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Abstract

We develop and estimate a new model of endogenous growth in bank efficiency and firm productivity in which banks adopt technology embedded in capital goods produced by entrepreneurs, and agents choose whether to become workers or capital-good-producing entrepreneurs. In this framework, bank efficiency influences firm productivity by affecting agents' occupational choices, while firm productivity affects bank efficiency through the relative price of capital goods. We find that increasing technology adoption in the banking system to the level in the top half of the distribution in the data accelerates the economy's long-term growth from 2% to 2.17%, and two-thirds of this gain stems from the amplification mechanism proposed. We also report empirical evidence based on U.S. bank, metropolitan, and state-level data that is in line with the critical comparative statics of the model.

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1 Introduction

As financial institutions increasingly adopt new technologies like Fintech and AI, understanding their economic implications is critical. While empirical evidence on the causal impact of these new technologies on bank, firm, and household-level outcomes is abundant, their economy-wide benefits, particularly their contribution to the cost of finance and aggregate growth, are difficult to quantify due to the complexity of the general equilibrium effects. In this paper, we develop and estimate a novel model in which banks adopt technology embedded in capital goods produced by entrepreneurs, which permits such quantification.

We find that increasing technology adoption in the banking system to the average level in the top half of the distribution of IT expenditure can significantly lower lending rates and raise per capita GDP growth from 2% to 2.17% in the counterfactual balanced growth path of the economy. We also demonstrate that more than two-thirds of this growth acceleration can be attributed to the endogenous bank technology adoption mechanism at the core of the model, with an exogenous increase in bank efficiency as in Greenwood, Sanchez and Wang (2010) accounting for only one-third of these gains.

The paper also provides direct empirical evidence based on bank, metropolitan area (MSA), and state-level data on some of the critical mechanisms at work in the model. In particular, we show that higher bank information technology (IT) acquisition causes a lower cost of bank intermediation and is associated with higher lending volumes to small businesses. Furthermore, we find that U.S. states or MSAs with more efficient banks have a more dispersed and less skewed firm-size distribution, aligned with our model's prediction of a shift in the firm-size distribution toward larger and more productive firms in response to higher bank IT adoption.

Our model features endogenous growth in both bank efficiency and firms' technological progress. As in Lucas (1978) and Buera and Shin (2013), a continuum of agents chooses between two occupations: worker or entrepreneur. This occupation choice compares the wage rate with the expected profits from entrepreneurship. The average ability of entrepreneurs in the economy determines the growth rate of aggregate firm productivity. Entrepreneurs employ workers to produce capital goods and must pay their wage bills in advance of sales.

The entrepreneurs' revenues are uncertain, and their realization is private information to them. Banks specialize in screening and monitoring entrepreneurs to finance their wage bills. A fixed number of banks compete à la Cournot in the loan market, playing a two-stage game as in Sutton (1991). In the first stage, banks invest in capital goods produced by entrepreneurs. These goods incorporate technology that enhances bank efficiency in transforming deposits into loans, as for instance in Boissay, Collard and Smets (2016). The average efficiency of individual banks determines the banking sector's overall efficiency. In the second stage, banks extend loans to entrepreneurs. Each bank offers an incentive-compatible loan contract that specifies the loan amount, the interest rate, and the recovery rate when borrowers cannot fully repay their loans.

The interplay between bank efficiency and firm productivity is at the model's core. As aggregate firm productivity increases, the relative price of capital goods falls, inducing banks to adopt more capital goods, thereby enhancing their efficiency in transforming deposits into loans and monitoring borrowers. This leads to faster aggregate bank efficiency growth. Increased aggregate bank efficiency reduces borrowing costs for entrepreneurs, enabling them to expand production and demand more labor, raising wages. Furthermore, the wage rate increases relatively more than the marginal profit of entrepreneurs, inducing less able agents to choose to be workers. This reallocation raises the average ability of entrepreneurs, contributing to a higher growth rate of aggregate firm productivity. Additionally, given that the firm size distribution exhibits a fat right tail, a higher threshold for occupation choice results in a more dispersed but less skewed distribution.

We estimate the model using the method of moments by targeting key stylized facts of the U.S. economy and directly estimating the critical parameter governing bank technology adoption based on matched FDIC Call Report-Harte Hanks Market Intelligence Computer Intelligence Technology data. Next, we assess the impact of higher bank technology adoption on economy-wide long-term economic growth as well as lending rates and standard deviation and skewness of the firm size distribution. To do so, we increase the IT share in the loan production function of banks to the average value estimated in the top half of the IT expenditure distribution in the data. In this counterfactual, we find that the cost of funds to entrepreneurs declines and long-run growth significantly accelerates. Facing a lower borrowing rate, entrepreneurs hire more, and the wage rate increases. The wage rate increases more than the marginal profit of entrepreneurs, inducing less able agents to become workers, thereby boosting aggregate productivity growth. As the threshold for occupation choice rises, the standard deviation of the firm-size distribution by employment increases while the skewness decreases.

The paper also empirically examines three main model predictions with bank, MSA, and state-level data. The first prediction is that as aggregate firm productivity advances and the relative price of capital goods declines, banks should adopt more IT and increase their efficiency. To estimate this critical mechanism in the model, we use Call Report data matched with proprietary bank-level IT spending data from the Harte Hanks Market Intelligence Computer Intelligence Technology database as in He, Jiang, Xu and Yin (2022). We proxy for bank efficiency using bank-level value added as a share of total intermediated loans, which we call the bank-level cost of financial intermediation (CFI) as in Philippon (2015).

In this step of the empirical analysis, to establish causality, we exploit bank distance from land-grant colleges as a proxy for the availability of human capital necessary to adopt new technologies, following Moretti (2004) and Pierri and Timmer (2022). We instrument banks' IT investment using the interaction of the change in the quality-adjusted relative price of capital (Eichengreen, 2015) with a measure of banks' distance to the nearest land-grant college.

Consistent with our model predictions, we find that banks with larger IT budgets have lower CFI, after controlling for bank-level characteristics, time, and bank-fixed effects. A one standard deviation increase in IT expenditure as a share of non-interest expenses causes a 0.044 standard deviation decrease in banks' CFI. Moreover, our empirical results suggest that this CFI decline is primarily driven by lower labor compensation rather than bank profitability (measured as net income per dollar of intermediated loans). This arguably suggests that a substitution effect between IT expenditure and labor may be driving the data, aligned with the implications of the extension of our model that includes labor in the banks' loan production function and is reported in the appendix.

Second, our model predicts that banks should lend more to entrepreneurs as they become more efficient. To investigate this implication, we employ data from the CRA Small Business Loan Database, focusing on small firms as they are more bank-dependent than large firms. We find that a lower bank CFI is significantly associated with faster growth in small business loans at the state level. In particular, a one standard deviation decrease in a bank's CFI is associated with a 0.05 standard deviation increase in the growth rate of small business loans, which translates into a 4.35 percentage point increase in loan volume growth.

Third, our theoretical model predicts that lower interest rates, driven by higher bank efficiency, should raise the threshold for occupational choice. This, in turn, leads to an increase in the standard deviation and a decrease in the skewness of the firm-size distribution. To empirically investigate this prediction, we use the Business Dynamics Statistics (BDS) dataset to construct firm-size distributions at the state or MSA level across the U.S. As the model predicts, we find that the state or MSA-level CFI, measured as the deposit-weighted average of the CFI of banks operating in a particular state or MSA, is negatively correlated with the standard deviation of the firm-size distribution and positively correlated with its skewness.

In this last step of the empirical analysis, to account for potential unobserved time-varying region characteristics, we also examine the relationship between CFI and standard deviation and skewness of the firm-size distribution across sectors within a given state or MSA by including state-year and sector-year fixed effects. The estimation results show that, within a given state or MSA, the standard deviation and the skewness of the firm-size distribution in sectors that depend more heavily on external finance are more strongly correlated with the state (MSA)-level CFI.

Related Literature

Our paper contributes to the literature along several dimensions. A well established literature models *firm* technology adoption and its impact on firm outcomes and economic growth (see, among several others, Jovanovic and Rob, 1989; Acemoglu, Aghion, Lelarge, Van Reenen and Zilibotti, 2007; Bloom, Genakos, Sadun and Van Reenen, 2012a; Bloom, Sadun and Reenen, 2012b; Perla and Tonetti, 2014; Benhabib, Perla and Tonetti, 2021; König, Storesletten, Song and Zilibotti, 2022). We complement this literature by focusing on bank IT adoption and its impact on long-run growth. Closely related to our paper is Lerner, Seru, Short and Sun (2024) that documents the evolution of financial innovation in the U.S. by looking at patent data. They find that IT firms and non-financial firms are the key drivers of financial innovation, as opposed to financial firms. They also show that the geographic distribution of financial innovation is clustered in specific geographies of the United States. Our paper provides a model of bank technology adoption, consistent with the idea that banks primarily acquire innovation produced by non-financial firms. Our empirical analysis also exploits geographic variation in complementary skills for technology adoption in identifying the causal effect of bank technology adoption on the cost of intermediation.

Many other studies examine how technology developed outside the financial sector has shaped the financial industry. On the theoretical front, Hauswald and Marquez (2003, 2006) and Vives and Ye (2025) investigate how advancements in IT enable banks to mitigate information asymmetry, enhance competition, and extend their lending reach. Similarly, He, Huang and Zhou (2023) analyzes the effects of "open banking," an information-sharing mechanism that allows borrowers to share their customer data, stored with banks or Fintech firms. This body of literature models bank IT adoption as a reduced-form cost function, representing their effort or investment in information acquisition. In contrast, in our model, technology adoption is a bank's choice to purchase capital goods that embed entrepreneurs' abilities. This technology adoption enhances bank intermediation efficiency, which subsequently spills back into both firm-level and aggregate productivity—a feedback effect that is absent in these models.

Other empirical studies consider the adoption of specific technologies and how they shape financial industry outcomes. For example, Hannan and McDowell (1984) examined the introduction of ATMs and the use of wire transfers. More recently, Jiang, Yu and Zhang (2022); Haendler (2022); Benmelech, Yang and Zator (2023); Koont (2024); Alok, Ghosh, Kulkarni and Puri (2024) investigated how mobile banking and digital banking have reshaped competition in the deposit market, for larger or smaller banks. Other research has focused on cloud computing and AI (Cong, Tang, Wang and Zhang, 2021), AI-based FinTech and investment (Bartram, Branke and Motahari, 2020), and FinTech more broadly (Goldstein, Jiang and Karolyi, 2019; Fuster, Plosser, Schnabl and Vickery, 2019; Berg, Burg, Gombović and Puri, 2020; Gopal and Schnabl, 2022). By adopting a general equilibrium approach within a tractable model, we not only quantify the causal impact of bank technology adoption on specific outcomes—such as intermediation costs, credit supply, and firm size distribution—but also assess its long-term effects on economic growth and productivity.

Studies that are closely related to the empirical analysis in this paper include Lewellen and Williams (2021), Pierri and Timmer (2022), Mezzanotti and Simcoe (2023), and Branzoli, Rainone and Supino (2023) that exploit bank-level data variation during the Great Recession and the COVID pandemic to estimate the causal effect of bank IT adoption on measures of bank performance. We estimate the impact of bank IT adoption on bank outcomes and the firm size distribution in both normal and crisis times over a similar sample period.

In particular, utilizing granular data on U.S. banks' spending on different categories of IT products, He, Jiang, Xu and Yin (2022) document trends in bank IT expenditure and provide causal evidence that banks invest in different types of technology goods to cater to different segments of the credit demand, that are deferentially exposed to information. Matching U.S. banks' IT spending to the mortgage processing process, Jiang, Jørring and Xu (2023) shows that bank IT adoption significantly impacts loan approval decisions and pricing accuracy, thereby enhancing profitability and containing losses, especially for loans given to marginal borrowers with weak credit profiles. We use the same data to explore the predictions of our theoretical model, and our findings are consistent with the granular evidence that these studies provide.

Our theoretical model is most closely related to the stochastic monitoring framework in Greenwood, Sanchez and Wang (2010), where the cost for banks to verify firms' states is determined by an exogenous level of bank efficiency. The critical difference is that we *endogenize* the level of bank efficiency by allowing banks to adopt capital goods from entrepreneurs. As in Buera and Shin (2013), our model features an occupation choice by heterogeneous agents. By allowing banks to adopt technology from entrepreneurs, we endogenize financial development and can quantify its feedback effects on economic growth and firm-size distribution. Our work is similar in spirit to de la Fuente and Marín (1996) and Laeven, Levine and Michalopoulos (2015). The former study features an exogenous screening cost that decreases as entrepreneurs' technology advances. The latter features an exogenously growing technology frontier in a Schumpeterian growth model from which entrepreneurs randomly adopt with banks that must innovate to efficiently monitor entrepreneurs. Our model critically differs in that both individual banks' efficiency and firm technological progress are endogenous in our setting.

More broadly, a very large body of literature has explored the theoretical and empirical relationship between financial development and economic growth, treating financial development and financial sector efficiency as exogenous drivers of firm and household outcomes, aggregate productivity, and economic growth (see Levine, 2005; Matsuyama, 2007, for surveys). However, the idea that firm innovation, productivity, and growth can influence financial development and intermediation efficiency, as suggested by Robinson (1954) and Lucas (1988), or more generally that intermediation efficiency and firm productivity co-evolve, has received relatively much less attention in the literature, with very few exceptions. For example, Berger (2003) provides an overview of how technological progress can improve the efficiency and variety of banking services. This paper examines the impact of firm productivity (as represented by entrepreneurs' ability) on bank efficiency within a tractable general equilibrium (GE) model that allows for a quantification of the feedback effect of endogenous bank technology adoption on long-run growth. The model we propose also provides a framework for empirically analyzing these linkages at the microeconomic level.

The remainder of the paper is organized as follows: Section 2 presents the model, Section 3 discusses its solution and properties. Section 4 describes the model estimation and results. Section 5 presents a counterfactual simulation of higher bank IT adoption. Section 6 empirically investigates some of the model's critical mechanisms. Section 7 concludes. Proofs and details of the analysis, including model extensions and robustness checks, are in the Appendix.

2 The model

In this section, we set up a model with banks' technology adoption featuring endogenous growth in both aggregate firm productivity and bank efficiency.

2.1 Entrepreneurs, workers, and the occupation choice

There is a continuum of agents with unit mass, each endowed with an individual ability level, θ, which determines their capacity to operate a firm. Each agent of type θ, drawn from a distribution on $\Theta = [\theta_{min}, \infty)$ with CDF $\mathbf{F}(\theta)$, decides whether to become an entrepreneur who operates a firm producing capital goods or to work as a worker, inelastically supplying one unit of homogeneous labor.[1] To make the dynamic model tractable, at the beginning of each period, agents are reassigned to their type. Before the reassignment, all agents join a risk-sharing plan, deciding on their consumption and saving, and there is no aggregate risk in the economy. Agents also own and operate banks and consumption goods firms.

Entrepreneurs

Suppose the type-θ agents choose to become entrepreneurs. Then, they have access to the following capital-good-producing technology that uses labor as sole input:

$$y_t(\theta) = \theta z_{t-1} l_t^{\xi}(\theta), \tag{1}$$

where $y_t(\theta)$ is output, $l_t(\theta)$ is the labor input, z_{t-1} is the aggregate level of firm productivity at $t-1$, and ξ governs the return to scale.[2] We assume $\xi < 1$, implying that the most productive entrepreneurs cannot control all resources. We further assume that the θ-entrepreneurs' project will be successful or fail with probabilities η and $1-\eta$, respectively. When projects fail, for simplicity but without loss of generality, we assume that all failed projects yield $\underline{\theta} < \theta_{min}$, where $\underline{\theta}$ is an estimated parameter.

Entrepreneurs do not have capital and must borrow from banks to pay workers in advance. If the project succeeds, the banks charge the lending rate $r_{lt}(\theta)$. Otherwise,

[1] Introducing heterogeneous abilities for workers is a possible extension of the model. The main mechanisms remain at work if entrepreneurs and workers are randomly matched without friction. In this setting, the threshold for occupational choice increases with worker ability, and the main results still hold. Incorporating search frictions is possible, but it would significantly increase model complexity.

[2] This production function is similar to the knowledge production process in the endogenous growth models of Romer (1990) and Lucas and Moll (2014), in which only human capital is used as an input.

banks require entrepreneurs to repay a fraction $x_t(\theta)$ of the loans.[3] Before learning the realization of their projects, type-θ entrepreneurs choose the labor $l_t(\theta)$ and borrowing from banks $b_t(\theta)$, taking as given the wage rate w_t, the relative price of capital goods p_t, the loan rate $r_{lt}(\theta)$, and the recovery rate $x_t(\theta)$, to maximize the expected profit, subject to the working capital constraint:

$$\max_{l_t(\theta),\, b_t(\theta)} \quad \eta\left(p_t\theta z_{t-1}l_t^{\xi}(\theta)-(1+r_{lt}(\theta))b_t(\theta)\right)+(1-\eta)\left(p_t\underline{\theta}z_{t-1}l_t^{\xi}(\theta)-x_t(\theta)b_t(\theta)\right), \tag{2}$$
$$s.t. \qquad w_t l_t(\theta)\leq b_t(\theta).$$

Solving the type-θ entrepreneurs' problem, we have:

$$\text{(labor demand)} \qquad l_t(\theta)=\left(\frac{\xi p_t z_{t-1}\bar{\theta}}{\left(\overline{1+r_{lt}(\theta)}\right)w_t}\right)^{\frac{1}{1-\xi}}, \tag{3}$$

$$\text{(loan demand)} \qquad b_t(\theta)=\left(\frac{\xi p_t z_{t-1}\bar{\theta}}{\left(\overline{1+r_{lt}(\theta)}\right)w_t^{\xi}}\right)^{\frac{1}{1-\xi}}, \tag{4}$$

$$\text{(profit)} \qquad \pi_t^E(\theta)=\left(\frac{1}{\xi}-1\right)\left(\overline{1+r_{lt}(\theta)}\right)w_t l_t(\theta)=\left(\frac{1}{\xi}-1\right)\left(\frac{\xi p_t z_{t-1}\bar{\theta}}{\left(\overline{1+r_{lt}(\theta)}\right)^{\xi}w_t^{\xi}}\right)^{\frac{1}{1-\xi}}, \tag{5}$$

where $\bar{\theta}=\eta\theta+(1-\eta)\underline{\theta}$ is the expected individual ability, and $\overline{1+r_{lt}(\theta)}=\eta(1+r_{lt}(\theta))+(1-\eta)x_t(\theta)$ is the expected loan repayment. The expected profit of type-θ entrepreneurs depends on their net markup $(1/\xi-1)$, the marginal cost of labor $(\left(\overline{1+r_{lt}(\theta)}\right)w_t)$, and the number of employed workers $(l_t(\theta))$. In equilibrium, expected profit increases with the price of capital goods and previous-period aggregate productivity and decreases with the expected loan rate and the wage rate.

