$\frac{\partial V(z,b;Q)}{\partial Q} = b' \geq 0, \qquad \frac{\partial V(z,b;Q)}{\partial z} = \beta^f(k')^{\alpha} \geq 0, \qquad \frac{\partial V(z,b;Q)}{\partial b} = -1 < 0 \quad .$$

The following derivations show that it is still possible to prove Propositions 1-3 for the general borrowing constraint $b' \leq g(k')$.

Proof of Proposition 1. Given that $V(z,b,;Q)$ is increasing in Q, the threshold $Q^{\min}(z,b)$ exists for $b > 0$, it is now implicitly defined by

$$0 = -b + Q^{\min}b'(z,Q^{\min}) - k'(z,Q^{\min}) + \beta^f[z(k'(z,Q^{\min}))^{\alpha} - b'(z,Q^{\min})]$$

Applying the implicit function theorem allows us to derive the comparative statics

$$\frac{\partial Q^{\min}(z,b)}{\partial z} = -\frac{\beta^f (k'(z,Q^{\min}))^\alpha}{b'(z,Q^{\min})} < 0, \qquad \frac{\partial Q^{\min}(z,b)}{\partial b} = \frac{1}{b'(z,Q^{\min})} > 0 \quad .$$

Proof of Proposition 2. $Q^{\max}$ now solves the implicit equation

$$b + [\beta^k - Q^{\max}]b'(z;Q^{\max}) = 0 \quad .$$

Clearly, $Q^{\max} \geq \beta^k$ for $b \geq 0$, as $b'(z;Q) \geq 0$. Additionally, applying the implicit function theorem allows us to derive the relationships

$$\frac{\partial Q^{\max}(z,b)}{\partial b} = \frac{1}{b'(z;Q^{\max}) + (Q^{\max} - \beta^k)\frac{\partial b'(z;Q^{\max})}{\partial Q}} > 0 \quad ,$$

$$\frac{\partial Q^{\max}(z,b)}{\partial z} = -\frac{(Q^{\max} - \beta^k)\frac{\partial b'(z;Q^{\max})}{\partial z}}{b'(z;Q^{\max}) + (Q^{\max} - \beta^k)\frac{\partial b'(z;Q^{\max})}{\partial Q}} < 0 \quad .$$

Proof of Proposition 3. Proposition 3 follows the same arguments as in the main text. The comparative statics with respect to $Q^*(b,z)$ follow from those of $Q^{\min}(z,b)$.

A.2 Parametrization for Numerical Examples

The static model has four parameters: $\alpha, \beta^f, \beta^k, \theta$. All plots are based on the parametrization in Table A.1.

Table A.1: Static Model Parametrization

Parameter	Description	Value
α	Returns to scale	0.35
β^f	Discount factor Firm	0.90
β^k	Discount factor Lender	0.98
θ	Borrowing constraint	0.70

A.3 Alternative Contracting Protocol

Our benchmark model is a Stackelberg game where the lender offers Q and the firm chooses how much to borrow for a given Q. Here, we consider an alternative case where the relationship lender offers a contract that specifies both an interest rate Q and a repayment amount b'. We focus on the more interesting case where $\beta^k < Q^{\min}(z,b)$, so that the firm would exit when borrowing from competitive lenders (i.e., the firm is in the evergreening region). Thus, the firm can either accept the (Q,b')-offer or default. Taking the firm's decision into account, the relationship lender is able to extract the maximum surplus from the contract, offering (Q,b') such that $V(z,b;Q)=0$. This is equivalent to

$$0 = -b + Qb' - k'(z,b;Q,b') + \beta^f \left[zk'(z,b;Q,b')^\alpha - b'\right] \quad ,$$

where $k'(z;b',Q)$ is the firm's optimal choice of capital, given the states (z,b) and the offered contract (Q,b').

First, assume that the firm is unconstrained, i.e. $b' < \theta k'(z,b;Q,b')$. Its capital policy is independent of lending terms and given by $k' = \left(\beta^f z\alpha\right)^{\frac{1}{1-\alpha}}$. The relationship lender's problem is then

$$\begin{aligned} &\max_{Q,b'} W = b - Qb' + \beta^k b' \\ \text{s.t.}\quad & 0 = -b + (Q-\beta^f)b' + (\beta^f z\alpha)^{\frac{1}{1-\alpha}}(1/\alpha - 1) \quad . \end{aligned}$$

One can use the constraint to replace for Q and turn the lender's problem into a univariate problem over b'

$$\max_{b'} \left(\beta^k - \beta^f\right) b' + (\beta^f z\alpha)^{\frac{1}{1-\alpha}}(1/\alpha - 1) \quad .$$

Clearly, the lender's problem is strictly increasing in b' given that $\beta^k > \beta^f$. Thus, the lender would like to choose $b' = \infty$, which cannot be an equilibrium. Assume then that the firm's borrowing constraint binds, the optimal capital policy must satisfy $k'(z;b',Q) = b'/\theta$. The relationship lender's problem can be written as

$$\begin{aligned} &\max_{Q,b'} W = b - Qb' + \beta^k b' \\ \text{s.t.} \quad & 0 = -b + Qb' - b'/\theta + \beta^f \left[z(b'/\theta)^\alpha - b' \right] \quad . \end{aligned}$$

Using the constraint to replace for Q, one can again turn the lender's problem into a univariate problem over b'

$$\max_{b'} \left(\beta^k - \beta^f - \frac{1}{\theta} \right) b' + \beta^f z \theta^{-\alpha} (b')^\alpha \quad .$$

The solution to this problem is

$$\begin{aligned} (b')^* &= \theta \left(\frac{\beta^f z \alpha}{1 - \theta(\beta^k - \beta^f)} \right)^{\frac{1}{1-\alpha}} \quad , \\ (k')^* &= \left(\frac{\beta^f z \alpha}{1 - \theta(\beta^k - \beta^f)} \right)^{\frac{1}{1-\alpha}} \quad , \\ Q^* &= \beta^f + \frac{1}{\theta} \left[1 - \frac{1 - \theta(\beta^k - \beta^f)}{\alpha} + b \left(\frac{1 - \theta(\beta^k - \beta^f)}{\alpha z \beta^f} \right)^{\frac{1}{1-\alpha}} \right] \quad . \end{aligned}$$

In this case, the allocations are the same as in the competitive lending equilibrium, with the difference that the lender is willing to lend as long as $Q \leq Q^{\max}(z,b)$. The MPKs are equalized across firms.