Bank technology adoption affects profits through the expected loan rate, both via an intensive and extensive margin. On the intensive margin, for a given wage rate, a lower expected loan rate reduces the marginal cost of labor, leading firms to hire more workers, increase production, and earn higher profits. However, a higher labor demand raises the wage rate. On the extensive margin, as we will show later, the occupational choice depends on the relative rather than absolute agents' income (entrepreneurs' profits or workers' wages). A lower loan rate reduces marginal costs and, given fixed markups, lowers marginal profit. Lower financing costs increase absolute profits but raise equilib-

[3] Entrepreneurs produce even though their projects fail. Given relative prices, banks earn more profits from each entrepreneur than under limited liability. However, entrepreneurs make zero ex-post profits in the failed state, and banks only partially recover the funds lent. If $\underline{\theta}=0$, the equilibrium outcomes would be the same as under limited liability.

rium wages due to increased labor demand, thereby increasing the opportunity cost of entrepreneurship (as agents can instead choose for payroll work). Thus, a lower lending rate makes it less attractive for marginal agents near the occupational threshold to operate, causing them to choose to be workers; thereby, it raises the occupation choice threshold for entrepreneurship, and aggregate productivity increases.

Workers and the occupation choice

The type-θ agents who choose to become workers inelastically supply one unit of homogeneous labor at the wage w_t. Agents choose to be workers if $\pi_t^E(\theta) < w_t$; otherwise, they become entrepreneurs, a standard condition for occupational choice as in Lucas (1978). Later, we will show that the entrepreneurs' profit in Equation (5) increases in θ and that, under certain parameter restrictions, there exists a threshold θ^* for which the marginal agent is indifferent between being a worker and an entrepreneur. All agents with ability above the threshold will become entrepreneurs, while those with ability below it will become workers.

Consumption and saving

For tractability, we assume that *ex ante* all agents sign up a risk-sharing plan so that at the end of each period, all earnings, denoted as inc_t, including all profits of the entrepreneurs, the banks, and then consumption-good producers, and the workers' wages are aggregated and redistributed equally among agents. We assume that the representative consumer in this plan has log-utility, i.e., $\mathbf{u}(c_t) = \log c_t$, with c_t denoting consumption. Given deposits from the previous period, d_{t-1} and the deposit rate r_d, agents choose consumption and the next-period deposit to maximize the present value of their lifetime utility, subject to their budget constraint, solving

$$\max_{\{c_{t+\tau},\, d_{t+\tau}\}} \sum_{\tau=0}^{\infty} \beta^{\tau}\, \mathbf{u}(c_{t+\tau}) \quad s.t. \quad c_t + d_t = inc_t + (1 + r_d)\, d_{t-1}, \tag{6}$$

where β denotes the discount factor.

2.2 Banks

We assume that there are n banks owned by all agents that transform deposits into loans to entrepreneurs, and they compete *a la* Cournot in the loan market.[4] Banks play a

[4]Bank entry could be endogenized, either by allowing agents a second occupation choice or with an arbitrage condition as in Hopenhayn (1992) and Melitz (2003). However, endogenous entry significantly

two-stage game in the spirit of Sutton (1991). In the first stage, they collect deposits from agents, taking the deposit rate as given, and use capital goods purchased from entrepreneurs to originate loans and monitor borrowers. This technology adoption decision allows banks to choose the level of individual efficiency with which they transform deposits into loans, giving them a competitive edge in the second stage of the game.[5] In the second stage, banks take their funding costs as given and syndicate loans to each entrepreneur with all other banks. The following two subsections describe each of these two stages in turn. The microfoundations of the optimal contract with stochastic monitoring outcomes and its solution are reported in Appendix A. Readers who are not interested in the microfoundations can skip these derivations.

The second stage: loan market equilibrium

A type-θ entrepreneur borrows a syndicated loan from all n banks. Bank $j \in \{1, \dots, n\}$ offers a loan amount $b_{jt}(\theta)$, taking as given its unit funding cost $1 + r_{jct}$ and the quantity of loans offered by other banks, i.e. $\{b_{it}(\theta)\}_{i \neq j}$. The inverse loan demand function from Equation (4) is given by

$$1 + r_{lt}(\theta) = \frac{\xi p_t z_{t-1} \bar{\theta}}{\eta \left(\sum_j b_{jt}(\theta) \right)^{1-\xi} w_t^{\xi}} - (\frac{1}{\eta} - 1) x_t(\theta), \tag{7}$$

where the total amount borrowed from all banks by the type-θ entrepreneur is $b_t(\theta) = \sum_j b_{jt}(\theta)$.

If the type-θ entrepreneurs' projects fail, banks collectively confiscate entrepreneurs' outputs, liquidate them, and recover $p_t \underline{\theta} z_{t-1} l_t^{\xi}(\theta)$.[6] Bank j recovers at most the "fair" share of the total project liquidation value, where the share is equal to the bank j's share in the syndicated loan to the type-θ entrepreneur, denoted as $s_{jt}(\theta) = b_{jt}(\theta) / \sum_l b_{lt}(\theta)$. Thus, denoting bank's j recovery rate as $x_{jt}(\theta)$, we assume that the following resource constraint on the bank's j contract holds:

$$x_{jt}(\theta) b_{jt}(\theta) \leq s_{jt}(\theta) p_t \underline{\theta} z_{t-1} l_t^{\xi}(\theta), \tag{8}$$

with $x_t(\theta) b_t(\theta) = \sum_j x_{jt}(\theta) b_{jt}(\theta)$.

Suppose that the realization of θ is known to the entrepreneurs, but not to the banks.

adds to the model's complexity without altering its properties.

[5]The model properties also do not change if we allow banks to use labor as an additional input in the loan production (see Appendix C) or if we introduce Cournot competition in the deposit market.

[6]The same outcome obtains through renegotiation as in Jermann and Quadrini (2012) with banks' bargaining power equal to 1.

To verify the state, banks need to exert costly effort $\mathbf{e}(\theta)$ per unit of fund. With enough effort, banks can always detect the realized states. In Appendix A, we derive the optimal contract for banks and a micro-founded specification for $\mathbf{e}(\theta)$ with stochastic monitoring outcomes as in Greenwood, Sanchez and Wang (2010). Additionally, we show that $\mathbf{e}(\theta)$ is increasing and concave in θ, implying that it is harder to verify the state of more able entrepreneurs as the size and complexity of their projects increase. As a result, here, we can assume that $\mathbf{e}(\theta)$ is increasing and concave without loss of generality.

Taking as given the loan amounts of other banks $\{b_{it}(\theta)\}_{i\neq j}$, the wage w_t, the relative price of capital goods p_t, and its own unit funding cost $1+r_{jct}$, bank j chooses the loan amount $b_{jt}(\theta)$ and the loan gross recovery rate $x_{jt}(\theta)$ that maximize expected profits from lending to the type-θ entrepreneurs subject to the inverse loan demand and the resource constraint in equations (7) and (8), respectively:

$$\max_{b_{jt}(\theta),x_{jt}(\theta)} \Big(\eta\left(1+r_{lt}(\theta)\right)+(1-\eta)x_{jt}(\theta)\Big)b_{jt}(\theta)-(1+\mathbf{e}(\theta))\left(1+r_{jct}\right)b_{jt}(\theta) \quad s.t. \ (7) \ and \ (8). \tag{9}$$

The bank's expected profit from lending to the type-θ entrepreneurs is equal to expected net interest income minus verification costs. Imposing symmetry on the banking system, the following proposition characterizes the solution of the equilibrium in the loan market for the type-θ entrepreneurs.

Proposition 1 (Symmetric loan market equilibrium) *Suppose all n banks are the same. Given the unit funding cost $1+r_{jct}$, the expected gross loan rate $\overline{1+r_{lt}(\theta)}$ is*

$$\overline{1+r_{lt}(\theta)}=\eta\left(1+r_{lt}(\theta)\right)+(1-\eta)x_{jt}(\theta)=\underbrace{\frac{1}{1-\frac{1-\xi}{n}}}_{markup}\left(1+\underbrace{\mathbf{e}(\theta)}_{verification\ cost}\right)\left(1+r_{jct}\right), \tag{10}$$

where the recovery rate is:

$$x_{jt}(\theta)=\frac{1}{\xi}\frac{\underline{\theta}}{\bar{\theta}}\frac{1+\mathbf{e}(\theta)}{1-\frac{1-\xi}{n}}\left(1+r_{jct}\right), \tag{11}$$

and the gross lending rate for the type-θ entrepreneurs is:

$$1+r_{lt}(\theta)=\frac{1}{\eta}\left(1-(1-\eta)\frac{1}{\xi}\frac{\underline{\theta}}{\bar{\theta}}\right)\frac{1+\mathbf{e}(\theta)}{1-\frac{1-\xi}{n}}\left(1+r_{jct}\right). \tag{12}$$

Furthermore, suppose that the common individual ability in the failed state is low enough, i.e.,

$$\underline{\theta}<\frac{\xi\eta}{1-\xi+\xi\eta}\theta_{min}, \tag{13}$$

then we have that $x_{jt}(\theta) < 1 + r_{lt}(\theta)$.
Proof: see Appendix B.1.

Several remarks are in order here. First, the spread between the expected gross loan rate and the unit funding cost depends on two factors: the bank markup $\frac{1}{1-\frac{1-\xi}{n}}$ and the verification cost $\mathbf{e}(\theta)$. Thus, a more competitive banking system lends at a lower expected gross loan rate. The verification cost $\mathbf{e}(\theta)$ increases in θ as it takes more effort to verify higher θ-entrepreneurs. Thus, the expected gross loan rate increases in θ. As banks can charge higher loan rates for more productive entrepreneurs, they lend to more able entrepreneurs first. Later, we will also see that adopting more capital goods reduces banks' unit funding cost $(1 + r_{jct})$ and hence also the lending rate, indirectly lowering verification costs per dollar lent. Thus, technology adoption makes screening less costly, ultimately influencing both loan pricing and the composition of funded projects.

Second, it is straightforward to show that the resource constraint (8) is always binding; otherwise, the marginal benefit of choosing a higher recovery rate would be positive while the marginal cost would be negligible. Combining the entrepreneurs' first-order conditions with this constraint, the ratio of the recovery rate to the expected gross loan rate is $\frac{\underline{\theta}}{\xi\bar{\theta}}$, which can be interpreted as the hair cut rate given default. The recovery rate increases with $\underline{\theta}$ and decreases with the expected individual ability $(\bar{\theta})$, implying that the loss given default is increasing in θ. Assumption (13) requires that the "common ability level" in the failed state $\underline{\theta}$ is sufficiently low relative to the lower bound of the individual ability θ_{min} so that the hair cut rate is smaller than the gross lending rate in the successful state $1 + r_{lt}(\theta)$.

Third, since entrepreneurs may partially default on their loans, the gross lending rate in Equation (12) includes a default premium $\frac{1}{\eta}\left(1-(1-\eta)\frac{1}{\xi}\frac{\underline{\theta}}{\bar{\theta}}\right)$. The premium is equal to $\frac{1}{\eta}$ minus the hair cut rate given default adjusted for the default odds $\frac{1-\eta}{\eta}$. Since the haircut rate is increasing in θ, the default premium is also increasing in θ. Assumption (13) ensures that this default premium is larger than 1.

The first stage: bank technology adoption

The existing literature typically assumes that banks acquire information to deal with information asymmetries between banks and their borrowers, often modeling this as a reduced-form cost function representing their efforts or investments in information acquisition.[7] However, these models typically abstract from the origin of the technologies

[7] See, among others, Broecker (1990), Rajan (1992), Thakor (1996), Holmstrom and Tirole (1997), Hauswald and Marquez (2003, 2006), and Boyd and De Nicolo (2005) for early contributions, and Green-

employed in these information acquisition processes.

We assume that, in the first stage of their decision problem, banks acquire technology embedded in goods produced by entrepreneurs to manage their intermediation efficiency and monitor borrowers at a lower cost in the second stage of their problem. In particular, noting that, from a long-run perspective, the U.S. financial system seems to conform well to constant returns to scale (Philippon, 2015), we assume that bank j combines technology embedded in capital goods with deposit to produce loans according to the following Cobb-Douglas production function:

$$B_{jt} = \gamma a_{jt}^{\nu} D_{j,t-1}^{1-\nu}, \tag{14}$$

where B_{jt} is the total funds lent in the second stage, $D_{j,t-1}$ is the deposits collected by bank j, a_{jt} denotes the level of individual bank efficiency selected, ν is the technology share, and γ is a scale parameter that accounts for other factors such as managerial ability, marketing expenditures, physical capital, etc. This specification is consistent with the industrial organization (IO) approach to banking (Sealey and Lindley, 1977; Freixas and Rochet, 1997). As we discuss later in Section 4, we estimate ν using bank-level data to be 0.06%, suggesting that the loan production function is approximately linear in deposits.

In line with empirical evidence on technological innovation and adoption in banking and finance more generally (e.g., Pierri and Timmer, 2022; Lerner, Seru, Short and Sun, 2024; He, Jiang, Xu and Yin, 2022), we assume that bank j purchases technology produced outside the financial system rather than investing in R&D and innovating independently. Specifically, we posit that

$$a_{jt} = \frac{a_{t-1}}{z_{t-1}} q_{jt}, \tag{15}$$

where a_{t-1} is the previous-period aggregate level of bank efficiency, and q_{jt} is the capital goods purchased from the entrepreneurs. This specification, including the external effect from the previous-period aggregate firm productivity, is in line with those used in the endogenous growth literature to model technology adoption by non-financial entrepreneurs, (see, for example, Romer, 1996; Aghion and Howitt, 2009; Acemoglu, 2009; Jones and Vollrath, 2013). The banking equilibrium also exists if we assume some curvature in q_{jt}. However, as noted in Romer (1996) and others, a linear functional form ensures a well-defined balanced growth path.[8] For the same reason, we enter z_{t-1} at the denominator of Equation (15), meaning that the higher the level of aggregate firm pro-

wood, Sanchez and Wang (2010), Martinez-Miera and Repullo (2017), and Vives and Ye (2025), for more recent developments.

[8]We discuss empirical evidence on this assumption in Appendix D.

ductivity, the more costly it is to originate loans and monitor borrowers.[9]

Given the previous-period aggregate bank efficiency a_{t-1} and aggregate firm productivity z_{t-1}, the relative price of capital-goods p_t, the deposit rate r_d, and the amount of funds to be lent B_{jt}, bank j chooses the amount of capital goods q_{jt} and deposits $D_{j,t-1}$ that minimize the total funding costs:

$$\left(1+r_{jct}\right)B_{jt} \equiv \min_{q_{jt},D_{j,t-1}} p_t q_{jt} + (1+r_d)D_{j,t-1}, \quad s.t. \quad B_{jt} = \gamma\left(\frac{a_{t-1}}{z_{t-1}}q_{jt}\right)^{\nu} D_{j,t-1}^{1-\nu}. \tag{16}$$

Solving this problem, we find that the bank j's demand for capital goods and deposits are, respectively,

$$\text{(capital good demand)} \qquad p_t q_{jt} = \nu\left(1+r_{jct}\right)B_{jt}, \tag{17}$$

$$\text{(deposit demand)} \qquad (1+r_d)\,D_{j,t-1} = (1-\nu)\left(1+r_{jct}\right)B_{jt}. \tag{18}$$

Solving for the unit funding cost, $1+r_{jct}$, we have:

$$1+r_{jct} = \frac{1}{\gamma}\left(\frac{z_{t-1}}{a_{t-1}}\frac{p_t}{\nu}\right)^{\nu}\left(\frac{1+r_d}{1-\nu}\right)^{1-\nu}. \tag{19}$$

The unit funding cost for bank j increases with the relative price of capital goods, the deposit rate, and the previous-period aggregate firm productivity, while it decreases with the previous-period aggregate bank efficiency. Equation (19) represents the critical channel through which firm productivity influences banking system efficiency and loan pricing. When the price of capital goods declines, banks adopt more capital goods, increasing their efficiency in transforming deposits into loans. This reduces their funding costs, lowers the verification cost in the second stage, and ultimately enables them to supply funds to entrepreneurs at lower rates.