Effectively, this solution corresponds to the bank taking over ownership of the firm and indirectly choosing investment via the binding borrowing constraint. Since the firm has no outside option (other than exit), the bank is able to extract the maximum surplus while setting the firm's value to zero. Furthermore, it holds that $Q^{\min}(z,b) \geq \beta^k \Leftrightarrow Q^* \geq \beta^k$. Thus, as long as the firm's states (z,b) are such that the firm would default in the competitive case, which is the situation that we consider, the price of debt offered by the lender Q^* will always be larger than the competitive price β^k. Taken together, if the bank offers both Q and b', the allocations of b' and k' coincide with the ones of the competitive case (without default), but the bank offers a price Q^* that is strictly larger and therefore a lower quantity of debt $Q^* b'$. In contrast, our empirical analysis shows that evergreening is associated with both lower interest rates and larger credit amounts. We therefore view the contracting protocol of our benchmark as the empirically relevant setting since it is consistent with the data in this regard.

A.4 Debt Forgiveness or Debt Restructuring

In this section, we derive the solution to the optimal contract under the assumption that the lender can restructure or forgive part of the legacy debt b ex-post. We assume that the lender can write off a share $1-\varphi$ of legacy debt b: the amount of debt that is written off is just enough such that the firm does not default, i.e. $V(z, \varphi b) = 0$, and the lender originates new debt at the risk-free price of $Q = \beta^k$.

Clearly, in the normal funding region $b \leq \bar{b}(z)$, there is no restructuring and the optimal contract is as before, with the lender setting $Q = \beta^k$. In the evergreening region $b > \bar{b}(z)$, the lender may prefer to restructure. Clearly, the lender forgives the smallest possible amount of debt that ensures that the firm is willing to operate while borrowing at $Q = \beta^k$, that is $V(z, b; Q = \beta^k) = 0$. One can show that this results in

$$\varphi = \frac{1-\alpha}{\alpha b} \frac{(\beta^f \alpha z)^{\frac{1}{1-\alpha}}}{[1-\theta(\beta^k - \beta^f)]^{\frac{\alpha}{1-\alpha}}}$$

where φ is the fraction of legacy debt b that is not forgiven. Note that $\varphi \in (0,1)$ in the evergreening region, and that the bank's payoff in this region is equal to $W = \varphi b$. We have that $W > 0$ as long as $\varphi > 0$, thus the bank never chooses to liquidate the firm regardless of b, and the bank and the firm are strictly better off by forgiving/restructuring debt in the liquidation region than by evergreening. It can be shown that the bank's payoff from restructuring is always at least as large as that of evergreening for any (z, b).

In this case, all firms borrow at the same interest rate $Q = \beta^k$ and borrow an amount that depends on productivity z but not on the amount of legacy debt b. Thus, evergreening occurs with respect to credit quantities but not loan prices—at odds with the empirical evidence that we uncover in Section 3. Additionally, there may be extra costs associated with debt restructuring that we do not explicitly consider and that may make debt forgiveness a less attractive option compared to evergreening.

A.5 Model with Bank Capital

We do not include bank capital regulation in the baseline model to emphasize that capital is not necessary for evergreening incentives to arise. As we show in this section, however, capital does magnify this phenomenon: less capitalized banks have greater incentives to evergreen.

To introduce capital in the model, we extend it along two simple dimensions. First, we assume that the bank is endowed with a stochastic level of capital. One can think of this endowment as profits from other business lines, i.e. mortgage lending. Bank capital is equal to a with probability $1-p$ and equal to $a-\Delta a$ with probability p. Second, we assume that the bank faces a soft capital requirement: it incurs some utility/profit cost if capital/earnings are below a certain threshold $\bar{e}$. This cost is given by $\varphi \max\{0, \bar{e} - \text{earnings}\}$. The cost is zero if earnings exceed the regulatory threshold $\bar{e}$. Otherwise, the bank pays a cost proportional to the shortfall and scaled by φ. We define bank capital or earnings before the bank originates the new loan:

$$\text{earnings} = \text{endowment} + \mathbb{I}[V(z,b;Q) \geq 0]b \quad .$$

Notice that if $a - \Delta a > \bar{e}$, the bank never has to pay the regulatory cost regardless of whether the firm defaults, so the problem is the same as before. For this reason, we focus on the more interesting case where $a - \Delta a < \bar{e}$, so that the bank incurs a regulatory cost if its non-lending profits are low and the firm does not repay (or the bank liquidates the firm). To simplify the algebra and without loss of generality, we also assume that $a > \bar{e}$. We assume that the bank must make the lending decision before observing the endowment shock. The bank's problem is then given by:

$$\begin{aligned}
W(z,b) = \max_{Q \geq \beta^k} (1-p) & \left\{ \mathbb{I}[V(z,b;Q) \geq 0] \left\{ a + b + (\beta^k - Q) b'(z;Q) \right\} + \mathbb{I}[V(z,b;Q) < 0] a \right\} \\
& + p\mathbb{I}[V(z,b;Q) \geq 0] \left\{ a - \Delta a + b + (\beta^k - Q) b'(z;Q) - \varphi \max\{0, \bar{e} - a + \Delta a - b\} \right\} \\
& + p\mathbb{I}[V(z,b;Q) < 0] \left\{ a - \Delta a - \varphi \max\{0, \bar{e} - a + \Delta a\} \right\} \quad ,
\end{aligned}$$

where we use the fact that $a > \bar{e}$ and so the bank does not pay any regulatory cost under the high endowment realization. The bank's payoff, if it decides to liquidate the firm, is given by

$$W^{liq} = (1-p)a + p\left[a - \Delta a - \varphi \max\{0, \bar{e} - a + \Delta a\}\right] \quad .$$

The same arguments from the baseline model can be used to solve the bank's problem. Given the constraint $Q \geq \beta^k$, the bank's payoff is strictly decreasing in Q, thus the bank sets it to the minimum value for which the firm does not default, as long as this value does not exceed $Q^{\max}(z,b)$. Proposition 2 can be extended to allow for bank capital as follows:

Proposition 5. *Let $Q^{\max}(z,b)$ denote the maximum Q at which the bank is willing to lend,*

$$Q^{\max}(z,b) : W(z,b;Q^{\max}) = W^{liq} \quad .$$

$Q^{\max}(z,b)$ solves the implicit equation

$$b + (\beta^k - Q)b'(z;Q) - p\varphi \max\{0, \bar{e} - a + \Delta a - b\} + p\varphi \max\{0, \bar{e} - a + \Delta a\} = 0 \quad .$$

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; (iv) It is increasing in p; (v) It is increasing in $\sigma \equiv \bar{e} - a + \Delta a$, strictly for large enough b.

The proof of the proposition is similar to that of Proposition 2 and it shows that all of the previous results still hold. Additionally, $Q^{\max}$ is increasing in the probability of the bank receiving a negative shock, and is weakly increasing in the regulatory shortfall σ, which depends negatively on the baseline level of capital a. The bank's optimal policy is still as defined in Proposition 3, with the difference that $Q^{\max}$ now depends on (p,σ). Since $Q^{\max}$ is increasing in σ, it is also decreasing in a: banks with lower capital have a higher $Q^{\max}$ and are therefore willing to lend for higher b, or lower z. The evergreening region is larger for less capitalized banks. This is illustrated in Figure 2.2, where we plot the $Q^{\max}$-curves for a low capital bank and for a high capital bank. The figure shows that a reduction in a leads to an upward expansion of the $Q^{\max}(z,b)$ function, and so it intersects $Q^{\min}$ at a higher value of b, resulting in a larger evergreening region. That is, there are levels of initial debt $b > \hat{b}(z, a_{high})$ for which the high capital bank chooses to liquidate the firm, but for which the low capital bank chooses to keep lending.

B Data

Table B.1: Compustat Variable Definitions.

Variable Name	Description	Compustat Name
Total Assets	Total firm assets	atq
Employer Identification Number	Used to match to TIN in Y14	ein
Total Liabilities	Total firm liabilities	ltq
Net Income	Firm net income (converted to 12-month trailing series)	niq
Total Debt	Debt in current liabilities + long-term debt	dlcq + dlttq
Sales	Total firm sales	saleq
Fixed Assets	Net property, plant, and equipment	ppentq

Notes: All data obtained from the Wharton Research Data Services. Nominal series deflated using the consumer price index for all items taken from St. Louis Fed's FRED database.

Table B.2: Variables from Y-9C filings.

Variable Code	Variable Label
BHCK 2170	Total Assets
BHCK 2948	Total Liabilities
BHCK 4340	Net Income
BHCK 3197	Earning assets that reprice or mature within one year
BHCK 3296	Interest-bearing deposit liabilities that reprice or mature within one year
BHCK 3298	Long-term debt that reprices within one year
BHCK 3408	Variable-rate preferred stock
BHCK 3409	Long-term debt that matures within one year
BHDM 6631	Domestic offices: noninterest-bearing deposits
BHDM 6636	Domestic offices: interest-bearing deposits
BHFN 6631	Foreign offices: noninterest-bearing deposits
BHFN 6636	Foreign offices: interest-bearing deposits
BHCA P793	Common Tier 1 Capital Ratio

Notes: The table lists variables that are collected from the Consolidated Financial Statements or FR Y-9C filings for Bank-Holding Companies from the Board of Governors' National Information Center database. The one-year income gap is defined as $(\text{BHCK}\,3197 - (\text{BHCK}\,3296 + \text{BHCK}\,3298 + \text{BHCK}\,3408 + \text{BHCK}\,3409))\,/\text{BHCK}\,2170$. Total deposits are given by $(\text{BHDM}\,6631 + \text{BHDM}\,6636 + \text{BHFN}\,6631 + \text{BHFN}\,6636)$. Nominal series are deflated using the consumer price index for all items taken from St. Louis Fed's FRED database.

Table B.3: FR Y-14 Variable Definitions.

Variable Name	Description / Use	Field No.
Zip code	Zip code of headquarters	7
Industry	Derived 2-Digit NAICS Code	8
TIN	Taxpayer Identification Number	11
Internal Credit Facility ID	Used together with BHC and previous facility ID to construct loan histories	15
Previous Internal Credit Facility ID	Used together with BHC and facility ID to construct loan histories	16
Term Loan	Loan facility type reported as Term Loan, includes Term Loan A-C, Bridge Loans, Asset-Based, and Debtor in Possession.	20
Credit Line	Loan facility type reported as revolving or non-revolving line of credit, standby letter of credit, fronting exposure, or commitment to commit.	20
Purpose	Credit facility purpose	22
Committed Credit	Committed credit exposure	24
Used Credit	Utilized credit exposure	25
Line Reported on Y-9C	Line number reported in HC-C schedule of FR Y-9C	26
Participation Flag	Used to determine whether a loan is syndicated	34
Variable Rate	Interest rate variability reported as "Floating" or "Mixed"	37
Interest Rate	Current interest rate	38
Guarantor Flag	Used to determine whether a loan is guaranteed	44
Date Financials	Financial statement date used to match firm financials to Y-14 date	52
Net Sales Current	Firm sales over trailing 12-month period	54
Operating Income	Sales less items such as cost of goods sold, operating expenses, amortization and depreciation	56
Interest Expense	Used in calculating average interest rate on all debt	58
Fixed Assets	Fixed assets	69
Total Assets	Total assets, current year and prior year	70
Short Term Debt	Used in calculating total debt	74
Long Term Debt	Used in calculating total debt	78
Probability of Default	Probability of default for firms (corresponds to internal risk rating for non-advanced BHCs)	88
Syndicated Loan	Syndicated loan flag	100

Notes: Nominal series are converted into real series using the consumer price index for all items taken from St. Louis Fed's FRED database. The corresponding "Field No." can be found in the data dictionary (Schedule H.1, pp. 162-217): https://www.federalreserve.gov/reportforms/forms/FR_Y-14Q20200331_i.pdf

B.1 Sample Restrictions and Filtering Steps

1. We restrict the sample to begin in 2012:Q3. The Y14 collection began in 2011:Q3, but there was a significant expansion in the number of BHCs required to submit Y14 commercial loan data until 2012:Q3. Moreover, the starting date in 2012:Q3 also affords a short phase-in period for the structure of the collection and variables to stabilize.

2. We constrain the sample to loan facilities with line reported on the HC-C schedule in the FR Y9-C filings as commercial and industrial loans, "other" loans, "other" leases, and owner-occupied commercial real estate (corresponding to Field No. 26 in the H.1 schedule of the Y14 to be equal to 4, 8, 9, or 10; see Table B.3). In addition, we drop all observations with NAICS codes 52 and 53 (loans to financial firms and real estate firms).

3. Observations with negative or zero values for committed exposure, negative values for utilized exposure, and with committed exposure less than utilized exposure are excluded.

4. When aggregating loans at the firm-level, we exclude observations for which the firm identifier "TIN" is missing. To preserve some of these missing values, we fill in missing TINs from a history where the non-missing TIN observations are all the same over a unique facility ID.

5. When using information on firms' financials in the analysis, we apply a set of filters to ensure that the reported information is sensible. We exclude observations (i) if total assets, total liabilities, short-term debt, long-term debt, cash assets, tangible assets, or interest expenses are negative, (ii) if tangible assets, cash assets, or total liabilities are greater than total assets, and (iii) if total debt (short term + long term) is greater than total liabilities.