2.3 Consumption goods production

We assume that there is a representative firm, owned by all agents, that produces the consumption good, Y_t^C, using the capital goods as inputs as follows:

$$Y_t^C = K_t^{\alpha}, \tag{20}$$

[9]The assumption captures the idea that, as technological progress advances, products and businesses become more complex to understand, analyze, and monitor. For example, lending to projects into EVs, Crypto, and AI is more complex than lending to commercial real estate or the food industry.

where K is the capital goods purchased from entrepreneurs and $\alpha \in (0,1)$ is the capital share. We further assume that the consumption good is the numeraire and normalize its price to 1. Consumption-goods producers choose the level of capital that maximizes profits, taking its relative price p_t as given:

$$\max_{K_t} K_t^{\alpha} - p_t K_t. \tag{21}$$

Solving Problem (21), the demand for capital goods is given by:

$$K_t = \left(\frac{\alpha}{p_t}\right)^{\frac{1}{1-\alpha}}, \tag{22}$$

and the profits by the consumption-good producer are given by:

$$\pi_t^C = (1-\alpha)\left(\frac{\alpha}{p_t}\right)^{\frac{\alpha}{1-\alpha}}. \tag{23}$$

2.4 Market clearing

We now discuss the market clearing conditions, assuming that, as shown below, there exists a threshold θ_t^* for which the marginal agent is indifferent between being an entrepreneur or a worker.

Deposit and loan market

Since every agent carries the same deposit balance d_{t-1} from the previous period, the total supply of deposits is given by $\int_{\theta_{min}}^{\infty} d_{t-1} \, \mathbf{d}\,\mathbf{F}(\theta)$. Under symmetry, all banks demand the same amount of deposits. The deposit market clearing condition is

$$\int_{\theta_{min}}^{\infty} d_{t-1} \, \mathbf{d}\,\mathbf{F}(\theta) = nD_{j,t-1}. \tag{24}$$

Aggregate loan demand across all entrepreneurs is $\int_{\theta_t^*}^{\infty} b_t(\theta) \, \mathbf{d}\,\mathbf{F}(\theta)$, where $b_t(\theta)$ is given in Equation (4). The total supply of loans is nB_{jt}, where B_{jt} is the loan volume originated by bank j as in Equation (14), net of the funds used for verifying the status $E_t = n\int_{\theta_t^*}^{\infty} \mathbf{e}_t(\theta) b_{jt}(\theta) \, \mathbf{d}\,\mathbf{F}(\theta)$, where $b_{jt}(\theta)$ is the loan provided by bank j to a type-θ entrepreneur. Thus, the loan-market clearing condition is

$$\int_{\theta_t^*}^{\infty} b_t(\theta) \, \mathbf{d}\,\mathbf{F}(\theta) = nB_{jt} - E_t. \tag{25}$$

Note here that the deposit and loan markets are connected through Equation (18).

Labor market

The labor supply is equal to the mass of agents choosing to become workers, which is $\mathbf{F}(\theta_t^*)$. Denote total labor demand by entrepreneurs as $L_t = \int_{\theta_t^*}^{\infty} l_t(\theta)\ \mathbf{d}\ \mathbf{F}(\theta)$. The labor-market clearing condition is

$$\mathbf{F}(\theta_t^*) = \left(\frac{1 - \frac{1-\xi}{n}}{(1 + r_{jct})w_t} p_t \xi z_{t-1} \right)^{\frac{1}{1-\xi}} \mathbf{G}(\theta_t^*). \tag{26}$$

where

$$\mathbf{G}(\theta_t^*) = \int_{\theta_t^*}^{\infty} \mathbf{g}(\theta)\ \mathbf{d}\ \mathbf{F}(\theta),\ \ with\ \ \mathbf{g}(\theta) = \left(\frac{\bar{\theta}}{1 + \mathbf{e}(\theta)} \right)^{\frac{1}{1-\xi}}, \tag{27}$$

with $\mathbf{g}(\theta)$ summarizing the heterogeneity in the labor demand in Equation (3), driven by the expected project realization and the verification cost.

Capital-good market

The aggregate supply of capital goods Y_t^K is equal to the aggregate output of all entrepreneurs and is given by $Y_t^K = \int_{\theta_t^*}^{\infty} \eta y_t(\theta) + (1-\eta) y_t(\underline{\theta})\ \mathbf{d}\ \mathbf{F}(\theta)$, with $y_t(\theta)$ defined in Equation (1). Capital goods are purchased by consumption-good producers, K_t in Equation (22), and banks, $Q_t = nq_{jt}$, with q_{jt} defined in Equation (17). Thus, the capital-good market clearing condition is

$$\frac{1}{\xi} \left(\left(\frac{1 - \frac{1-\xi}{n}}{(1 + r_{jct})w_t} \right)^{\xi} p_t \xi z_{t-1} \right)^{\frac{1}{1-\xi}} \mathbf{H}(\theta_t^*) = K_t + Q_t. \tag{28}$$

where

$$\mathbf{H}(\theta_t^*) = \int_{\theta_t^*}^{\infty} \mathbf{h}(\theta)\ \mathbf{d}\ \mathbf{F}(\theta),\ \ with\ \ \mathbf{h}(\theta) = \left(\frac{\bar{\theta}}{(1 + \mathbf{e}(\theta))^{\xi}} \right)^{\frac{1}{1-\xi}}, \tag{29}$$

and $\mathbf{h}(\theta)$ summarizes the heterogeneity in the entrepreneurs profits in Equation (5).

Consumption-good market and the economy resource constraint

All agents consume the same amount at the end of each period. Aggregate demand for consumption goods is given by $C_t = \int_{\theta_{min}}^{\infty} c_t\ \mathbf{d}\ \mathbf{F}(\theta)$. The consumption-good market clearing condition is

$$Y_t^C = C_t, \tag{30}$$

where Y_t^C is the supply of consumption-goods as in Equation (20). Additionally, at the end of each period, profits by entrepreneurs, banks, and the consumption-good producers and wages are aggregated and redistributed equally across agents.

3 Equilibrium and its properties

In this section, we define the intratemporal equilibrium of the economy and characterize the properties of its solution. We then specify the law of motion of aggregate firm productivity and bank efficiency and derive the balanced growth path of the economy.

3.1 Timeline and intratemporal symmetric equilibrium

The model timing, for each date t, is as follows.

1. Given previous-period aggregate bank efficiency a_{t-1} and aggregate firm productivity z_{t-1} and the deposit rate r_d, each agent is assigned an individual ability θ drawn from a distribution on Θ, joins the risk sharing plan, and chooses to become an entrepreneur or worker.

2. Bank $j \in \{1, \ldots, n\}$ collects deposits $D_{j,t-1}$, purchases q_{jt} units of capital goods, transforms deposits into loans, and then competes *a la* Cournot in the loan market.

3. The entrepreneurs realize their abilities and repay the banks.

4. Profits and wages are collected and redistributed equally to all agents. All agents consume c_t and save d_t. The deposit, loan, labor, and capital-good markets clear, and aggregate firm productivity z_t and bank efficiency a_t are updated.

We can now define an intratemporal symmetric equilibrium as follows.

Definition 1 (Intratemporal symmetric equilibrium) *Given the previous-period deposit period d_{t-1}, aggregate bank efficiency a_{t-1} and aggregate firm productivity z_{t-1}, and the deposit rates r_d, for each period t, an intratemporal symmetric equilibrium consists of wage rate w_t, capital-good price p_t, bank demand of capital goods q_{jt}, unit cost of funds r_{jct}, deposit demand by banks $D_{j,t-1}$, total credit supply B_{jt}, individual consumption c_t and deposit d_t, redistributed income int_t, a threshold for occupation choice θ_t^*, labor demanded by the θ-type entrepreneur $l_t(\theta)$, corresponding loan rate $r_{lt}(\theta)$, loan recovery rate $x_t(\theta)$, loan supply $b_{jt}(\theta)$, and aggregate quantities $\{Y_t^C, C_t, Y_t^K, K_t, Q_t, L_t, B_t, E_t\}$ such that*

1. *Given w_t, p_t, $r_{lt}(\theta)$, $x_t(\theta)$, and θ_t^*, θ-type entrepreneur maximizes profits as in (2);*

2. *Given p_t, w_t, r_{jct}, and θ_t^*, bank j maximizes profits as in (9) under symmetry and then, given p_t and r_d, bank j minimizes its funding cost as in (16);*

3. *Given inc_t and r_d, all agents maximize their utility as in (6);*

4. *Given θ_t^*, the loan rate $r_{lt}(\theta)$ and the recovery rate $x_t(\theta)$ clears the loan market, the relative price of capital goods p_t clears the capital-good market, and the wage w_t clears the labor market.*

5. *The threshold θ_t^* solves the occupation choice problem.*

We solve this equilibrium in four steps. First, we solve the entrepreneurs' and agents' problems and derive the loan demand function, taking as given the price of capital goods, the wage rate, the loan rate, the recovery fraction, and the threshold of occupation choice. Second, we characterize the two-stage game played by banks, taking as given the price of capital goods, the wage rate, the loan demand function, and the occupation threshold. Third, given the threshold for occupation choice, we determine the equilibrium in the loan, deposit, labor, and capital-good markets. Finally, the occupation choice determines the threshold. Appendix B provides the details. Here, we discuss the properties of this equilibrium.

To provide intuition for the agents' trade-offs in their occupation choice, consider two polar cases. Suppose all agents choose to be workers, and no capital goods are produced. In this case, the price of capital goods is infinite, and the marginal benefit of being an entrepreneur also is infinity, inducing some agents to become entrepreneurs. Similarly, when all agents choose to be entrepreneurs, the wage rate goes to infinity, encouraging some agents to become workers. Thus, it must be the case that some agents choose to become workers while others are entrepreneurs. We first assume the existence of a threshold level of individual ability θ_t^* such that the marginal agents are indifferent between being workers or entrepreneurs and then use the fixed point theorem to verify the existence and uniqueness of such a threshold. Proposition 2 summarizes this result.

Proposition 2 (Existence and uniqueness of the occupation threshold) *Suppose banks are symmetric and Assumption (13) holds. Further assume that*

$$\eta\left(1+\mathbf{e}\left(\theta_{min}\right)\right) > \xi\left(\eta\theta_{min}+(1-\eta)\underline{\theta}\right)\mathbf{e}'\left(\theta_{min}\right). \tag{31}$$

Then, for any $\{a_{t-1}, z_{t-1}, r_d\}$, there exists a unique θ_t^*, such that

$$\pi_t^E\left(\theta_t^*\right) = w_t, \tag{32}$$

such that for $\theta > \theta_t^*$, $\pi_t^E(\theta) > w_t$, whereas $\pi_t^E(\theta) < w_t$ for $\theta < \theta_t^*$.
Proof: see Appendix B.2.

Assumption (31) ensures that the function $\mathbf{h}(\theta)$, defined in Equation (29), is increasing. Substituting for the unit funding cost from Equation (19) and the wage rate from Equation (26) into the agents' arbitrage condition (32), we have that the threshold of occupation choice must satisfy the following condition:

$$\frac{\xi}{1-\xi}\left(1-\frac{1-\xi}{n}\right)\frac{\mathbf{G}(\theta_t^*)}{\mathbf{F}(\theta_t^*)\,\mathbf{h}(\theta_t^*)}=\frac{1}{\gamma}\left(\frac{z_{t-1}}{a_{t-1}}\frac{p_t}{\nu}\right)^{\nu}\left(\frac{1+r_d}{1-\nu}\right)^{1-\nu}, \tag{33}$$

where from the market clearing condition (28), p_t is given by

$$p_t=\alpha\left(\left(1-\xi\nu\left(1-\frac{1-\xi}{n}\right)\right)\left(\frac{\mathbf{F}(\theta_t^*)}{\mathbf{G}(\theta_t^*)}\right)^{\xi}\mathbf{H}(\theta_t^*)\,z_{t-1}\right)^{-(1-\alpha)}. \tag{34}$$

Equation (33) determines how a_{t-1}, z_{t-1}, r_d, n, and ν affect the occupation choice. This threshold, in turn, determines all other endogenous variables, including wage rate, price of capital goods, unit funding cost, and loan rate. The next proposition summarizes the critical comparative statics that drive the model properties.

Proposition 3 (Comparative statics of the occupation choice threshold) *Suppose that banks are symmetric, Assumption (13) and (31) hold, and the occupation choice threshold is determined by Equation (33). We have*

$$\frac{\partial\,\theta_t^*}{\partial\,r_d}<0,\quad \frac{\partial\,\theta_t^*}{\partial\,a_{t-1}}>0,\quad \frac{\partial\,\theta_t^*}{\partial\,z_{t-1}}<0,\quad \textit{and}\quad \frac{\partial\,\theta_t^*}{\partial\,n}>0. \tag{35}$$

Moreover, there exist a factor share of capital goods $\hat{\nu}\in(0,1)$, such that

$$\frac{\partial\,\theta_t^*}{\partial\,\nu}\begin{cases}\le 0 & for\ \nu\le\hat{\nu}\\ >0 & for\ \nu>\hat{\nu}.\end{cases} \tag{36}$$

Proof: see Appendix B.3.

To provide intuition, rewrite the arbitrage condition in Equation (33) as

$$\pi^E(\theta_t^*)=w_t\quad or\quad \underbrace{\underbrace{\left(\frac{1}{\xi}-1\right)}_{net\ markup}\ \underbrace{\overline{(1+r_{lt}(\theta^*))w_t}}_{marginal\ cost\ of\ labor}}_{marginal\ profit\ of\ entrepreneur}\ \underbrace{\mathbf{F}(\theta_t^*)\frac{\mathbf{g}(\theta_t^*)}{\mathbf{G}(\theta_t^*)}}_{labor\ demand}=w_t. \tag{37}$$

The expected profit from being an entrepreneur depends on three factors: the firm's net markup, the marginal cost of labor, and the labor demand given by the the roduct of $\mathbf{F}(\theta_t^*)$ (the total labor supply) and $\mathbf{g}(\theta_t^*)/\mathbf{G}(\theta_t^*)$ (the share of labor employed by the type-θ^*

entrepreneurs). The product of the first two terms in Equation (37) is the marginal profit of the type-θ^* entrepreneurs. In equilibrium, the agents' occupation choice only depends on the *expected* gross loan rate, which determines the *relative* income of the marginal agent. For a given wage, a lower loan rate lowers the entrepreneurs' profits relative to workers' wage rate, inducing less able agents to choose to be workers, increasing the threshold of occupation choice, and increasing aggregate productivity.

The wage rate affects both entrepreneurs' marginal profit and worker income in the same way. A decrease in the loan rate reduces entrepreneurs' marginal cost. With a fixed markup, this leads to a lower marginal profit for entrepreneurs. While more productive entrepreneurs respond by expanding labor demand to increase total profits (thereby driving up the equilibrium wage rate with higher labor demand), this adjustment makes operating a business less attractive for marginal agents near the initial occupation choice threshold. Consequently, these agents switch to working for wages, leading to an increase in the occupation choice threshold and higher aggregate productivity. In other words, the occupation choice depends on relative rather than absolute income. Although lower loan rates increase profits in absolute terms (through reduced financing costs), they also raise the opportunity cost of entrepreneurship because the equilibrium wage rate rises via general equilibrium effects.

As the previous-period aggregate bank efficiency a_{t-1} increases, or the deposit rate r_d decreases, the unit funding cost declines so that entrepreneurs can borrow at a lower rate. Lower borrowing costs allow entrepreneurs to produce and hire more, increasing the wage. As the expected gross loan rate declines, the marginal profit of entrepreneurs rises relatively less than the wage. Hence, some less able agents choose to become workers, and θ^* increases. As aggregate firm productivity z_{t-1} increases, capital-good production, wages, and loan demand rise, leading to an increase in the expected loan rate. Thus, the marginal profit of entrepreneurs rises relatively more than the wage. Thus, some less able agents choose to be entrepreneurs, and θ^* decreases. As the number of banks n in the system increases, market power in the loan market declines, leading to a lower expected loan rate. Thus, some less able agents choose to be workers, and θ^* increases.

The intuition for the comparative statics in Equation (36), which drives the simulations that we report below, is more complex. Suppose first that the price of capital goods is fixed. Increasing the factor share ν of capital goods in Equation (17) and (18) raises the "marginal product" of capital goods in transforming deposits into loans. In equilibrium, to produce one unit of loans, banks substitute deposits for capital goods. However, the impact of this structural change on the unit funding cost of banks depends on the "elasticity" of capital goods adoption by banks with respect to ν, i.e., $\Delta \log q_{jt}/\Delta \log \nu$, which we call adoption elasticity and is the percentage increase in capital goods adoption for one percent increase in ν. If this elasticity is greater than one, a higher ν requires banks to spend more on capital goods than they save on deposits, leading to a higher unit funding cost. If this elasticity is equal to or less than one, the unit funding cost decreases as ν increases.

To analyze how this adoption elasticity responds to a changing value of ν. Consider first the case in which banks do not adopt any capital goods, i.e., $\nu = 0$. In this case, the marginal product of an additional unit of capital goods is infinite, meaning that a small increase in the share leads to an infinite percentage increase in capital goods adopted, resulting in an infinite adoption elasticity. When the quantity of capital goods increases further, the marginal product decreases, causing the adoption elasticity to decline as the share increases. When the share approaches one, where banks predominantly rely on technology to transform deposits, a one percent increase in the share barely results in any increases in capital adoption due to the relatively low marginal product. Consequently, the adoption elasticity approaches zero. As a result, when ν is sufficiently small, the adoption elasticity is greater than one, leading to a higher unit funding cost, which, in turn, raises the loan rate and lowers the threshold for occupation choice. In contrast, when ν is sufficiently high, a higher share leads to a lower unit funding cost and also a lower loan rate, thereby increasing the threshold for occupation choice.