6. A loan facility may include both credit lines and term loans. We assume that all unused credit (i.e., committed exposure - utilized exposure) takes the form of unused capacity on the firm's credit lines. That is, we include unused borrowing capacity on a firm's term loans in the total unused credit line measure.

7. When using the interest rate on loans in our calculations, we exclude observations with interest rates below 0.5 or above 50 percent to minimize the influence of data entry errors.

C Risk-Reporting and Bank Capital

Table C.1: Reported PDs and Bank Capital − Local Projections.

	(i)	(ii)	(iii)
Capital	0.12***	0.11***	0.19**
	(0.04)	(0.04)	(0.09)
Fixed Effects			
Firm × Time	✓	✓	
Syndicate × Time			✓
Bank		✓	✓
Portfolio Risk Controls		✓	✓
Bank Controls	✓	✓	✓
R-squared	0.03	0.03	0.03
Observations	313,556	304,914	29,894
Number of Firms	10,018	9,912	1,855
Number of Banks	32	32	30

Notes: Estimation results for $\text{PD-Gap}_{i,j,t+2} - \text{PD-Gap}_{i,j,t} = \beta\Delta Capital_{j,t-1} + \gamma X_{j,t-1} + \alpha_{i,t} + \kappa_j + u_{i,j,t+2}$. Column (iii) restricts the sample to loans within the same syndicate. Portfolio risk controls: RWA/total assets, weighted portfolio PD. Bank controls: bank size (natural log of total assets), return on assets (net income/total assets), deposit share (total deposits/total assets), and banks' income gap. Standard errors in parentheses are clustered by bank. Sample: 2014:Q4-2020:Q4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

D PDs, Bank Capital, and Credit Supply

D.1 Regression Estimates and Bank Capital

Table D.1: Loan Characteristics.

	Low-PD = 0		Low-PD = 1				
Variable	**Obs.**	**Mean**	**Obs.**	**Mean**	**Diff. Means**	**Diff. 95% Confidence**	
Sample 2019:Q4-2020:Q2							
Loan Size	320	20.5	347	21.25	-.74	-7.88	6.4
Variable-Rate	320	.21	347	.23	-.02	-.08	.04
Syndicated	310	.16	332	.15	0	-.06	.06
Maturity	320	23.81	347	23.77	.04	-2.18	2.26
Sample 2018:Q1-2020:Q2							
Loan Size	2263	21.17	2411	23.54	-2.37	-5.13	.39
Variable-Rate	2263	.25	2411	.25	0	-.02	.02
Syndicated	2140	.14	2313	.14	0	-.02	.02
Maturity	2259	24.15	2407	23.7	.44	-.41	1.29

Notes: The table differentiates loans by their classification as Low-PD in the samples of Tables 3.2 and D.3, and tests whether various loan characteristics differ across those buckets.

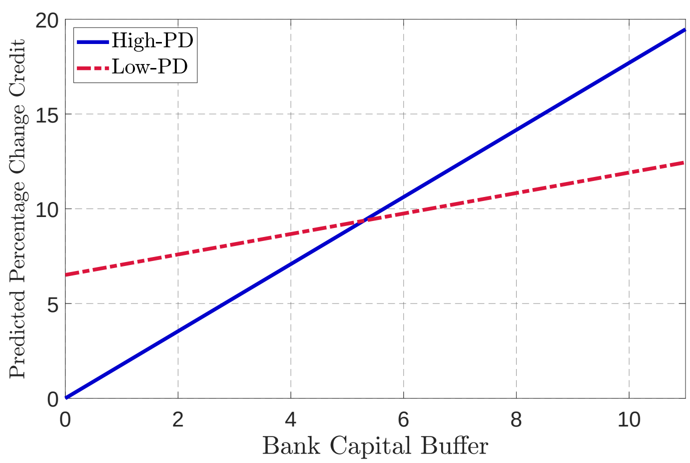

Figure D.1: Graphical Illustration of Regression Coefficients.

Notes: The figure plots the regression estimates from column (iii) of Table 3.2, $\beta_1 = 1.77$, $\beta_2 = 6.51$, $\beta_3 = -1.23$, constant=0. Bank capital buffers in 2019:Q4 range from 1.66 to 10.19 among the Y14-banks in our sample.

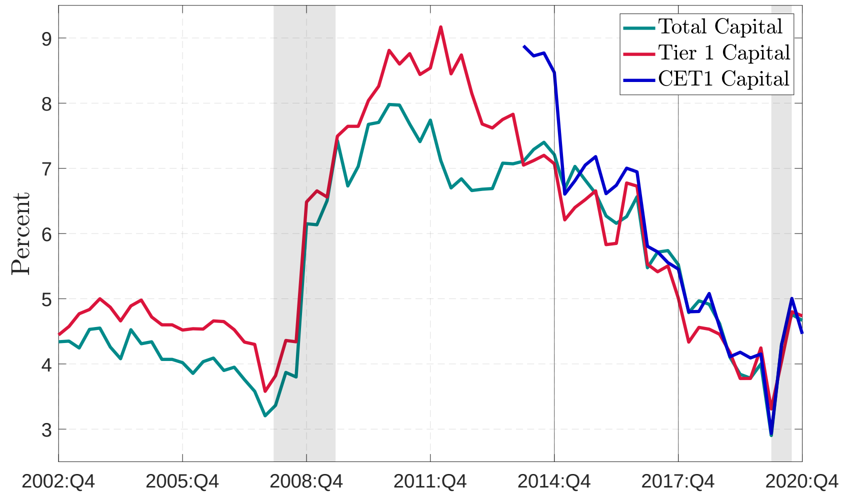

Figure D.2: Bank Capital Buffers.

Notes: For each date, the figure shows the median of the CET1, Tier 1, and total capital buffer across the Y14-banks. Capital buffers are defined as the difference between capital ratios and requirements. Gray bars denote NBER recessions.

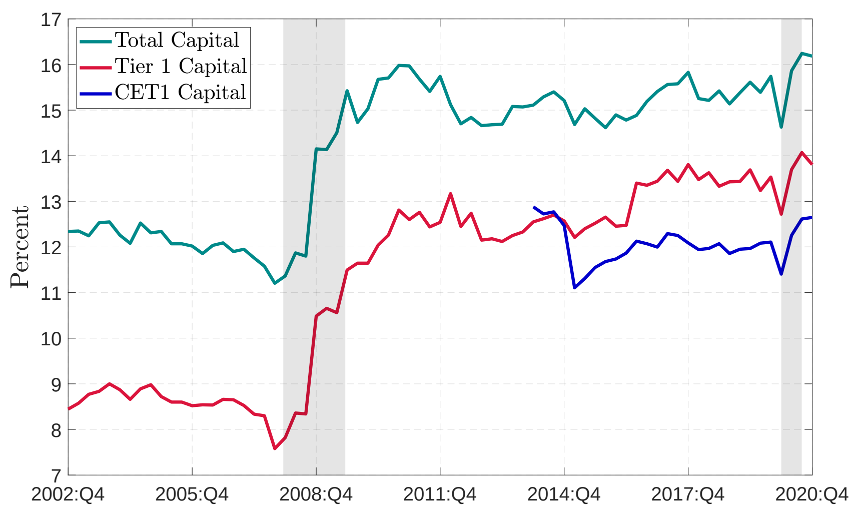

Figure D.3: Bank Capital Ratios.