Let's now return to the case in which the relative price of capital goods can change. As banks demand more capital goods, the relative price of capital increases, which pushes up the marginal cost of adopting more capital goods. The mechanism described above remains in play, but compared to the case in which the relative price of capital is fixed, it raises the threshold for ν above which the adoption elasticity is equal to one. As we shall see below, the value of ν that we estimated from micro-level data is above the threshold such that when ν increases, the threshold for occupation choices increases.

3.2 Intertemporal equilibrium and balanced growth path

We now derive and discuss the model's balanced growth path (BGP). We first specify the law of motion for z_t and a_t, and then derive the economy's BGP. Following Melitz (2003) and Perla and Tonetti (2014), we posit that the aggregate firm productivity at the end of period t is given by the average ability of the entrepreneurs in the economy:

$$z_t(\theta_t^*) \equiv \frac{1}{1-\mathbf{F}(\theta_t^*)}\int_{\theta_t^*}^{\infty}(\eta\theta + (1-\eta)\underline{\theta})\,z_{t-1}\,\mathbf{d}\,\mathbf{F}(\theta) = \Big(\eta\mathbf{E}(\theta|\theta \geq \theta_t^*) + (1-\eta)\underline{\theta}\Big)z_{t-1}, \qquad (38)$$

where $\mathbf{E}(\theta|\theta \geq \theta_t^*)$ is the conditional average ability of entrepreneurs. Thus, the aggregate firm productivity evolves endogenously at a rate that depends on the occupation choice threshold. As the threshold rises, only more able agents choose to become entrepreneurs, and aggregate productivity growth increases. Similarly, we posit that aggregate bank efficiency is given by

$$a_t(\theta_t^*) \equiv \frac{\tau}{n}\sum_j a_{jt} = \tau \frac{a_{t-1}}{z_{t-1}} q_{jt}, \tag{39}$$

where τ is a scale parameter and the second equality derives from Equation (15) under symmetry.

Substituting the relative price of capital goods from Equation (34) in the bank j demand for capital goods in Equation (17), we have

$$q_{jt} = \frac{\nu\xi}{n}\left(1 - \frac{1-\xi}{n}\right)\left(\frac{\mathbf{F}(\theta_t^*)}{\mathbf{G}(\theta_t^*)}\right)^{\xi} \mathbf{H}(\theta_t^*) z_{t-1}. \tag{40}$$

Thus, the aggregate bank efficiency defined in Equation (39) becomes

$$a_t(\theta_t^*) = \frac{\tau\nu\xi a_{t-1}}{n}\left(1 - \frac{1-\xi}{n}\right)\left(\frac{\mathbf{F}(\theta_t^*)}{\mathbf{G}(\theta_t^*)}\right)^{\xi} \mathbf{H}(\theta_t^*). \tag{41}$$

Equation (41) implies that the aggregate bank efficiency depends on the occupation choice threshold θ_t^* and the previous-period aggregate bank efficiency a_{t-1} and aggregate firm productivity z_{t-1}. We can now characterize the BGP of our economy.

Proposition 4 (Balanced growth path existence and uniqueness) *Denote the gross rate of growth of aggregate firm productivity and bank efficiency as $g_{zt}(\theta_t^*) = z_t(\theta_t^*)/z_{t-1}$ and $g_{at}(\theta_t^*) = a_t(\theta_t^*)/a_{t-1}$, respectively, where $z_t(\theta_t^*)$ and $a_t(\theta_t^*)$ are defined in Equation (38) and (41), respectively. Assuming that the economy starts in period $t = 1$ and Assumption (13) and (31) hold, for any $\{a_0, z_0\}$, there exists a threshold θ^* so that solves Equation (33) evaluated at $\{a_0, z_0\}$, and the economy evolves along the following BGP:*

1. $g_z(\theta^*) = \eta\mathbf{E}(\theta|\theta \geq \theta_t^*) + (1-\eta)\underline{\theta}$;

2. *there exists a $\tau > 0$ so that $g_a = g$, where $g = g_z^{\alpha}(\theta^*)$ and $a_t/z_t^{\alpha} = a_0/z_0^{\alpha}$ for $\forall$ $t>0$;*

3. *the occupation choice threshold θ_t^* is constant at θ^*;*

4. *the unit funding cost r_{jct}, the lending rate $r_{lt}(\theta)$, and the recovery rate $x_{jt}(\theta)$ for any type-θ entrepreneur are constant;*

5. *the production of capital goods Y^K, and the quantity of capital goods purchased by the final-good producer (K_t) and banks (Q_t) grow at the gross rate $g^{1/\alpha}$, while the price of capital goods contracts at the gross rate $g^{1-1/\alpha}$;*

6. *the aggregate deposit volume d_t, final-good production Y_t^C, aggregate consumption C_t, the wage rate w_t, the profits of type-θ entrepreneur $\pi_t^E(\theta)$, total income inc_t, and the bank's profits lending to the entrepreneur $\pi_{jt}^B(\theta)$ also all grow at the gross rate of g.*

Proof: see Appendix B.4.

Note here that, along the BGP, both aggregate bank efficiency and firm productivity increase. Proposition 3 implies that, on the one hand, higher aggregate firm productivity increases loan demand and lending rates, which create a 'push' effect on the threshold for occupation choice. On the other hand, more efficient banks offer borrowers lower lending rates, and this generates a 'pull' effect on the threshold for occupation choice. Along the BGP, the ratio of aggregate bank efficiency to (share-adjusted) aggregate firm productivity, a_t/z_t^α, remains constant to satisfy Equation (33). This ensures that the two opposing forces offset each other, keeping also the threshold for occupation choice and the expected loan rate constant along the BGP.

It is straightforward to show that g_z increases with the threshold of occupational choice. As more able agents choose to become entrepreneurs, the average ability of entrepreneurs in the economy rises, leading to higher aggregate productivity growth. Additionally, the scale parameter τ in Equation (15), as well as in the second property of the BGP equilibrium, ensures that the growth rate of bank efficiency matches the GDP growth rate.

4 Model estimation

In this section, we estimate the model. We first discuss functional form assumptions and the calibration of the parameters that can be directly pinned down from the data or have values commonly used in the literature. Next, we discuss the estimation of the remaining parameters. The full set of model parameters is

$$\{\alpha,\ \beta,\ \gamma,\ \eta,\ r_d,\ z_0,\ \nu,\ \xi,\ \psi,\ \theta_{min},\ \underline{\theta},\ \sigma,\ n,\ \tau,\ a_0,\ z_0\}.$$

Table 1 reports their calibrated or estimated values together with the moments they target. Since we want to estimate the economy's BGP, whenever we use data, the sample is the "earliest available start-year" to 2019. The proprietary bank-level data on IT expenditure that we use to calibrate γ, estimate ν, and calibrate our counterfactual simulation in the next section of the paper is only available from 2010 to 2019.

We assume that the agents' individual ability follows a Pareto distribution with CDF

$$\mathbf{F}(\theta) = 1 - \left(\frac{\theta_{min}}{\theta}\right)^{\psi}, \tag{42}$$

where ψ is the curvature parameter. Thus, firm size roughly follows the 'Zipf's law' as in Axtell (2001) and Gabaix (2016). Consistent with the solution to the micro-founded bank contract in Appendix A, we assume that the verification effort per unit of loan is

$$\mathbf{e}(\theta) = (1-\eta)\sigma\left(\frac{\eta(\theta - \underline{\theta})}{(1-\xi)(\eta\theta + (1-\eta)\underline{\theta})} - 1\right). \tag{43}$$

We calibrate the parameters $\{\alpha, \beta, \gamma, \eta, r_d, \kappa, z_0\}$. The capital share in final goods production is set to 0.42, and the discount factor to 0.984, within the range of typical values in the literature. The probability of successful project realization, η, is set to 0.973, matching a 2.7% average annual delinquency rate on business loans from 1987 to 2019, as reported by the Board of Governors of the Federal Reserve System (series code: DRBLACBS). We set the deposit rate, r_d, to 1.65%, equal to the average 3-month treasury bill rate from 1984 to 2019 (series code: DTB3), deflated by the consumer price index. Finally, we normalize initial aggregate firm productivity, z_0, to one.

Next, we calibrate γ and estimate ν using proprietary micro-data on banks' IT budgets from Harte Hanks Market Intelligence Computer Intelligence Technology data (CiTDB hereafter), which we also use in the empirical analysis in Section 6. According to Equation (14), if there is no bank technology adoption (i.e., $\nu = 0$), the loan-to-deposit ratio equals γ. Using our matched Call-Report-CiTDB data, we calibrate γ to 0.77, which corresponds to the asset-weighted average loan-to-deposit ratio in the first quartile of the distribution of *IT expense intensity* (i.e., IT expenses to non-interest expenses). In our dataset, the asset-weighted average IT expense intensities in the first, second, third, and fourth quartiles are 0.005, 0.013, 0.034, and 0.236, respectively. We focus on the first quartile as the average IT intensity is close to zero, allowing us to directly infer a value for γ from the raw data.[10]

Based on Equation (14), we estimate ν by regressing the log of the bank loan-to-

[10] In the second, third, and fourth quartiles, the asset-weighted average loan-to-deposit ratios are 0.79, 1.09, and 1.16, respectively. Values bigger than one suggest that high IT-intensity banks use other funding sources in addition to deposits—something we abstract from in this paper.

Table 1
Parameter Values and Data Moments

	Name	Value	Target
Calibrated parameters			
α	Capital share in final-good production	0.420	US aggregate capital share
β	Discount factor	0.984	$1/(1+r^d)$
γ	Parameter governing loan-to-deposit ratio	0.771	Loan-to-deposit ratio for lowest IT-adopted banks
η	Prob. of project success	0.973	Average delinquency rate in 1987-2019
r_d	Real deposit rate	1.65%	3-month treasury bill rate in 1984-2019
z_0	Initial productivity along BGP	1	Normalized to one
Estimated parameter from microdata			
	Name	**Value**	
ν	Share of capital goods adopted by banks in funds transformation	0.06%	
Estimated parameters with method of moments			
	Name	**Value**	
ξ	Labor share in capital goods production	0.800	
ψ	Shape parameter for ability distribution	9.341	
θ_{min}	Lower bound of Θ	0.753	
$\underline{\theta}$	Common value of θ when project fails	0.380	
σ	Scale parameter in the verification technology	0.536	
n	Number of banks	11	
τ	Scale parameter for growth rate of bank efficiency	3.73E(+4)	
a_0	Initial bank efficiency along BGP	1.39E(+210)	
Targeted moments			
	Moments	**Model**	**Data**
	CFI	1.89%	1.89% (1965-2019 average in Philippon (2015)
	Growth of productivity implied by BGP	4.85%	4.83% ($g^{1/\alpha}$ implied by BGP)
	Growth of bank efficiency implied by BGP	2.01%	2.00% (g implied by BGP)
	Average loan recovery rate	47.65%	47.65% as in Altman and Kishore (1996)
	Expected loan rate	4.08%	5.73% 1984-2019 average real bank prime loan rate
	Capital adequacy ratio	4%	4% Tier 1 capital ratio required by Basel II
	Share of entrepreneurs	11.10%	11.20% as in Holter, Stepanchuk and Wang (2023)
	Elasticity of firm share wrt to size	2.06	2.06 as in Gabaix (2016)

deposit ratio on the log of the IT-expense-to-deposit ratio:

$$\log \frac{B_{jt}}{D_{j,t-1}} = \nu \log \frac{q_{jt}}{D_{j,t-1}} + \omega_t + \zeta_j + \epsilon_{jt}, \tag{44}$$

where ω_t and ζ_j are time and bank fixed effects, respectively. We run the regression with annual data from 2010 to 2019, consistent with our other bank-level evidence in Section 6, and find a point estimate of 0.06%, statistically significant at the 99% level, and a value that is very close to the median IT expense intensity, which is 0.066%. Table D.2 in Appendix D reports the details, including a robustness check on the specification in Equation (15), which assumes that individual bank efficiency is linear in the quantity of capital goods adopted by banks.

We estimate the remaining eight parameters and the threshold for the occupation choice using the method of moments with equal weighting as there is no simulation uncertainty.[11] Unfortunately, we do not directly observe bank efficiency in the data. As a proxy, we use the cost of financial intermediation (CFI) in Philippon (2015), which is defined as the ratio of bank value added relative to total intermediated assets. We target CFI at 1.89%, the average observed between 1965 and 2019. In the model, bank value added coincides with profits, while total intermediated assets correspond to total loans. Thus, the model-based CFI is

$$\phi \equiv \frac{\Pi_t^B}{\int_{\theta^*}^{\infty} b(\theta) \mathbf{d}\, \mathbf{F}(\theta)} = \frac{\xi}{n} \frac{\mathbf{G}(\theta_t^*)}{\mathbf{F}(\theta_t^*)\mathbf{h}(\theta_t^*)}, \tag{45}$$

where $\Pi_t^B = \sum_j \pi_{jt}^B = n \int_{\theta_t^*}^{\infty} \pi_{jt}^B(\theta)\ \mathbf{d}\ \mathbf{F}(\theta)$, and $b(\theta)$ is borrowing by the type-θ entrepreneurs in Equation (4), $\mathbf{G}(\theta_t^*)$ is the aggregator of heterogeneity in labor demand in Equation (27), and $\mathbf{h}(\theta_t^*)$ is the the heterogeneity factor in entrepreneurs' profits in Equation (29). It is straightforward to show that ϕ_t is decreasing in the threshold of occupation choice, as $\mathbf{G}(\theta_t^*)$ is decreasing in θ_t^* while $\mathbf{h}(\theta_t^*)$ is increasing in θ_t^* under Assumption (13). Recall also that ϕ_t is constant along the BGP, consistent with the finding in Philippon (2015) that the CFI for the whole US financial industry is roughly constant over the the past century.

Using Equation (38) and (41), the gross growth rate of aggregate firm productivity and aggregate bank efficiency can be expressed as, respectively,

$$g_z = \frac{z_t}{z_{t-1}} = \frac{\eta\psi}{\psi - 1}\theta_t^* + (1-\eta)\underline{\theta}, \tag{46}$$

and

$$g_a = \frac{a_t}{a_{t-1}} = \frac{\tau\nu\xi}{n}\left(1 - \frac{1-\xi}{n}\right)\left(\frac{\mathbf{F}(\theta_t^*)}{\mathbf{G}(\theta_t^*)}\right)^{\xi} \mathbf{H}(\theta_t^*). \tag{47}$$

We target an annual growth rate of real GDP per capita as in Equation (20) of 2% along the BGP, obtained by regressing log of real GDP per capita on a constant and a linear trend from 1950 to 2019. Proposition 4 implies that aggregate bank efficiency must grow at the same rate, i.e., $g_a = 1.02$, while the growth of aggregate firm productivity in the capital-good sector is 4.83%, i.e., $g_z = 1.048$, consistent with the evidence in Caliendo, Parro, Rossi-Hansberg and Sarte (2018).

[11] The model-implied moments and the associated parameters are summarized in Table D.1 in Appendix D, showing this is an exactly identified system of simultaneous equations from which is hard to isolate which moment identifies each parameter.

Using Equation (11) and (12), the average recovery rate in the model is,

$$\bar{x} = \frac{1}{1-\mathbf{F}(\theta^*)}\int_{\theta^*}^{\infty} x(\theta)\,\mathbf{d}\,\mathbf{F}(\theta) = \frac{\underline{\theta}(1+r_{jc})}{\xi\,(1-\mathbf{F}(\theta^*))\left(1-\frac{1-\xi}{n}\right)}\int_{\theta^*}^{\infty}\left(\frac{1}{\mathbf{g}(\theta)}\right)^{1-\xi}\mathbf{d}\,\mathbf{F}(\theta), \tag{48}$$

where $x(\theta)$ is solved from Equation (11) and r_{jc} is solved in Equation (19). We target a value of 47.65% that is the average rate for senior unsecured loans from 1982-1995 in Altman and Kishore (1996) and implies a loss-given-default of 52.35%. The average of the expected gross loan rate in Equation (10) is given by:

$$\frac{\int_{\theta^*}^{\infty}\overline{1+r_{lt}(\theta)}\,\mathbf{d}\,\mathbf{F}(\theta)}{1-\mathbf{F}(\theta^*)} = \frac{(1+r_{jct})\int_{\theta^*}^{\infty} 1+\mathbf{e}(\theta)\,\mathbf{d}\,\mathbf{F}(\theta)}{(1-\mathbf{F}(\theta^*))\left(1-\frac{1-\xi}{n}\right)}. \tag{49}$$

We target it at 5.73%, an average real bank prime loan rate from 1984 to 2019 based on data from the Board of Governors of the Federal Reserve System (series code: DPRIME).