Notes: For each date, the figure shows the median of the CET1, Tier 1, and total capital ratios across the Y14-banks. Gray bars denote NBER recessions.

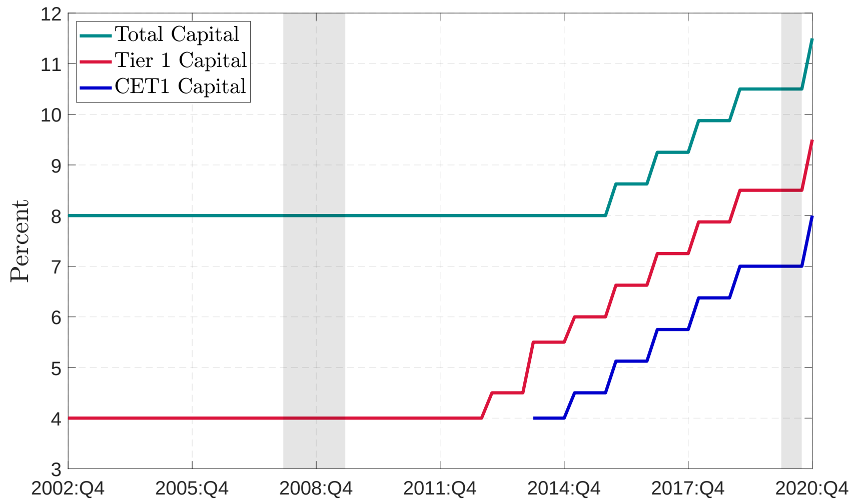

Figure D.4: Bank Capital Requirements.

Notes: For each date, the figure shows the median of the CET1, Tier 1, and total capital requirements across the Y14-banks. Gray bars denote NBER recessions.

Table D.2: High Capital Buffers – Credit Supply.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Capital	-0.17	0.09	0.10	-0.19	0.40	
	(0.29)	(0.25)	(0.32)	(0.36)	(0.52)	
Low-PD		0.88	0.92	-1.22	-1.16	5.22**
		(0.80)	(1.87)	(2.37)	(4.12)	(2.18)
Capital × Low-PD			-0.01	0.26	0.27	-0.62
			(0.38)	(0.44)	(0.71)	(0.39)
Fixed Effects						
Firm × Rate × Time	✓	✓	✓			✓
Firm × Rate × Syn. × Time				✓		
Firm × Rate × Pur. × Time					✓	
Bank × Time						✓
Bank Controls	✓	✓	✓	✓	✓	
R-squared	0.54	0.55	0.55	0.56	0.55	0.58
Observations	10,309	6,606	6,606	6,135	3,160	6,535
Number of Firms	835	581	581	551	307	574
Number of Banks	32	26	26	26	25	23

Notes: Estimation results for regression (3.2). All specifications include firm-time fixed effects that additionally vary by rate type (adjustable- or fixed-rate) and whether the loan is syndicated (column iv) or the loan purpose (column v). Columns (i)-(v) include various bank controls and column (vi) includes bank-time fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2014:Q4 - 2017:Q4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table D.3: Low Capital Buffers − Credit Supply.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Capital	0.18	0.17	0.95**	1.13***	1.68**	
	(0.30)	(0.34)	(0.40)	(0.40)	(0.64)	
Low-PD		0.63	5.46***	5.92***	6.82**	5.24**
		(1.30)	(1.89)	(1.86)	(2.58)	(2.25)
Capital × Low-PD			-1.29***	-1.64***	-1.63**	-1.14**
			(0.36)	(0.35)	(0.63)	(0.41)
Fixed Effects						
Firm × Rate × Time	✓	✓	✓			✓
Firm × Rate × Syn. × Time				✓		
Firm × Rate × Pur. × Time					✓	
Bank × Time						✓
Bank Controls	✓	✓	✓	✓	✓	
R-squared	0.51	0.54	0.54	0.54	0.54	0.57
Observations	6,977	4,674	4,674	4,188	3,617	4,649
Number of Firms	683	495	495	455	396	491
Number of Banks	29	27	27	26	27	24

Notes: Estimation results for regression (3.2). All specifications include firm-time fixed effects that additionally vary by rate type (adjustable- or fixed-rate) and whether the loan is syndicated (column iv) or the loan purpose (column v). Columns (i)-(v) include various bank controls and column (vi) includes bank-time fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2018:Q1 - 2020:Q2. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

D.2 Robustness

Table D.4: Low Capital Buffers − Interest Rates.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Capital	-0.00	-0.00	-0.01*	-0.01**	-0.01**	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Low-PD		0.01**	-0.02**	-0.02**	-0.03**	-0.03***
		(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Capital × Low-PD			0.01***	0.01***	0.01***	0.01***
			(0.00)	(0.00)	(0.00)	(0.00)
Fixed Effects						
Firm × Rate × Time	✓	✓	✓			✓
Firm × Rate × Syn. × Time				✓		
Firm × Rate × Pur. × Time					✓	
Bank × Time						✓
Bank Controls	✓	✓	✓	✓	✓	
R-squared	0.88	0.89	0.89	0.88	0.87	0.91
Observations	6,538	4,399	4,399	3,944	3,416	4,368
Number of Firms	652	474	474	433	379	470
Number of Banks	29	27	27	26	27	24

Notes: Estimation results for regression (3.2), where the dependent variable is given by changes in interest rates $i^k_{i,j,t+2} - i^k_{i,j,t}$. Interest rates are weighted by used credit and observations within the 1% tails of the dependent variable are excluded. All specifications include firm-time fixed effects that additionally vary by rate type (adjustable- or fixed-rate) and whether the loan is syndicated (column iv) or the loan purpose (column v). Columns (i)-(v) include various bank controls and column (vi) includes bank-time fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2018:Q1 - 2020:Q2. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table D.5: Low Capital Buffers − Omitting Firm Fixed Effects.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Capital	0.13	0.54**	0.92***	1.05***	1.14***	
	(0.17)	(0.24)	(0.29)	(0.31)	(0.29)	
Low-PD		-0.07	2.37*	2.97**	2.85**	2.93**
		(0.97)	(1.22)	(1.22)	(1.29)	(1.07)
Capital × Low-PD			-0.66**	-0.81***	-0.73***	-0.65**
			(0.24)	(0.18)	(0.26)	(0.25)
Fixed Effects						
Rate × Time	✓	✓	✓			✓
Rate × Syn. × Time				✓		
Rate × Pur. × Time					✓	
Bank × Time						✓
Bank Controls	✓	✓	✓	✓	✓	
R-squared	0.01	0.02	0.02	0.02	0.03	0.05
Observations	84,274	8,033	8,033	7,529	7,996	8,022
Number of Firms	15,258	1,135	1,135	1,093	1,133	1,135
Number of Banks	31	27	27	27	27	27