For simplicity, we do not explicitly consider banks' balance sheets and their capital adequacy policy in the model derivations. However, to aid the model's estimation, we add a capital requirement constraint that is assumed to be binding exactly along the BGP. Equation (18) establishes a relationship between banks' assets and liabilities. Thus, the implied capital adequacy ratio by bank j, which is constant along the BGP, can be expressed as:

$$\mathrm{CAR}_{jt} = \frac{B_{jt}-D_{j,t-1}}{\kappa B_{j,t}} = \frac{1}{\kappa}\left(1-\frac{1}{\gamma}\left(\frac{1-\nu}{\nu}\frac{z_{t-1}}{a_{t-1}}\frac{p_t}{1+r_d}\right)^{\nu}\right), \tag{50}$$

where B_{jt} is the lending by bank j, $D_{j,t-1}$ is the deposits collected by bank j, and κ is a scale parameter accounting for risk weighting. We target a capital adequacy ratio of 4% as in Corbae and D'Erasmo (2021), which is the Tier 1 capital adequacy ratio mandated under Basel II. Given the assumed 2.7% probability of default and 52.35% loss-given-default, we then calibrate κ to 0.646 by following the BIS internal ratings-based approach.[12]

The model-implied share of entrepreneurs in the population, $1-\mathbf{F}(\theta^*)$, is targeted at a value of 11.2% as in Holter, Stepanchuk and Wang (2023). Given $\mathbf{F}(\theta)$ in Equation (42), the log of the firm-size density is

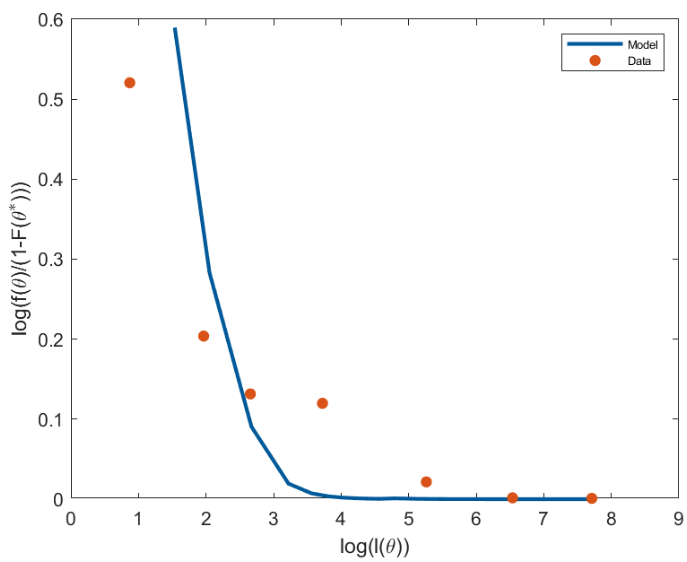
$$\log\left(\frac{\mathbf{f}(\theta)}{1-\mathbf{F}(\theta_t^*)}\right) = \log\psi + \log\theta^* - (1+\psi)\log\theta. \tag{51}$$

[12] See here for details: https://www.bis.org/basel_framework/chapter/CRE/31.htm.

Using Equation (3), we can then express the log of the firm size by employment as

$$\log l(\theta) = \log \mathbf{F}(\theta^*) - \log \mathbf{G}(\theta^*) + \frac{1}{1-\xi} \log \left(\frac{\eta\theta + (1-\eta)\underline{\theta}}{1 + (1-\eta)\mathbf{e}(\theta)} \right), \tag{52}$$

which is non-linear in $\log\theta$. Axtell (2001) and Gabaix (2016) estimate a slope of -2.06 in the linear relationship between the log of firm-size density and the log of the firm size. In our model, the corresponding moment is $\Delta \log(\mathbf{f}(\theta)/(1-\mathbf{F}(\theta_t^*)))/\Delta \log l(\theta)$. We assume that the last term of Equation (52), $\log((\eta\theta + (1-\eta)\underline{\theta})/(1+(1-\eta)\mathbf{e}(\theta))$, is close to $\log\theta$. This simplifies the expression for the slope moment to $-(1+\psi)(1-\xi)$, which we target at -2.06.[13] We then empirically check the assumption made and find that it is not violated in our simulation, conditional on the other estimated parameters. Specifically, we first use the estimated parameters to compute the implied firm size distribution (labor employed by each type-θ entrepreneur) and the corresponding density. We then regress the log of the firm-size density on a constant and the log of the firm size. The point estimate is -2.11, which is very close to the target.



Notes: The figure compares the firm-size distribution generated by the model (blue line) with the empirical distribution (red dots). The y-axis is the log of the firm-size density as defined in Equation (51). The x-axis is the log of the firm size (labor employed by each type-θ entrepreneur) as defined in Equation (52).

Figure 1

Firm size distribution - comparing model and data

[13] Alternatively, one could take a linear approximation of $\log((\eta\theta + (1-\eta)\underline{\theta})/(1+(1-\eta)\mathbf{e}(\theta))$ and express it as a function of $\log\theta$, but the model-implied slope would be sensitive to the reference point chosen for the approximation.

The remaining eight estimated parameters minimize the following criterion, conditional on the threshold of occupation choice solving Equation (33):

$$\min_{\xi,\,\psi,\,\theta_{min},\,\underline{\theta},\,\sigma,\,n,\,\gamma,\,\tau,\,\theta^*} \sum_i \frac{|\text{model}(i)-\text{data}(i)|}{|\text{model}(i)|+|\text{data}(i)|} \quad s.t. \quad \theta^* \text{ solves equation (33)}, \tag{53}$$

where i indexes the ith moment. The third panel of Table 1 reports the estimated values and the matched moments. The model matches all data moments quite closely, except for the expected loan rate, which is underestimated.[14]

The firm-size distribution is not targeted in estimation, and we use it for evaluation purposes. Figure 1 compares the firm-size distribution generated by the model (blue line) with the empirical distribution (red dots). The empirical firm-size distribution is computed based on the Business Dynamics Statistics (BDS) data, using establishment size as a proxy for firm size in the model. The model-based firm-size distribution is obtained by solving the model on a grid of 10^7 points, which are equally spaced on the CFD of θ. Firms are then grouped into bins of varying widths, with smaller bin widths assigned to smaller firms and progressively larger bin widths used for larger firms. Specifically, firms with 1 to 10 employees are grouped into two bins with a width of 5: [1-5] and [6-10]. Firms with 11 to 100 employees are assigned to bins with a width of 10, those with 101 to 500 employees are assigned to bins with a width of 50, and those with 501 to 5000 employees to bins with a width of 100. The frequencies within each bin are then aggregated to facilitate the analysis. Figure 1 shows that the model-generated distribution closely aligns with the empirical data, including capturing the tail of the distribution to some extent. Additional empirical validation of the model's implications for the firm-size distribution with BDS data will be presented in the last section of the paper.

5 Quantifying bank technology adoption

In this section, we counterfactual simulate the impact of higher bank technology adoption and illustrate its general equilibrium effects. We consider an increase in the share of capital goods in the loan production function. We first illustrate the mechanisms at work by plotting the sequence of intratemporal equilibria as in Proposition 2. We then evaluate the long-term growth impacts of this structural change along the new BGP.

[14]Note here that the model-generated firm-size distribution may not have a well-defined standard deviation or skewness because the target shape parameter estimated in Axtell (2001) and Gabaix (2016) is less than 3. We compute these moments as specified in Equation (54), truncating the distribution's support at 5,000 employees, consistent with the BDS data. This limitation also explains why we do not use these moments as estimation targets.

5.1 Transmission mechanisms

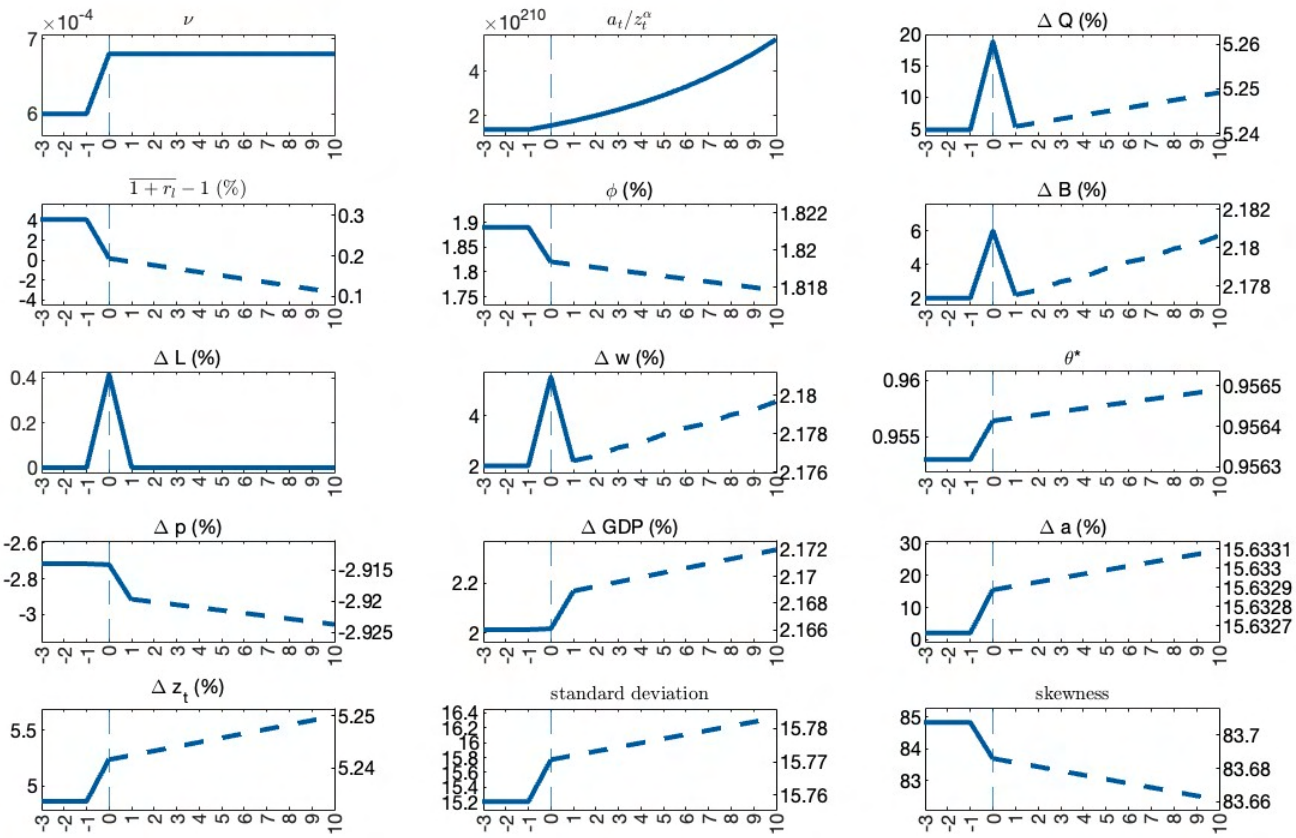
In this counterfactual, we increase the share of capital goods used in the loan production function, ν, from 0.06% to 0.07%, without changing any other parameter. This change represents a shift from the *average* factor share as estimated in our baseline model to the level estimated for banks in the top half of the IT expense intensity distribution. To pin down the new value from bank-level data, we re-estimate Equation (44) by adding an interaction term between the log of the IT-expense-to-deposit ratio and a dummy variable equal one for banks that are in the top half of the IT expense intensity distribution—see Appendix D for details. Thus, assuming that the economy is in BGP until period -1, at time $t = 0$, we permanently increase ν from 0.06% to 0.07% without further changes. We then let the economy evolve for ten periods, consistent with Proposition 2. Figure 2 reports the simulation results.

In the estimated model, the cutoff point for the adoption share $\hat{\nu}$ in Proposition 3 is 4.49E(-150), much smaller than the estimated value of ν. As a result, consistent with Proposition 3, in period $t = 0$, increasing ν to 0.07% leads to more capital goods adoption (ΔQ as in Equation 40), increasing bank efficiency (a_j as in Equation 15), lowering the funding cost ($1 + r_{jc}$ as in Equation 19), the expected loan rate ($\overline{1 + r_{lt}}$ as in Equation 49), and the CFI (ϕ as in Equation 45). The number of banks is constant in the model and affects both their pricing power and market share. While the loan rate reflects the former, the CFI captures both pricing and market power, which explains why the CFI declines much less than the average of expected loan rate in period 0.

A lower expected loan rate induces more capital goods production, leading to higher growth in loan (ΔB as in Equation 25) and labor demands (ΔL where $L = \mathbf{F}(\theta_t^*)$) and the wage rate ($\Delta w$ as in Equation 26). As the expected loan rate declines, the expected profits of entrepreneurs at the margin ($\pi^E(\theta_t^*)$) increase less than the wage (w_t), and less able agents choose to become workers, with θ^* increasing. Given the right-skewed firm-size distribution, at $t = -1$, a higher threshold shifts the distribution further to the right, resulting in an increase in its standard deviation and a decrease in its skewness, as defined in Equation (54) below.

Additionally, agents who choose to be entrepreneurs borrow more and produce significantly more. However, given that their technology is constrained by previous period aggregate firm productivity z_{t-1}, this produces only a slight acceleration in the relative price of capital goods decline (Δp, as in Equation 34, barely visible in Figure 2). The small decrease in the input costs for the final-good producer leads to only a slightly higher GDP growth in period 0 (Y_t^C as in Equation 20).

At the end of period 0, both aggregate bank efficiency and firm productivity are higher



Notes: The figure illustrates the economy's response to an increase in ν. The economy is on the initial BGP path until period -1. At $t = 0$, the value of ν increases from 0.06% to 0.07%. From this point on, the economy evolves for ten periods, consistent with Proposition 2. All dashed lines after period 0 are scaled on the right axis. Aggregate firm productivity and bank efficiency follow the dynamics outlined in Equation (38) and (41), respectively. Capital goods adoption by banks is solved from Equation (40). Equation (49) solves the expected loan rate. The CFI is solved in Equation (45). The total volume of loans is solved using Equation (25). Labor in equilibrium is represented by $\mathbf{F}(\theta^*)$. Wages are solved using Equation (26). The threshold for occupation choice is solved using Equation (33). The price of capital is determined by Equation (34). GDP is measured by the final outputs. The growth rates of aggregate bank efficiency and productivity are derived from Equation (47) and (46), respectively. The standard deviation and the skewness of the firm-size distribution are calculated as in Equation (54), using all grid points in the simulation.

Figure 2
Economy Response to Higher ν

than in period $t = -1$, along the initial BGP. Moreover, aggregate bank efficiency increases much more than aggregate firm productivity at 15.6% and 5.2%, respectively. As a result, at the end of period 0, the ratio of aggregate bank efficiency to aggregate firm productivity a_0/z_0^α is higher than in the initial BGP or the new BGP associated with $\nu = 0.07\%$. Additionally, since we are keeping all other parameters constant, including the scaling factor for aggregate efficiency τ in Equation (41), this ratio continues to increase over time steadily, and the economy cannot converge to the new BGP associated with $\nu = 0.07\%$.

The growth differential between aggregate bank efficiency and firm productivity at the end of period 0 has another implication. In the model, the expected gross loan rate is affected by both credit demand and supply. On the one hand, higher aggregate firm productivity increases loan demand, which raises the loan rate above its period 0 level. On the other hand, more efficient banks offer borrowers a lower lending rate compared to the period 0 level. Since aggregate bank efficiency at $t = 0$ grows significantly more than aggregate firm productivity, the latter effect dominates, resulting in an expected loan rate and a CFI that declines further, albeit only slightly, in period 1, after a sharp decline in period 0, continuing to decline indefinitely, driven by the steady increase in a_0/z_0^{α}.

In period 1, a lower loan rate continues to stimulate production, leading to slightly faster growth in loan and labor demands and in the wage rate. With a lower expected loan rate, less able entrepreneurs exit and choose to become workers, and θ^* increases. Boosted by significantly higher previous-period aggregate firm productivity z_0, capital goods output growth outpaces demand growth in the banking sector, and the relative price of capital markedly declines. This lowers the production costs in the final goods sector, and economy-wide GDP growth takes off.[15]

Moreover, lower capital goods prices encourage banks to adopt more capital goods, resulting in even higher bank efficiency and further reductions in expected loan rates in the future. This creates a positive feedback effect that sustains the acceleration of growth. As the figure shows, the dynamics after period 1 continue indefinitely because, as we have noted, all other parameters are constant, and the economy is not recalibrated to converge to its new BGP, to which we turn next. This implies that the simulation plotted in Figure 2 does not represent the transition dynamics but rather describes the implications of the counterfactual structural change through a sequence of intratemporal equilibria, as in Proposition 2.

5.2 Long-run impacts

We now evaluate how the long-run moments of the economy change when we permanently increase the share of capital goods in loan production and allow the economy to move from the initial to a new BGP. In this counterfactual, consistent with Proposition 4, unlike in Figure 2, we recalibrate τ to evaluate the long-term impact of increased bank technology adoption on the new BGP. To isolate and quantify the importance of bank

[15] As the changes from period one onward are much smaller than those in period 0, these model responses (dashed blue-lines) are scaled on the right axis.

technology adoption, we also simulate an exogenous increase in bank technology of comparable magnitude.

Table 2
Higher Bank Technology Adoption: Comparing Balanced Growth Paths

	Baseline (1)	Higher ν (2)	Higher γ and $\nu = 0$ (3)
Growth rate of GDP	2.01%	2.17%	2.06%
CFI	1.89%	1.82%	1.87%
Average of expected loan rate	4.08%	0.19%	2.92%
SD of firm-size distribution	15.21	15.77	15.37
Skewness of firm-size distribution	84.8	83.7	84.5

Note: The table reports long-run moments along the baseline and counterfactual BGPs. Column (1) reports the baseline BGP, as estimated in Section 4. In Column (2), ν is increased from 0.06% to 0.07%, and τ is reduced by 14.1% as required in Proposition 4. In Column (3), ν is set to zero and γ is increased so that, in period 0, the term γa_{jt}^{ν} in Equation (14) matches the same level in Column (2). The growth rate of GDP is equal to g_z^{α}, where g_z is defined in Equation (46). The CFI is solved in Equation (45). The average of expected loan rate $\overline{1+r_l}-1$ is defined in Equation (49). The standard deviation and skewness of the firm-size distribution are defined in Equation (54), using all grid points in the simulation.

Column (1) of Table 2 reports selected moments of the baseline BGP as in Table 1. Column (2) reports the counterfactual moments. Increasing the capital goods share in loan production from 0.06% to 0.07% makes banks more efficient in transforming deposits into loans, as captured by the lower CFI. Banks can now offer loans with significantly lower expected loan rates. As we noted earlier, the number of banks is constant in the model, affecting their pricing power and market share. While the sharp loan rate decline captures the former, the modest CFI decrease reflects both factors, implying that it is important to preserve or enhance the competitive playing field in the banking system to fully reap the benefits of bank technology adoption.

The lower expected loan rates encourage less able entrepreneurs to exit and become workers, while enabling the remaining more able entrepreneurs to borrow and produce more. As the threshold for occupational choice rises, the average ability of entrepreneurs in the economy increases, leading to higher aggregate productivity growth. This results in faster output growth in the capital goods sector, which in turn accelerates the rate of decline in the relative price of capital. A relative price of capital that falls faster, in turn, encourages the final-good producer to also produce at a faster pace, thereby boosting the economy-wide per capita GDP growth rate from 2.01% to 2.17%. By comparison, Jayaratne and Strahan (1996) find that U.S. bank branching deregulation raised average state-level real GDP or income growth by 0.5-1% per year. Our estimated effects are smaller, but not negligible, especially because expressed in GDP per capita terms.

As a result of these changes, the standard deviation of the firm-size distribution also increases by 3.7% from 15.21 in the baseline to 15.77 in the counterfactual and the skewness decreases by 1.3% from 84.8 to 83.7–changes that are consistent with the average ten-year percent changes in the standard deviation and skewness of the US firm-size distribution in the U.S. after 2000, which are 1.25% and -1.3%, respectively, as shown in Figure 3 below.

The two-way interaction between firm productivity and aggregate bank efficiency driven by endogenous bank technology adoption lies at the heart of our model. To isolate the amplification effect stemming from bank technology adoption, we also simulate an exogenous increase in bank efficiency that shuts down the endogenous adoption channel. Specifically, in this scenario reported in Column (3) of Table 2, we replace the model's dynamic technology adoption process with a one-time exogenous change in bank efficiency while maintaining all other parameters at their baseline values. This is implemented by shutting down endogenous bank technology adoption by setting ν to zero and by increasing the scale parameter γ so that, in period 0, at the time of the structural change, the term γa_{jt}^{ν} in Equation (14) matches the same level in Column (2). Therefore, the experiment mimics an economy in which banks experience exogenous efficiency gains rather than through costly investment in technological adoption as in Greenwood *et al.* (2010).

The results in Column (3) of Table 2 indicate that long-run growth increases to only 2.06% in this case, compared to 2.17% with endogenous adoption. The 11-basis-point difference is more than two-thirds of the total long-run growth impact of endogenously transitioning to higher levels of bank technology adoption, underscoring the quantitative significance of the amplification mechanism at work. Other outcomes in Column (3) differ from Column (2) by a similar proportion.

6 Empirical evidence

In this section, we empirically explore three key predictions of the model. First, as the relative price of capital declines, we should see banks adopting more capital goods, which in turn should enhance their efficiency. Second, more efficient banks should increase lending to entrepreneurs, especially small and medium firms that are more bank-dependent. Third, more efficient banks should charge lower interest rates, raising the threshold for occupational choice and leading less able agents to choose for employment rather than entrepreneurship. This further implies that higher bank efficiency should be linked to an increase in the standard deviation and a decrease in the skewness of the firm-size distribution, assuming a right-skewed distribution as in Equation (42). We investigate the first prediction using bank-level data, and the second and third predictions using state- or MSA-level data.

6.1 Data and measurement

As a proxy for bank efficiency, throughout the empirical analysis, we use the CFI at the individual bank level. Using FDIC Call Reports data, we calculate the bank CFI as the ratio of its value added to the loans it intermediates. In our data, a bank's value added is the sum of employee compensation and net income, and the intermediated loans include different types of loans and leases. We also analyze the employee compensation and net income components separately. We measure the CFI at the state or MSA level as a weighted average of all banks with branches operating in a given state or MSA using deposit shares as weights.

We measure bank IT adoption using a bank's IT budget as a share of total non-interest expenses, referring to this variable as IT expense intensity. The data are proprietary from the Harte Hanks Market Intelligence Computer Intelligence Technology database (CiTDB hereafter), which covers over three million establishments in all industries from 2010 to 2019. Harte Hanks collects and sells this data to technology companies, who use it for marketing purposes.[16] We match Call Reports and CiTDB data by bank name as in Cuesta, Jiang, Jorring and Xu (2023).

Following Decker, Haltiwanger, Jarmin and Miranda (2014), to analyze the firm-size distribution across states or MSAs, or by sector across states or MSAs, we use the Business Dynamics Statistics (BDS) database, which reports the aggregate number of firms and employees within specific bins by number of employees from 1985 and 2019. Specifically, the BDS database reports state and MSA-level firm sizes. State-level firm sizes (aggregate and by sector) use employee bins of 1-4, 5-9, 10-19, 20-99, 100-499, 500-999, 1000-2499, 2500-4999, 5000-9999, and 10,000+. MSA-level firm sizes (aggregate and by sector) are reported with coarser bins of 1-19, 20-499, and 500+, respectively. We then calculate the average firm size of each bin within each group (state, MSA, state by sector, and MSA by sector). If the average number of employees within a particular bin size for different

[16]This data has been extensively used in other studies. See, for instance, Forman, Goldfarb and Greenstein (2012), De Ridder (2024) in the literature of labor and firm productivity, as well as Bloom, Garicano, Sadun and Reenen (2014) in the literature of information and organization. More recently, this dataset has also been used to explore the patterns and consequences of IT adaptation in the financial sector (see, for example, Modi, Pierri, Timmer and Peria, 2022; Charoenwong, Kowaleski, Kwan and Sutherland, 2022; He, Jiang, Xu and Yin, 2021; Kwan, Lin, Pursiainen and Tai, 2023, among others). He, Jiang, Xu and Yin (2021) provide a detailed comparison between the CiTDB and FR Y-9C voluntary disclosure of bank IT expenses at the bank holding company level, finding a close match between the two sources.

Table 3
Summary Statistics

Bank IT (Bank-Year Level)	Mean	S.D.	25-th	Median	75-th
CFI	0.018	0.026	0.014	0.017	0.021
Net income/Int loans	0.013	0.01	0.011	0.013	0.015
Salaries/Int loans	0.017	0.021	0.014	0.017	0.020
IT/Non-interest expense	0.140	0.282	0.004	0.023	0.148
Software/Total IT	0.331	0.128	0.225	0.333	0.394
Communication/Total IT	0.093	0.094	0.043	0.070	0.098
Hardware/Total IT	0.166	0.107	0.073	0.179	0.231
Other/Total IT	0.437	0.218	0.351	0.418	0.566
Log(Assets)	12.82	1.23	11.92	12.64	13.54
Equity/Assets	0.099	0.038	0.076	0.092	0.111
Security/Assets	0.267	0.144	0.161	0.253	0.359
CI loan/Total loan	0.125	0.086	0.063	0.110	0.170
RE loan/Total loan	0.774	0.145	0.693	0.794	0.881
Personal loan/Total loan	0.046	0.069	0.010	0.025	0.054
$\mathbf{sd}_s$	2215.1	645.9	1765.1	2145.8	2667.6
$\mathbf{sd}_m$	922.2	156.84	820.1	925.5	1026.7
$\mathbf{sd}_{is}$	708.5	360.9	456.9	648.3	924.3
$\mathbf{sd}_{im}$	839.8	528.9	477.6	919.1	1225.4
$\mathbf{skewness}_s$	10.133	3.505	7.644	9.515	11.564
$\mathbf{skewness}_m$	1.681	0.470	1.373	1.611	1.906
$\mathbf{skewness}_{is}$	2.795	1.925	1.525	2.409	3.590
$\mathbf{skewness}_{im}$	1.415	1.106	0.722	1.186	1.797
EFD	0.243	0.234	0.039	0.256	0.320

Note: The table provides summary statistics on bank IT expense and bank balance sheets. "CFI" is the ratio of value added to intermediated loans and leases. "Salary/Int. Loans" and "Net Income/Int. Loans" is the ratio of employee compensation and net income to intermediated loans and leases, respectively. "IT/Non-interest Expense" is total IT budget as a share of non-interest expenses, with the IT budget further broken down into software, communication, hardware, and other categories. All bank data, except for the IT budget, are from the US Call Reports, while IT budget data are from CiTDB. The sample includes 3,515 matched bank records for banks that remained operational for at least three consecutive years over 2010-2019 period and were incorporated in the continental states. Data are winsorized at the top and bottom 2.5%, except for the log of assets. $\mathbf{sd}_{s(m)}$ and $\mathbf{skewness}_{s(m)}$ denote the standard deviation and skewness of the firm-size distribution for state s or MSA m. $\mathbf{sd}_{i,s(m)}$ and $\mathbf{skewness}_{i,s(m)}$ denote the standard deviation and skewness of the firm-size distribution for sector i in state s or MSA m. $\mathbf{EFD}_i$ measures external finance dependence for sector i.

groups (state, MSA, state-sector, or MSA-sector) is smaller than the lower threshold of the bin, we replace it with the national average. This is more common for bins with larger size, due to truncation or reporting restrictions. For each bin, we then measure the density of a specific firm size by calculating the share of firms in that bin over the total number of firms within the group. The sample standard deviation and skewness of the firm size distributions are then calculated as follows:

$$\mathbf{sd} = \sqrt{\sum_i (l_i - \mathbf{avg})^2 \mathbf{p}_i} \text{ and } \mathbf{skew} = \sum_i \left(\frac{l_i - \mathbf{avg}}{\mathbf{sd}}\right)^3 \mathbf{p}_i, \text{ with } \mathbf{avg} = \sum_i l_i \mathbf{p}_i \tag{54}$$

where i is the index for the ith bin, l_i represents the average employee count in the ith bin, and $\mathbf{p}_i$ denotes the corresponding density for the ith bin.

To characterize the external finance dependence (EFD) of a given sector, we follow the two-step procedure in Rajan and Zingales (1998), and than take the average EFD measure between 1980 and 1984. Since the sector definitions in the BDS follow the NAICS classification, we use the SIC-to-NAICS crosswalk to assign each public firm to a NAICS sector and then calculate the median EFD within each sector. We exclude two sectors—– "agriculture, forestry, fishing and hunting," and "finance, insurance, and real estate"—– resulting in a final sample of 15 sectors.

Table 3 reports summary statistics for our bank-level CFI, its two components, IT expense intensity, and bank characteristics. The average CFI at the bank level is 1.83%, very close to the CFI for the whole financial system used in our benchmark calibration (1.89%). There is also considerable heterogeneity in CFI across banks. The average IT intensity is 14% with a 28.2% standard deviation. In terms of bank characteristics, we consider the log of assets as a proxy for bank size, the equity-to-asset ratio to characterize the capital structure, and the ratio of securities as a share of total assets as a proxy of banks' liquidity. Finally, we also consider the shares of commercial and industrial (CI) loans, real estate (RE) loans, and personal loans in the total loans to proxy for banks' lending profile or specialization.

6.2 Bank technology adoption and the CFI

To explore the first prediction, we consider the conditional correlations between IT expense intensity and the bank-level CFI, using the following specification:

$$\mathbf{CFI}_{b,t} = \beta \mathbf{IT}_{b,t-1} + \gamma \mathbf{X}_{b,t-1} + \alpha_b + \alpha_t + \epsilon_{b,t} \tag{55}$$

where α_b and α_t are bank- and year-fixed effects, respectively. **IT** is the IT expense intensity and lagged by one year since installing new IT equipment and training employees may take some time. **X** is the vector of lagged bank-level characteristics discussed above. We cluster standard errors at the bank level.

Table 4 reports the results from OLS estimation of Equation (55). The benchmark result in Column (1) shows that the coefficient of the IT expense intensity is negative and statistically significant. In economic terms, a one standard deviation increase in IT expense intensity is associated with 0.044 standard deviation decrease in the bank CFI. Using the summary statistics above, this means that a 28.2% increase in IT expense intensity is associated with a 1.25 percentage point reduction in CFI.

Table 4
IT Adoption and CFI: OLS Estimates

	CFI		Salary/Int. loans		Net income/Int. loans	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbf{IT}_{b,t-1}$	-0.0444***	-0.0417***	-0.0342***	-0.0326***	-0.0056	-0.0045
	(0.0070)	(0.0072)	(0.0049)	(0.0050)	(0.0043)	(0.0042)
log(Assets)		-0.6508***		-0.3352***		-0.3520***
		(0.0526)		(0.0356)		(0.0462)
Equity/Assets		0.0781***		0.0146		0.0911***
		(0.0211)		(0.0134)		(0.0179)
Security/Assets		-0.0461***		-0.0642***		0.0487***
		(0.0163)		(0.0099)		(0.0135)
CI loan/Total loan		0.0385		0.0154		0.0311
		(0.0246)		(0.0147)		(0.0221)
RE loan/Total loan		0.0315		0.0057		0.0285
		(0.0315)		(0.0181)		(0.0293)
Personal loan/Total loan		0.0876***		0.0257		0.0761***
		(0.0275)		(0.0171)		(0.0215)
Bank FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Obs	24,625	24,625	24,625	24,625	24,625	24,625
Adj R^2	0.68	0.69	0.80	0.81	0.41	0.43

Note: The table presents the point estimates for β from Equation (55). The dependent variables are the bank-level CFI and its components, the ratios of employee compensation or net income to intermediated loans and leases. The main explanatory variable is the lagged IT expense intensity. The control variables are the bank-level characteristics (the log of assets, the equity-to-asset ratio, the ratio of securities to total assets, and the shares of CI loans, RE loans, and personal loans in total loans). The full sample includes 3,515 banks that remained operational for at least three consecutive years over 2010-2019 period and were incorporated in the continental states. The sample period is from 2010 to 2019. Bank and year fixed effects are included. All standard errors are clustered at the bank level. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

In Column (3) and (5), we examine how the two components of the CFI, employee compensation and net income, correlate with the change in IT expense. A one standard deviation increase in IT expense intensity is associated with 0.0342 standard deviation decrease in "Salary/Int. Loans," and with a 0.0056 standard deviation increase (but not statistically significant) in "Net Income/Int. Loans". The results suggest that bank IT adoption may replace labor as there is no statistically significant association with income per unit of intermediated loans. Importantly, this substitution effect is consistent with a generalized version of our model presented in Appendix C, in which labor also enters the loan production function. In Colums (2), (4), and (6), we estimate the regression Equation (55) with bank-year control variables included, and the results are qualitatively and quantitatively similar.

In Appendix E.1, we estimate the same relationship by using different IT sub-component, including specifically "Software," which is arguably critical for loan transformation and production. Our results are robust. In Appendix E.2, we also conduct a similar test using other measures of bank performance and find that higher IT adoption is negatively associated with interest rates and positively correlated with the loan-to-deposit ratio.

Next, we want to establish a causal link between technology adoption and bank efficiency. We instrument technology adoption using a shift-share variable that interacts the change in a measure of the relative price of capital goods (the first difference in the log of capital prices between the current year and the previous year) with a bank-specific measure of the availability of skilled human capital needed for technology adoption. The latter is the mile distance from a bank's headquarter county centroid to the nearest land-grant colleges, following Moretti (2004) and Pierri and Timmer (2022). The relative price of capital is the quality-adjusted measure in Eichengreen (2015). The rationale is that a bank's distance from land-grant colleges serves as an indicator of its access to the human capital needed for adopting IT, thus reflecting a bank's exposure to technological progress.[17]

The specification of the two-stage regression model is the following,

$$\mathbf{IT}_{bt} = \beta \Delta \mathbf{CP}_{t-1} \times \mathbf{LGC}_b + \delta' \mathbf{X}_{bt} + \alpha_b + \alpha_t + \epsilon_{b,t} \quad (56)$$

$$\mathbf{CFI}_{bt} = \tilde{\beta} \widehat{\mathbf{IT}}_{b,t-1} + \gamma' \mathbf{X}_{b,t-1} + \tilde{\alpha}_b + \tilde{\alpha}_t + \tilde{\epsilon}_{b,t}. \quad (57)$$

where α_b and $\tilde{\alpha}_b$ are the bank fixed effects, and α_t and $\tilde{\alpha}_t$ are the year fixed effects. **IT** is IT expense intensity defined as before. Δ**CP** is the log difference in the relative price of capital. **LGC** is the distance to the nearest land-grant college. $\widehat{\mathbf{IT}}$ is the fitted value from the first stage. **X** is the vector of bank characteristics used in the correlation analysis. We cluster standard errors at the bank level.

Column (1) of Table 5 reports the first stage results. The F-statistics for the first-stage regression is 51.416, well above the threshold for weak instruments in Stock and Yogo (2005). The interaction term is positive and statistically significant, indicating that the farther the distance and the larger the decline in relative price of capital, the more a bank spends on IT technology per dollar of non-interest expense.[18]

Column (2) reports the estimation results from the second stage. The coefficient in the second-stage is qualitatively and quantitatively consistent with the OLS estimate. The IV estimate is negative and statistically significant at the 95% significance level. Similarly, as shown in Columns (3) and (4), we find that banks may substitute labor with IT technology as IT adoption does not seem to have a statistically significant impact on net income per

[17] In our sample, the distance between a bank's headquarter county centroid and the nearest land-grant college has a mean of 156 miles and a standard deviation of 147 miles, giving rise to rich variation in exposure to availability of high-skilled human capital.

[18] Recall that the quality-adjusted relative price of capital always declines over our sample period.