Notes: Estimation results for regression (3.2). All specifications include time fixed effects that additionally vary by rate type (adjustable- or fixed-rate) and whether the loan is syndicated (column iv) or the loan purpose (column v). Columns (i)-(v) include various bank controls and column (vi) includes bank-time fixed effects. Standard errors in parentheses are two-way clustered by bank and firm. Sample: 2018:Q1 - 2020:Q2. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table D.6: Low Capital Buffers − Alternative Fixed Effects.

	(i)	(ii)	(iii)	(iv)
Capital	1.02***	0.88***	0.70**	0.84**
	(0.25)	(0.27)	(0.32)	(0.36)
Low-PD	2.78*	2.75*	2.61	2.37**
	(1.35)	(1.55)	(1.74)	(1.04)
Capital × Low-PD	-0.77***	-0.79**	-0.76**	-1.10***
	(0.25)	(0.30)	(0.33)	(0.22)
Fixed Effects				
Time	✓			
Location × Time		✓		
Location × Industry × Time			✓	
Location × Industry × Size × Time				✓
Bank Controls	✓	✓	✓	✓
R-squared	0.01	0.09	0.29	0.39
Observations	8,033	5,839	5,402	3,609
Number of Firms	1,135	843	749	571
Number of Banks	27	27	27	26

Notes: Estimation results for regression (3.2). All specifications include time fixed effects that additionally vary by location (state-level) in columns (ii)-(iv), industry (two-digit NAICS code) in columns (iii) and (iv), and firm size (deciles of the unconditional firm size distribution) in column (iv). All regressions include various bank controls. Standard errors in parentheses are two-way clustered by bank and firm. Sample: 2018:Q1 - 2020:Q2. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table D.7: Low Capital Buffers − Probability of Default.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Capital	0.07	0.11	0.07	0.13	0.36	
	(0.37)	(0.35)	(0.35)	(0.30)	(0.40)	
PD		-0.11	-0.27*	-0.27**	-0.21	-0.28
		(0.10)	(0.14)	(0.12)	(0.13)	(0.17)
Capital × PD			0.05	0.04	-0.01	0.05
			(0.04)	(0.04)	(0.03)	(0.05)
Fixed Effects						
Firm × Rate × Time	✓	✓	✓			✓
Firm × Rate × Syn. × Time				✓		
Firm × Rate × Pur. × Time					✓	
Bank × Time						✓
Bank Controls	✓	✓	✓	✓	✓	
R-squared	0.5	0.51	0.51	0.52	0.51	0.54
Observations	9,930	7,263	7,263	6,348	5,701	7,251
Number of Firms	969	754	754	674	606	752
Number of Banks	29	27	27	27	27	26

Notes: Estimation results for regression (3.2), where Low-$\text{PD}^k_{i,j,t}$ is replaced by $\text{PD}^k_{i,j,t}$. All specifications include firm-time fixed effects that additionally vary by rate type (adjustable- or fixed-rate) and whether the loan is syndicated (column iv) or the loan purpose (column v). Columns (i)-(v) include various bank controls and column (vi) includes bank-time fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2018:Q1 - 2020:Q2. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table D.8: Low Capital Buffers − Low-PD Interactions.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Capital	0.28	0.30	1.18*	1.29**	2.04**	
	(0.33)	(0.30)	(0.65)	(0.60)	(0.80)	
Low-PD		-23.52	29.03	20.58	68.99	44.40
		(58.28)	(71.36)	(87.25)	(72.53)	(63.60)
Capital × Low-PD			-1.62*	-1.93**	-2.23**	-1.69*
			(0.83)	(0.86)	(0.98)	(0.89)
Fixed Effects						
Firm × Rate × Time	✓	✓	✓			✓
Firm × Rate × Syn. × Time				✓		
Firm × Rate × Pur. × Time					✓	
Bank × Time						✓
Bank Controls	✓	✓	✓	✓	✓	
Bank Controls × Low-PD	✓	✓	✓	✓	✓	✓
R-squared	0.54	0.54	0.54	0.54	0.54	0.57
Observations	4,674	4,674	4,674	4,188	3,617	4,649
Number of Firms	495	495	495	455	396	491
Number of Banks	27	27	27	26	27	24

Notes: Estimation results for regression (3.2). All specifications include firm-time fixed effects that additionally vary by rate type (adjustable- or fixed-rate) and whether the loan is syndicated (column iv) or the loan purpose (column v). Columns (i)-(v) include various bank controls. All specifications include interaction terms of each of the bank controls with Low-PD. Column (vi) includes bank-time fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2018:Q1 - 2020:Q2. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table D.9: Low Capital Buffers − Extended Sample Splits.

	(i) Low Prod.	(ii) High Prod.	(iii) Large Loans	(iv) Small Loans	(v) Low Payout	(vi) High Payout
Capital	0.55	-0.12	0.67	2.22	0.45*	0.26
	(0.36)	(0.18)	(0.50)	(1.45)	(0.24)	(0.27)
Low-PD	3.29**	0.82	7.01**	6.12	2.23**	1.37
	(1.23)	(1.24)	(2.63)	(4.34)	(1.04)	(1.18)
Capital × Low-PD	-0.70**	-0.03	-1.44***	-2.24	-0.48*	-0.20
	(0.30)	(0.32)	(0.41)	(1.36)	(0.28)	(0.30)
Fixed Effects						
Firm × CL × Rate × Time	✓	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓	✓
R-squared	0.65	0.66	0.63	0.5	0.63	0.64
Observations	4,307	4,281	1,672	1,642	3,462	3,442
Number of Firms	560	487	197	225	470	455
Number of Banks	27	27	27	19	27	27