Table 5

IT Adoption and CFI: IV Estimates

	First-stage	Second-stage			First-stage	Second-stage		
		CFI	Salary / Int. loans	Net income / Int. loans		CFI	Salary / Int. loans	Net income / Int. loans
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \mathbf{CP}_{t-1} \times \mathbf{LGC}_b$	0.1828***				0.4699***			
	(0.0253)				(0.0631)			
$\widehat{\mathbf{IT}}_{b,t-1}$		-0.0793**	-0.0871**	-0.0270		-0.0638*	-0.0740**	-0.0134
		(0.0342)	(0.0353)	(0.0488)		(0.0338)	(0.0350)	(0.0489)
log(Assets)					0.0464	-0.1773***	-0.1299***	-0.1969***
					(0.0594)	(0.0151)	(0.0156)	(0.0218)
Equity/Assets					-3.3716***	1.5293***	0.8481***	2.2701***
					(0.9299)	(0.2604)	(0.2701)	(0.3770)
Security/Assets					0.0657***	-0.0153**	-0.0423***	0.0484***
					(0.0252)	(0.0067)	(0.0070)	(0.0098)
CI loan/Total loan					-0.1090***	-0.0001	-0.0050	0.0103
					(0.0400)	(0.0108)	(0.0112)	(0.0157)
RE loan/Total loan					-0.0065	0.0277*	0.0184	0.0349
					(0.0655)	(0.0165)	(0.0171)	(0.0238)
Personal loan/Total loan					0.1063**	0.0189*	0.0052	0.0392**
					(0.0435)	(0.0114)	(0.0119)	(0.0166)
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
F-stat	51.416				50.117			
Obs	23,275	23,275	23,275	23,275	23,249	23,249	23,249	23,249
Adj R^2	0.15	-0.28	-0.30	-0.17	0.15	-0.22	-0.25	-0.16

Note: Column (1) and (5) of the table report the point estimates for β from the first-stage estimation in Equation (56). Column (2)-(4) and (6)-(8) report the point estimates for $\tilde{\beta}$ from the second-stage estimation in Equation (57). In the first stage, the dependent variable is IT expense intensity, defined as the IT budget divided by total noninterest expenses. The instrumental variable used is the product of the log difference in the quality-adjusted relative price of capital from Eichengreen (2015) and the bank's distance to the nearest land-grant colleges, following the methods of Moretti (2004) and Pierri and Timmer (2022). In the second stage, the dependent variables are the bank-level CFI or the ratios of employee compensation or net income to intermediated loans and leases. The control variables are the log of assets, the equity-to-asset ratio, the ratio of securities to total assets, and the shares of CI loans, RE loans, and personal loans in total loans. The full sample consists of 3,515 banks that remained operational for at least three consecutive years over 2010-2019 period and were incorporated in the continental states. The sample period is from 2010 to 2019. Bank and year-fixed effects are included. All standard errors are clustered at the bank level. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

unit of intermediated loans. Columns (5)-to-(8) reports the IV estimation results with bank-level control variables. The IV estimates are even larger in absolute magnitude compared with our OLS estimates.

6.3 Bank CFI and small business loan growth

Next, we check whether more efficient banks extend more small business loans to entrepreneurs, using the CRA Small Business Loan Database. We estimate the following regression at the *bank-state-year* level:

$$Y_{b,s,t} = \beta \mathbf{CFI}_{b,t-1} \text{ } or \text{ } \mathbf{IT}_{b,t-1} + \gamma \mathbf{X}_{b,t-1} + \alpha_b + \alpha_{st} + \epsilon_{b,s,t} \qquad (58)$$

where α_b is bank-fixed effect and α_{st} is state-year fixed effect controlling for unobserved, time-varying factors such as shifts in demand or supply of loans and regulatory changes. The dependent variable Y is the annual log-difference in the nominal value of small business loans by bank b in state s. The CRA Small Business Loan Database tracks lending by banks to small businesses with annual revenues below one million dollars in each county. We aggregate the county-level data to the state-level for each bank and year. The main explanatory variable is the bank's CFI or the IT expense intensity in year $t-1$. **X** is the same vector of bank characteristics discussed in Section 6.2. Standard errors are clustered at the bank level.

Table 6
CFI, IT Expenditure and Small Business Loan Growth

	Δln(Small business loan)			
	(1)	(2)	(3)	(4)
$\mathbf{CFI}_{b,t-1}$	-0.0500**	-0.0379*		
	(0.0218)	(0.0212)		
$\mathbf{IT}_{b,t-1}$			0.0858*	0.0797**
			(0.0508)	(0.0396)
log(Assets)		0.1952**		0.2469*
		(0.0975)		(0.1476)
Equity/Asset		-0.0525		0.0016
		(0.0366)		(0.0609)
Security/Asset		0.0245		-0.0077
		(0.0365)		(0.0488)
CI loan/Total loan		-0.0010		0.0382
		(0.0635)		(0.0923)
RE loan/Total loan		-0.0670		-0.0946
		(0.0767)		(0.1556)
Personal loan/Total loan		-0.0769		-0.1668
		(0.0569)		(0.1285)
State × year FE	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y
Obs	4,544	4,544	2,641	2,643
Adj R^2	0.01	0.00	0.00	-0.01

Note: The table reports the point estimates for β in Equation (58). The dependent variable is the log difference in the nominal stock of small business loans from the CRA Small Business Loan Database. The main explanatory variable is either lagged CFI or lagged IT expense intensity of the corresponding bank. The control variables are the log of assets, the equity-to-asset ratio, the ratio of securities to total assets, and the shares of CI loans, RE loans, and personal loans in total loans. State-by-year and bank-fixed effects are included. All standard errors are clustered at the bank level. $***$ $p < 0.01$, $**$ $p < 0.05$, $*$ $p < 0.1$.

Table 6 reports the estimation results. It shows that a lower CFI is significantly associated with the faster growth of small business loans that a bank makes in a particular state. One standard deviation decrease in a bank's CFI is associated with 0.05 standard deviation faster growth of small business loans, which is equivalent to 4.35 percentage points faster growth in small business loan growth (standard deviation of small business loans growth being 0.87). Similarly, higher IT expense intensity is positively associated with the growth of small business loans, which is also in line with the model's second prediction.

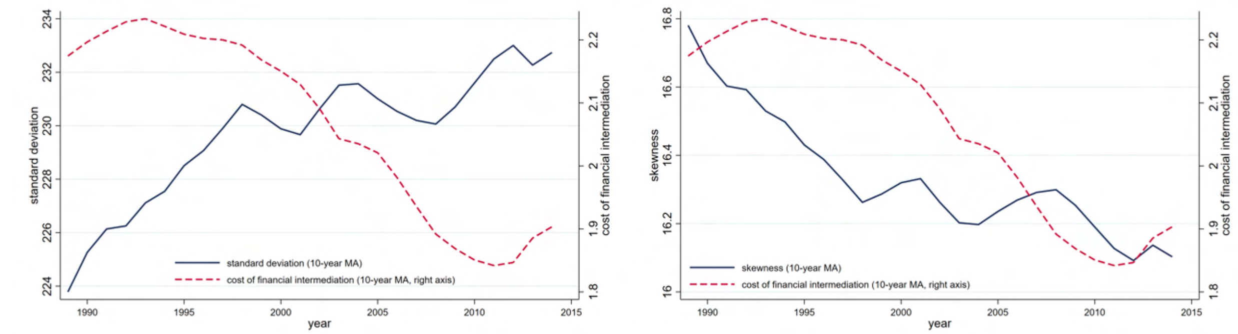
6.4 Bank CFI and satandard deviation and skewness of the firm-size distribution

One stylized fact of the "creative destruction" view of the growth process is that smaller firms tend to exit more frequently than larger ones, while those that survive tend to grow more rapidly, resulting in a dispersed and highly skewed firm size distribution (see Aghion, Akcigit and Howitt, 2014, for a survey). Figure 3 shows that both the standard deviation and the skewness of the U.S. firm-size distribution are associated with bank efficiency, as measured by the cost of financial intermediation in Philippon (2015) and denoted as CFI. For example, the standard deviation of the U.S. firm-size distribution by number of employees (Panel a) has increased to 231.6 in the 2000s, and 232.7 in the 2010s, from an average of 227.5 in the 1990s (i.e., by 1.8% in the 2000s and 0.5% in the 2010s). By contrast, from an average level of 2.22% in the 1990s, the CFI has steadily declined to 2.04% in the 2000s and 1.90% in the 2010s. Similarly, the skewness of the U.S. firm-size distribution (Panel b) has declined, starting from an average of 16.5 in the 1990s to 16.2 in the 2000s and 16.1 in the 2010s (i.e., by 1.8% in the 2000s and by 0.6% in the 2010s). At the same time, the relative price of capital goods steadily declined in the United States, as, for example, documented in Eichengreen (2015), albeit at a slowing rate. Given the assumed right-skewed distribution in Equation (42), in this section, we explore whether higher bank efficiency for a given region is associated with a larger standard deviation and lower skewness of the firm-size distribution in that region.

To estimate the correlation between the CFI and the standard deviation or skewness of the firm-size distribution at the state or MSA level, we estimate the following regression equation:

$$Y_{s(m),t} = \beta \mathbf{CFI}_{s(m),t-1} + \mathbf{X}_{s,t-1} + \alpha_{s(m)} + \alpha_t + \epsilon_{s(m),t} \tag{59}$$

where $\alpha_{s(m)}$ and α_t represent state (MSA) and year fixed effects, respectively. The dependent variable, $Y_{s(m),t}$, is the standard deviation or the skewness of the firm-size distribution in state s or MSA m for year t. **CFI** is the deposit-weighted CFI at the state or MSA level, lagged by one year, based on the assumption that it may take time for more efficient banks to start affecting the firm-size distribution. **X** includes the log of real GDP per capita, the unemployment rate, and the log of the consumer price index. The sample



(a) Standard Deviation and CFI

(b) Skewness and CFI

Note: The aggregate cost of financial intermediation (CFI, red, dashed line, right scales) is defined as in Philippon (2015) as value added of the financial system over total intermediate assets. The standard deviation (Panel a) and skewness (Panel b) of the firm-size distribution by number of employees (black solid lines, left scales) are calculated using the Business Dynamics Statistics (BDS) dataset, as in Decker, Haltiwanger, Jarmin and Miranda (2014) (see Equation (54) in Section 6.1). All lines plotted are the 10-year moving averages, with each point in the figure representing the midpoint (i.e., the fifth year) of a 10-year moving average from 1989 to 2014.

Figure 3

U.S. Firm-size Distribution and the Aggregate CFI

covers 50 states and District of Columbia and 917 MSAs, from 1985 to 2019. We cluster standard errors at the state or MSA level, respectively.

Column (1) and (2) of Table 7 report the results at the state level, suggesting that a lower state-level CFI (more efficient banks in that state) significantly correlates with a higher standard deviation and lower skewness of the firm-size distribution as implied by our model. Column (5) and (6) display point estimates at the MSA level. The results are similarly in line with the model's third prediction.

Since unobserved state or MSA characteristics may simultaneously affect both bank efficiency and the firm-size distribution in that region, we exploit sectoral variation within a given state (MSA) to examine how the firm-size distribution across different sectors covaries with bank efficiency. Specifically, we incorporate state(MSA)-by-year fixed effect to control for these unobserved time-varying characteristics. We expect that, in sectors more dependent on external finance, the firm-size distribution will exhibit a stronger association with the CFI. To test this, we consider an interaction term between state- or MSA-level CFI and the EFD as the following specification:

$$Y_{i,s(m),t} = \beta \mathbf{CFI}_{s(m),t-1} \times \mathbf{EFD}_i + \alpha_{i,s(m)} + \alpha_{s(m),t} + \alpha_{i,t} + \epsilon_{i,s(m),t}. \tag{60}$$

Here, the dependent variable, $Y_{i,s(m),t}$, represents the standard deviation or skewness of the firm-size distribution for sector i in state s or MSA m for year t. **CFI** refers to

Table 7

CFI and SD and Skewness of Firm-size Distribution

	State level				MSA level			
	$\mathbf{sd}_{s,t}$ (1)	$\mathbf{skew}_{s,t}$ (2)	$\mathbf{sd}_{i,s,t}$ (3)	$\mathbf{skew}_{i,s,t}$ (4)	$\mathbf{sd}_{m,t}$ (5)	$\mathbf{skew}_{m,t}$ (6)	$\mathbf{sd}_{i,m,t}$ (7)	$\mathbf{skew}_{i,m,t}$ (9)
$\mathbf{CFI}_{s(m),t-1}$	-536.26**	2.44**			-370.47***	0.81***		
	(255.229)	(0.944)			(134.328)	(0.293)		
$\mathbf{CFI}_{s(m),t-1} \times \mathbf{EFD}_i$			-422.37*	2.73***			-842.83**	1.20**
			(222.521)	(0.827)			(333.770)	(0.602)
$\log \mathbf{price\ index}_{s,t-1}$	284.31	-1.65*			-17.82	-0.07		
	(297.654)	(0.903)			(26.756)	(0.068)		
$\mathbf{unemployment\ rate}_{s,t-1}$	11.84	-0.03			-0.59	-0.00*		
	(8.529)	(0.021)			(0.728)	(0.002)		
$\log \mathbf{GDP}_{s,t-1}$	-545.52***	2.51***			-32.61*	0.09*		
	(137.850)	(0.479)			(18.749)	(0.047)		
$\log \mathbf{income}_{s,t-1}$	984.07***	-3.06***			-7.93	-0.08		
	(280.989)	(0.947)			(34.309)	(0.088)		
Obs	1,692	1,692	23,177	23,177	27,077	27,077	265,147	265,147
State (MSA) FE	Yes	Yes	No	No	Yes	Yes	No	No
Year FE	Yes	Yes	No	No	Yes	Yes	No	No
Sector (MSA) × sector FE	No	No	Yes	Yes	No	No	Yes	Yes
State (MSA) × year FE	No	No	Yes	Yes	No	No	Yes	Yes
Sector× year FE	No	No	Yes	Yes	No	No	Yes	Yes
R^2	0.98	0.99	0.95	0.92	0.94	0.95	0.88	0.85

Note: Column (1), (2), (5), and (6) report the point estimates for β from Equation (59). Column (3), (4), (7), and (8) report the point estimates for β from Equation (60). The dependent variables in Column (1), (3), (5), and (7) are the standard deviation of the firm-size distribution for a given state, state-by-sector pair, MSA, and MSA-by-sector pair, respectively. The dependent variables in Column (2), (4), (6), and (8) are the skewness of the firm-size distribution for the same level of aggregation. The state(MSA)-level CFI is a weighted average of the bank CFI across all banks operating in that state (MSA), with deposit shares used as weights. The external finance dependence (EFD) variable measures the extent to which a sector depends on external finance, following the two-step procedure outlined in Rajan and Zingales (1998). The main explanatory variable is either the state-level CFI or its interaction with EFD. The control variables include the log of real GDP per capita, the unemployment rate, and the log of the consumer price index. The sample covers 15 sectors spread over 50 states, and the District of Columbia, or 917 MSAs. The sample period goes from 1985 to 2019. State (MSA) and year fixed effects are included in Column (1)-(2) and (5)-(6). State (MSA)-by-sector, state (MSA)-by-year, and sector-by-year fixed effects are included in Column (3)-(4) and (7)-(8). Standard errors are clustered at the state level in Column (1) and (2), at the state-by-sector level in Column (3) and (4), at the MSA level in Column (5) and (6), and at the MSA-by-sector level in Column (7) and (8). $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

the deposit-weighted CFI at the state or MSA level, while **EFD** is the external finance dependence measure as in Rajan and Zingales (1998). $\alpha_{i,s(m)}$ captures state(MSA)-by-sector fixed effect, controlling for time-invariant characteristics of a sector in a given state (MSA), such as endowment advantages of sector i. $\alpha_{s(m),t}$ represents state(MSA)-by-year fixed effect, which control for time-varying state (MSA) characteristics, such as business cycles or regulatory changes. Finally, $\alpha_{i,t}$ is sector-by-year fixed effect, controlling for any time-varying sector-specific characteristics, such as technological advancements or outsourcing. The sample covers 15 sectors spread over 50 states and the District of Columbia, or 917 MSAs, from 1985 to 2019.

Column (3) and (4) of Table 7 present the estimation results at the state level, indicating that within a given state, a lower state-level CFI is significantly associated with a higher standard deviation and lower skewness in the firm-size distribution for sectors that are more dependent on external financing. Column (7) and (8) provide the results at the MSA level, with consistent findings.

7 Conclusions

In this paper, we build, estimate, and evaluate a new model of growth and finance in which banks adopt technology embedded in capital goods produced by entrepreneurs. Agents choose whether to be workers or capital goods-producing entrepreneurs. We show that, in this setting, aggregate firm productivity affects bank efficiency and vice versa. When we estimate the model based on long-run moments of the US economy and matched Call Report-Harte Hanks Market Intelligence CiTDB data. We find that increasing banking technology adoption to the level prevailing in the upper half of the distribution of the data can lower lending rates and the overall cost of bank intermediation. The latter increases the standard deviation and lowers the skewness in the firm-size distribution, boosting credit supply and leading to faster long-run growth. The paper also reports microeconomic evidence that aligns with the bank technology adoption mechanisms at the core of the model.

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A The micro foundation of $\mathbf{e}(\theta)$

In this section, we provide the microfoundations for the specification of the effort function $\mathbf{e}(\theta)$, assuming stochastic monitoring as in Greenwood, Sanchez and Wang (2010). As banks can observe the entrepreneurs' type but not the outcome of their project, success (S) or failure (F), they must exert a costly effort $e_{jt}^{k}(\theta)$ to verify the the state $k \in \{S, F\}$, with cost of $e_{jt}^{k}(\theta)(1 + r_{jct})b_{jt}(\theta)$. Unlike the standard case in which banks can detect the true state with certainty by exerting the effort, we assume that banks can only detect the true state with a certain probability $\mathbf{Pr}(e_{jt}(\theta))$, as in Greenwood, Sanchez and Wang (2010), which is also assumed to be increasing, twice-differentiable, and concave in efforts $e_{jt}(\theta)$ with $\mathbf{Pr}(0) = 0$.