Notes: Estimation results for regression (3.2), where the dependent variable is the change in used term loans in columns (iii) & (iv), and committed credit lines and term loans in the remaining columns. The samples are split at the median at time t according to net income relative to assets in columns (i) & (ii), the size of the loan in columns (iii) & (iv), and payouts relative to assets (v) & (vi). All specifications include firm-time fixed effects that additionally vary by whether the loan is a credit line or a term loan (CL), the rate type (adjustable- or fixed-rate) and various bank controls. Standard errors in parentheses are clustered by bank. Sample: 2018:Q1 - 2020:Q2. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

D.3 Effects at the Firm Level

In this section, we test whether the lending distortions also persist at the firm level, affecting total firm debt and investment. To this end, we estimate

$$\begin{aligned} \frac{y_{i,t+2} - y_{i,t}}{0.5 \cdot (y_{i,t+2} + y_{i,t})} =& \alpha_i + \tau_{m,t} + \beta_1 \widetilde{\text{Capital}}_{i,t} + \beta_2 \widetilde{\text{Low-PD}}_{i,t} \\ &+ \beta_3 \widetilde{\text{Low-PD} \times \text{Capital}}_{i,t} + \gamma X_{i,t} + u_{i,t} \end{aligned} \tag{D.1}$$

where $y_{i,t}$ denotes an outcome for firm i, α_i is a firm fixed effect, $\tau_{m,t}$ is an industry-time fixed effect, and $X_{i,t}$ is a vector of firm controls. As dependent variables, we consider changes in total firm debt and fixed assets as an approximation for investment. The regressors associated with β_1, β_2, and β_3 represent exposures to bank capitalization and risk assessments that firms have through their term borrowing. That is, each regressor is defined as $\widetilde{R}_{i,t} = \sum_j R_{i,j,t} \times \text{Term Loan}_{i,j,t}/\text{Debt}_{i,t}$ where $R_{i,j,t}$ is given by $\text{Capital}_{j,t}$, $\text{Low-PD}^k_{i,j,t}$, or the interaction of the two, and firms' term-loan-to-debt ratios are used as weights to aggregate the exposures across lenders.[28]

The estimation results for regression (D.1) are reported in Table D.10. Columns (ii) and (iv) show that the credit supply effects persist at the firm level. Their total debt adjusts by a similar amount as for the regressions reported in Table (D.3), indicating that firms do not alter their credit across preexisting or new lenders. These debt changes also translate into investment adjustments, showing that other resources like firm cash-holdings do not fully compensate for credit adjustments.

Table D.10: Effects at the Firm Level − Credit Supply.

	Δ Total Debt		Investment	
	(i)	(ii)	(iii)	(iv)
Capital	0.14***	2.62**	-0.17***	2.08***
	(0.04)	(1.03)	(0.01)	(0.75)
Low-PD		6.11		9.25***
		(4.37)		(3.33)
Capital × Low-PD		-3.55***		-1.50**
		(0.86)		(0.62)
Fixed Effects				
Firm	✓	✓	✓	✓
Time × Industry	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
R-squared	0.4	0.4	0.39	0.39
Observations	82,204	82,204	74,926	74,926
Number of Firms	13,861	13,861	12,081	12,081
Number of Banks	37	37	37	37

Notes: Estimation results for regression (D.1), where $y_{i,t}$ is either given by total firm debt in columns (i) and (ii) or fixed assets in columns (iii) and (iv). All specifications include firm fixed effects, industry-time fixed effects, and various firm controls dated at time t: cash, net income, tangible assets, liabilities (all relative to assets), firm size (natural log of total assets), public-firm-indicator, total term loans/debt, total observed unused credit/debt. Standard errors in parentheses are two-way clustered by main-bank and firm. Sample: 2016:Q3-2020:Q4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

[28] We note three details about regression (D.1). First, we include firm fixed effects to capture time-invariant firm-specific changes of debt and investment, and to estimate these effects consistently, we extend the estimation back to 2016:Q3 to allow for a sufficiently long sample covering four years of data. Second, the variable Low-PD$^{k}_{i,j,t}$ takes either values of zero or one and the associated coefficients are only identified because of the relative size shares of term borrowing across lenders. Third, apart from the exclusion of credit lines, we lift all other sample restrictions in comparison with regression (3.2), such as the exclusion of bank-firm observations with multiple credit types.

D.4 Alternative Identification Approach

In this section, we present the results of an alternative identification approach that further supports our theory but also highlights the virtues of our main empirical strategy. The approach differentiates banks by the share of a firm's total debt that they hold, building on the idea that banks with a larger debt-share have stronger incentives to evergreen loans. Similar to regression (3.2), we estimate for firm i, bank j, and loan type k:

$$\begin{aligned}\frac{L^k_{i,j,t+2} - L^k_{i,j,t}}{0.5 \cdot (L^k_{i,j,t+2} + L^k_{i,j,t})} =& \alpha^k_{i,t} + \beta_1 \text{Debt-Share}_{i,j,t} \\ &+ \beta_2 \text{Debt-Share}_{i,j,t} \times \text{COVID}_{t+2} + \gamma X_{j,t} + u^k_{i,j,t}\end{aligned} \tag{D.2}$$

where $\text{Debt-Share}_{i,j,t} = \text{Loan}_{i,j,t}/\text{Firm Debt}_{i,t}$ and COVID_{t+2} is a binary indicator that equals one if $t+2$ is a quarter in 2020.[29] To control for firm credit demand, we follow again Khwaja and Mian (2008) and include firm-time fixed effects $\alpha^k_{i,t}$. However, this approach faces potential identification challenges. That is because firm credit demand may differ across banks depending on the amount of credit that a firm has borrowed in the past. For example, a motivation to diversify borrowing in normal times would give $\beta_1 < 0$ absent credit supply effects. That is why we also include the interaction $\text{Debt-Share}_{i,j,t} \times \text{COVID}_{t+2}$ in regression (D.2) that is supposed to address the question: Compared to normal times, when firm cash-flow sharply declined during the COVID-19 crisis, did banks decrease their credit supply relatively less to firms if they held a larger ex-ante debt-share? The results in Appendix Table D.11 confirm this hypothesis, showing that $\beta_2 > 0$ which is statistically significant at conventional confidence levels across a number of specifications. However, these results may only reflect credit supply effects under the assumption that firms did not shift their credit demand towards their (relationship) lenders with whom they have borrowed more in the past—a possibility that we cannot exclude. This discussion illustrates why we prefer our main identification approach that obtains cross-sectional variation from bank capital positions and risk reporting. In fact, the correlations of ex-ante debt shares with the regres-

[29] As in regression (3.2), we consider only term loans and differentiate fixed and adjustable rate loans as separate loan types k.

sors in (3.2) are close to zero.[30] Instead, banks assess the importance of similar loans differently due to their risk reporting and regulatory incentives. Our main approach is therefore not subject to the mentioned identification concerns.

Table D.11: Debt-Share Regressions − Credit Supply.

	(i)	(ii)	(iii)	(iv)
Debt-Share	-12.28**	-12.08**	-9.55	-13.57**
	(5.40)	(4.63)	(6.27)	(6.23)
Debt-Share × COVID	26.36**	32.23***	25.50*	21.80*
	(12.40)	(11.61)	(14.72)	(12.50)
Fixed Effects				
Firm × Rate × Time	✓			✓
Firm × Rate × Time × Syn.		✓		
Firm × Rate × Time × Pur.			✓	
Bank × Time				✓
Bank Controls	✓	✓	✓	
R-squared	0.55	0.56	0.54	0.6
Observations	10,653	8,780	7,192	10,485
Number of Firms	1,008	889	729	999
Number of Banks	36	35	35	34

Notes: Estimation results for regression (D.2), where the dependent variable is percentage change in term loans. All specifications include firm-time fixed effects that additionally vary by rate type (adjustable- or fixed-rate) and whether the loan is syndicated (column ii) or the loan purpose (column iii). Columns (i)-(iii) include various bank controls and column (iv) includes bank-time fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2012:Q3 - 2020:Q4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

E Dynamic model

E.1 Proofs

Proof of Proposition 4. Given the fixed supply of labor N, a given stock of capital K, and a distribution of firms $\lambda(s)$ with mass M, we can write the planner's

[30] Specifically, the correlation coefficient between Debt-Share$_{i,j,t}$ and Capital$_{j,t}$ is -0.03 and between Debt-Share$_{i,j,t}$ and Low-PD$_{i,j,t}$ is 0.02 for the estimation sample in Table D.3.

problem as

$$\max_{k,n} \int z k^{\alpha} n^{\nu} \mathrm{d}\lambda(s)$$

$$\text{s.t.} \quad \int k \mathrm{d}\lambda(s) \leq K \quad ,$$

$$\int n \mathrm{d}\lambda(s) \leq N \quad .$$

It is straightforward to show, after some algebra, that the solution to this problem is given by

$$k = \frac{z^{\frac{1}{1-\alpha-\nu}}}{\int z^{\frac{1}{1-\alpha-\nu}} \mathrm{d}\lambda(s)} K \quad , \quad n = \frac{z^{\frac{1}{1-\alpha-\nu}}}{\int z^{\frac{1}{1-\alpha-\nu}} \mathrm{d}\lambda(s)} N \quad .$$

Notice that the planner equates the MPK across all firms. Computing aggregate TFP then gives us

$$TFP^{*} = \frac{\int z \left[\frac{z^{\frac{1}{1-\alpha-\nu}}}{\int z^{\frac{1}{1-\alpha-\nu}} \mathrm{d}\lambda(s)} K \right]^{\alpha} \left[\frac{z^{\frac{1}{1-\alpha-\nu}}}{\int z^{\frac{1}{1-\alpha-\nu}} \mathrm{d}\lambda(s)} N \right]^{\nu} \mathrm{d}\lambda(s)}{K^{\alpha} N^{\nu}} = \left[\int z^{\frac{1}{1-\alpha-\nu}} \mathrm{d}\lambda(s) \right]^{1-\nu-\alpha} \quad .$$

This allows us to write output in the planner's economy as in the proposition:

$$Y^{*} = TFP^{*} K^{\alpha} N^{\eta} = M^{1-\alpha-\eta} \mathbb{E}[z^{\frac{1}{1-\alpha-\nu}}]^{1-\nu-\alpha} K^{\alpha} N^{\eta} \quad .$$

E.2 Bank Capital in the Dynamic Model

We extend the dynamic model to incorporate a notion of bank capital in a way that is similar to the static model. We assume that with probability φ the bank has to pay a cost of violating a regulatory constraint given by

$$\zeta b \leq \mathbb{I}[V(s;Q) \geq 0] b + [1 - \mathbb{I}[V(s;Q) \geq 0]] \psi(s) \quad .$$

The constraint states that the bank's payoff from a loan must be at least as large as a fraction ζ of the face value of the loan. One can think of ζ as a type of capital requirement or a maximum loss-given-default constraint. Noting that the constraint is never violated in case of repayment, we adapt the bank's problem in 4.7 as:

$$W(s) = \max_{Q \geq Q^n(s)} \mathcal{P}(s;Q) \left[b - \mathcal{B}(s;Q)Q + \beta^k \mathbb{E}_{z'}[W(z', \mathcal{B}(s;Q), \mathcal{K}(s;Q)|z] \right] + [1 - \mathcal{P}(s;Q)] \left[\psi(s) - \varphi \max\{\zeta b - \psi(s), 0\} \right] \quad ,$$

where $Q^n(s)$ is defined as in the original problem.

E.3 Zombie Firm Classifications

We describe in more detail how our measure of subsidized firms correlates with different types of zombie classifications that are used in the literature. We focus on the following classification measures:

1. Favara, Minoiu and Perez-Orive (2022) (FMP): (i) Leverage above median; (ii) Interest-coverage ratio (ICR) below 1; (iii) Negative average sales growth over the previous 3 years.

2. McGowan, Andrews and Millot (2018) (MAM): (i) ICR below 1 for 3 consecutive years; (ii) At least 10 years old.

3. Schivardi, Sette and Tabellini (2022) (SST): (i) Return on assets below the risk-free rate; (ii) Leverage above 40%.

4. Banerjee and Hofmann (2022) (BH): (i) ICR below 1 for 2 consecutive years; (ii) Tobin's Q below median.

5. Caballero, Hoshi and Kashyap (2008) (CHK): (i) Interest rate below the risk-free rate.

Table E.1: Zombie classification criteria in the RLE.

	% of Zombies	False Positives, %	True Positives, %	Balanced Accuracy, %
FMP	5.67	4.05	28.35	62.15
MAM	6.53	6.58	5.70	49.56
SST	24.20	19.94	83.97	82.01
BH	2.59	2.34	6.19	51.93
CHK	0.01	0.00	0.13	50.07

Table E.1 reports the results from applying each of these definitions to the RLE, along with different measures of diagnostic ability relative to our definition of subsidized firms. We consider the false positive rate (FPR), which is equal to the ratio of false positives to positives, the true positive rate (TPR), equal to the ratio of true positives to positives, and the balanced accuracy measure, which is the average between the TPR and true negative rates (TNR). Within our model, the SST and FMP measures are most successful in achieving a high TPR relative to FPR.[31] These are also the two measures that do the best in terms of the balanced accuracy measure, which also takes into account a classification measure's ability to correctly identify non-zombies (the TNR).

[31] In receiver operating characteristic (ROC) analysis, a binary classifier is considered to be perfect if it attains a FPR of 0 and a TPR of 1.