To prevent free-riding and coordination issues, we further assume that all banks exert effort to verify the project's state. When misreporting is detected, banks can charge the amount $m_{jt}^{kk'}(\theta)$, where $k, k' \in \{S, F\}$ and $k \neq k'$, denotes the case in which the entrepreneurs realize k but report k'. The penalties $m_{jt}^{FS}(\theta)$ and $m_{jt}^{FS}(\theta)$ charged by bank j cannot exceed the bank's fair share of the total funds recovered, leading to the following resource constraints:

$$m_{jt}^{SF}(\theta) \leq s_{jt}(\theta) p_t \theta z_{t-1} l_t^{\xi}(\theta), \tag{A.1}$$

$$m_{jt}^{FS}(\theta) \leq s_{jt}(\theta) p_t \underline{\theta} z_{t-1} l_t^{\xi}(\theta), \tag{A.2}$$

where the revenue received by all banks is $p_t \theta z_{t-1} l_t^{\xi}(\theta)$ ($p_t \underline{\theta} z_{t-1} l_t^{\xi}(\theta)$) when the project succeeds (fails) but the entrepreneur reports otherwise.

The monotonicity and concavity of the detecting probability implies that the likelihood of detecting the true state increases in effort, but the marginal benefit of exerting additional effort diminishes. Consequently, bank j structures its loan offer, ensuring that the repayment is incentive-compatible as follows:

$$(1 + r_{lt}(\theta)) b_{jt}(\theta) \leq \mathbf{Pr}\left(e_{jt}^{F}(\theta)\right) m_{jt}^{SF}(\theta) + \left(1 - \mathbf{Pr}\left(e_{jt}^{F}(\theta)\right)\right) x_{jt}(\theta) b_{jt}(\theta), \tag{A.3}$$

$$x_{jt}(\theta) b_{jt}(\theta) \leq \mathbf{Pr}\left(e_{jt}^{S}(\theta)\right) m_{jt}^{FS}(\theta) + \left(1 - \mathbf{Pr}\left(e_{jt}^{S}(\theta)\right)\right) (1 + r_{lt}(\theta)) b_{jt}(\theta). \tag{A.4}$$

Equation (A.3) represents the incentive-compatible constraint (ICC) for successful entrepreneurs. It asserts that if successful entrepreneurs truthfully report their state, the scheduled repayment, $(1 + r_{lt}(\theta)) b_{jt}(\theta)$, cannot exceed the expected payoff from cheating, which is represented by the right-hand side of Equation (A.3). When cheating, the entrepreneur faces a probability $\mathbf{Pr}\left(e_{jt}^{F}(\theta)\right)$ of being detected and penalized with $m_{jt}^{SF}(\theta)$, and a complementary probability $1 - \mathbf{Pr}\left(e_{jt}^{F}(\theta)\right)$ of evading detection. In the latter case, they only pay the amount associated with the failed state, $x_{jt}(\theta) b_{jt}(\theta)$, which we refer to as the evasion payment. Similarly, Equation (A.4) defines the ICC for a failed entrepreneur.

Taking as given the loan amount of the other banks $\{b_{it}(\theta)\}_{i \neq j}$, the wage w_t, the relative price of capital goods p_t, and its unit funding cost $1 + r_{jct}$, bank j chooses the loan amount $b_{jt}(\theta)$, the loan-recovery rate $x_{jt}(\theta)$, the penalties $m_{jt}^{SF}(\theta)$ and $m_{jt}^{FS}(\theta)$, and the verification efforts $e_{jt}^{S}(\theta)$ and $e_{jt}^{F}(\theta)$ that maximize its expected profit from lending to the type-θ entrepreneur while inducing truthful reporting as follows:

$$\begin{aligned}\max \quad & \Big(\eta\,(1+r_{lt}(\theta)) + (1-\eta)x_{jt}(\theta)\Big)b_{jt}(\theta) - \left(1+r_{jct}\right)b_{jt}(\theta) \\ & -\left(\eta e^{S}_{jt}(\theta) + (1-\eta)\eta e^{F}_{jt}(\theta)\right)\left(1+r_{jct}\right)b_{jt}(\theta), \\ s.t. \quad & (7),\ (8),\ (A.1),\ (A.2),\ (A.3),\ and\ (A.4).\end{aligned} \tag{A.5}$$

We note here that the bank's expected profit from the type-θ entrepreneur in Problem (A.5) equals the expected net interest income minus expected verification costs. Imposing symmetry, the following proposition characterizes the solution of the equilibrium in the loan market for the type-θ entrepreneur.

Proposition 5 (Symmetric loan market equilibrium) *Suppose all n banks are the same and Assumption (13) holds. Given the wage w_t, the relative price of capital goods p_t, and the unit funding cost $1+r_{jct}$, the solution of Problem (A.5) for contract offered to the type-θ entrepreneur by bank j is given by:*

$$e^{S}_{jt}(\theta) = 0, \tag{A.6}$$

$$e^{F}_{jt}(\theta) = \mathbf{e}(\theta) = \mathbf{Pr}^{-1}\left(\xi - \frac{(1-\xi)\underline{\theta}}{\eta(\theta-\underline{\theta})}\right), \tag{A.7}$$

$$1+r_{jt}(\theta) = \frac{\xi\bar{\theta}-(1-\eta)\underline{\theta}}{\xi\eta\bar{\theta}}\frac{1+(1-\eta)\mathbf{e}(\theta)}{1-\frac{1-\xi}{n}}\left(1+r_{jct}\right), \tag{A.8}$$

$$x_{jt}(\theta) = \frac{\underline{\theta}}{\xi\bar{\theta}}\frac{1+(1-\eta)\mathbf{e}(\theta)}{1-\frac{1-\xi}{n}}\left(1+r_{jct}\right), \tag{A.9}$$

$$b_{jt}(\theta) = \frac{1}{n}\left(\frac{\bar{\theta}}{1+(1-\eta)\mathbf{e}(\theta)}\frac{\left(1-\frac{1-\xi}{n}\right)p_t\xi z_{t-1}}{\left(1+r_{jct}\right)w_t^{\xi}}\right)^{\frac{1}{1-\xi}}, \tag{A.10}$$

$$m^{SF}_{jt}(\theta) = \frac{\theta}{\xi n}\left(\left(\frac{\bar{\theta}}{1+(1-\eta)\mathbf{e}(\theta)}\frac{1-\frac{1-\xi}{n}}{\left(1+r_{jct}\right)w_t}\right)^{\xi}p_t\xi z_{t-1}\right)^{\frac{1}{1-\xi}}, \tag{A.11}$$

$$m^{FS}_{jt}(\theta) = \frac{\underline{\theta}}{\xi n}\left(\left(\frac{\bar{\theta}}{1+(1-\eta)\mathbf{e}(\theta)}\frac{1-\frac{1-\xi}{n}}{\left(1+r_{jct}\right)w_t}\right)^{\xi}p_t\xi z_{t-1}\right)^{\frac{1}{1-\xi}}, \tag{A.12}$$

where $\bar{\theta} = \eta\theta + (1-\eta)\underline{\theta}$, and $\mathbf{Pr}^{-1}(\cdot)$ is the inverse function of $\mathbf{Pr}(\cdot)$. Given the unit funding cost $1+r_{jct}$, the expected gross loan rate is

$$\overline{1+r_{lt}(\theta)} = \eta\,(1+r_{lt}(\theta)) + (1-\eta)x_{jt}(\theta) = \underbrace{\frac{1}{1-\frac{1-\xi}{n}}}_{markup}\left(1+\underbrace{(1-\eta)\mathbf{e}(\theta)}_{verification\ cost}\right)\left(1+r_{jct}\right). \tag{A.13}$$

Moreover, the effort function $\mathbf{e}(\theta)$ is increasing and twice-differentiable in θ, and $x_{jt}(\theta) < 1+r_{lt}(\theta)$.

Proof: *We first show that there exists a unique solution to the banks' problem. It is straightforward to* *show that all resource constraints are binding since otherwise, the marginal benefits of rising x, m^{FS}, and m^{SF} are positive while the marginal cost is negligible. Thus, x, m^{FS}, and m^{SF} can be solved with Equation (8), (A.2) and (A.1), respectively. Thus, the ICC for reporting successful state is not binding. As efforts is costly, we have $e^S = 0$. As the loan repayment for the successful project $(1+r_{lt})b_{jt}(\theta)$ falls between the penalty m^{SF} and the escape payment $x_{jt}b_{jt}$ banks will exert just enough efforts to make the ICC constraint binding, i.e. making entrepreneurs indifferent between telling the truth and misreporting. In this case, we have $\mathbf{Pr}\left(e^F_{jt}(\theta)\right) = \xi - \frac{(1-\xi)\theta}{\eta(\theta-\underline{\theta})}$. Thus, the efforts in this case is given by Equation (A.7). Assumption (13) ensures that the probability of detecting the true state is positive even for the lowest ability agent. Thus, the Lagrangian for the second stage is given by*

$$\mathcal{L} = \xi p_t \left(\eta\theta + (1-\eta)\underline{\theta}\right) z_{t-1} b_{jt}(\theta) / \left(\left(\sum_j b_{jt}(\theta)\right)^{1-\xi} w_t^{\xi}\right) - \left(1 + (1-\eta)\mathbf{e}(\theta)\right)\left(1 + r_{jct}\right) b_{jt}(\theta).$$

Under symmetry and using the first order conditions, we have that the expected loan rate is given by

$$\eta\left(1 + r_{lt}(\theta)\right) + (1-\eta)x_{jt}(\theta) = \left(1 + (1-\eta)\mathbf{e}(\theta)\right) / \left(1 - (1-\xi)/n\right)\left(1 + r_{jct}\right). \tag{A.14}$$

Combining Equation (A.14) with (7), we obtain Equation (A.9), (A.10), and (A.8). Using (A.10), we obtain Equation (A.11) and (A.12). QED.

Finally, assume that bank j's probability of detecting the true state of the type–θ entrepreneur is the following increasing and concave function in e_j:

$$\mathbf{Pr}(e_{jt}(\theta)) = \frac{e_{jt}(\theta)}{e_{jt}(\theta) + \sigma}. \tag{A.15}$$

Using Equation (A.7), we can solve for the verification effort per unit of loan as

$$\mathbf{e}(\theta) = \sigma\left(\frac{\eta(\theta - \underline{\theta})}{(1-\xi)\left(\eta\theta + (1-\eta)\underline{\theta}\right)} - 1\right), \tag{A.16}$$

which is the functional form we adopt in our quantitative analysis in Section 4 of the paper.

When $\eta = 1$, entrepreneurs always realize their assigned type, eliminating information asymmetry and obviating the need for verification efforts. Assumption (13) in Proposition 1 ensures that this function form $\mathbf{e}(\theta)$ satisfies Assumption (31) in Proposition 2 and 3.

B Proofs for propositions

In this Appendix, we provide proof of all the formal statements in the paper's main text.

B.1 Proof of Proposition 1

Proof: We first show that there exists a unique solution to the banks' problem. It is straightforward to show that the resource constraint is binding, since otherwise, the marginal benefit of rising x is positive while the marginal cost is negative. Thus, x can be solved with Equation (8).

Thus, the Lagrangian for the second stage is given by

$$\mathcal{L} = \xi p_t \left(\eta\theta + (1-\eta)\underline{\theta}\right) z_{t-1} b_{jt}(\theta) / \left(\left(\sum_j b_{jt}(\theta) \right)^{1-\xi} w_t^{\xi} \right) - (1+\mathbf{e}(\theta)) \left(1 + r_{jct}\right) b_{jt}(\theta).$$

Under symmetry and using the first order conditions, we have that the expected gross loan rate is given by Equation (10). Combining the first-order condition of entrepreneurs with the binding constraint (8), we have $x_{jt}(\theta) = \frac{\theta}{\xi\bar{\theta}}(1 + r_{lt}(\theta))$. Thus, using equation Equation (10), we have the lending rate in the successful state

$$1 + r_{lt}(\theta) = \frac{1}{\eta}\left(1 - (1-\eta)\frac{\theta}{\xi\bar{\theta}}\right)(1 + r_{lt}(\theta)). \text{ } QED.$$

B.2 Proof of Proposition 2

Here, we first assume that there is a solution for Equation (32) and then verify its existence and uniqueness. Using the market clearing condition for the loan market, we have that $B_t = nB_{jt} = \left((1-(1-\xi)/n) p_t \xi z_{t-1} / \left((1+r_{jct}) w_t^{\xi}\right)\right)^{\frac{1}{1-\xi}} \mathbf{H}(\theta_t^*)$, where $\mathbf{H}(\theta_t^*)$ is defined in Equation (29). Thus, the total amount of capital goods adopted by banks is given by $Q_t = nq_{jt} = \nu v_t \frac{B_t}{p_t} = \nu v_t \left((1-(1-\xi)/n)/(1+r_{jct})(p_t/w_t)^{\xi} \xi z_{t-1}\right)^{\frac{1}{1-\xi}} \mathbf{H}(\theta_t^*)$. Therefore, combining the market clearing condition of the capital market in Equation (28) with the market clearing condition of the labor market in Equation (26), we can solve for the price of capital goods as in Equation (34). Thus, the wage rate is obtained from the labor market clearing condition in Equation (26) as $w_t = (\mathbf{G}(\theta^*)/\mathbf{F}(\theta^*))^{1-\xi}(1+r_{jct}) p_t \xi z_{t-1}/(1-(1-\xi)/n)$ where $1 + r_{jct}$ is given in Equation (19) and p_t is solved in Equation (34). Thus, Equation (32) is solved in Equation (33).

Now, we must verify the existence of the threshold and show its uniqueness. First, we rewrite Equation (33) as $\mathbf{LHS}(\theta) = \mathbf{RHS}$, where

$$\mathbf{LHS}(\theta) = \left(\frac{\mathbf{G}(\theta)}{\mathbf{F}(\theta)}\right)^{1-\nu\xi(1-\alpha)} \frac{(\mathbf{H}(\theta))^{\nu(1-\alpha)}}{\mathbf{h}(\theta)} \tag{B.1}$$

$$\mathbf{RHS} = \frac{1-\xi}{\xi\gamma\left(1-\frac{1-\xi}{n}\right)} \left(\frac{z_{t-1}^{\alpha}}{a_{t-1}} \frac{\alpha}{\nu} \left(1 - \xi\nu\left(1 - \frac{1-\xi}{n}\right)\right)^{-(1-\alpha)} \right)^{\nu} \left(\frac{1+r_d}{1-\nu}\right)^{1-\nu} \tag{B.2}$$

We now note that $\frac{\mathbf{G}(\theta)}{\mathbf{F}(\theta)}$ is decreasing in θ. Thus, under assumption that $\mathbf{h}(\theta)$ is increasing in θ, it is easy to show that the $\mathbf{LHS}(\theta)$ is decreasing in θ. Moreover, $\lim_{\theta\to\theta_{min}} \mathbf{LHS}(\theta) \to \infty$ and $\lim_{\theta\to\infty} \mathbf{LHS}(\theta) = 0$. Because $\pi^E(\theta)$ is increasing in θ, for any finite z_{t-1}, a_{t-1}, and r_d, there exists a unique θ^* with $\mathbf{LHS}(\theta_t^*) = \mathbf{RHS}$, such that for $\theta \geq \theta_t^*$, $\pi^E(\theta) \geq w_t$, while $\pi^E(\theta) < w_t$ for $\theta < \theta_t^*$, as $\mathbf{LHS}(\theta_t^*) = \mathbf{RHS}$ implies that Equation (33) holds. QED.

B.3 Proof of Proposition 3

We define **LHS**(θ) and **RHS** as in Equation (B.1) and (B.2). As shown in Section B.2, $\frac{\partial\,\mathbf{LHS}(\theta)}{\partial\,\theta} < 0$. Moreover, it is straightforward to show that,

$$\frac{\partial\,\theta_t^*}{\partial\,z_{t-1}} = \frac{\frac{\partial\,\mathbf{RHS}}{\partial\,z_{t-1}}}{\frac{\partial\,\mathbf{LHS}(\theta_t^*)}{\partial\,\theta_t^*}} < 0; \;\; \frac{\partial\,\theta_t^*}{\partial\,a_{t-1}} = \frac{\frac{\partial\,\mathbf{RHS}}{\partial\,a_{t-1}}}{\frac{\partial\,\mathbf{LHS}(\theta_t^*)}{\partial\,\theta_t^*}} > 0;$$

$$\frac{\partial\,\theta_t^*}{\partial\,r_d} = \frac{\frac{\partial\,\mathbf{RHS}}{\partial\,r_d}}{\frac{\partial\,\mathbf{LHS}(\theta_t^*)}{\partial\,\theta_t^*}} < 0; \;\; and \;\; \frac{\partial\,\theta_t^*}{\partial\,n} = \frac{\frac{\partial\,\mathbf{RHS}}{\partial\,r_d}}{\frac{\partial\,\mathbf{LHS}(\theta_t^*)}{\partial\,\theta_t^*}} > 0.$$

Now, define $f(\nu) = \nu\left(\log\frac{\alpha z_0^\alpha}{a_0} - (1-\alpha)\log\left(1-\nu\xi\left(1-\frac{1-\xi}{n}\right)\right) - \log\nu\right) + (1-\nu)(\log(1+r_d) - \log(1-\nu))$. Thus, for $\forall\ \nu \in (0,1)$, we have,

$$f'(\nu) = \log\frac{\alpha z_0^\alpha}{a_0} - \log(1+r_d) - \log(1-\nu) - \log\nu - (1-\alpha)\log\left(1-\nu\xi\left(1-\frac{1-\xi}{n}\right)\right) + \frac{(1-\alpha)\nu\xi\left(1-\frac{1-\xi}{n}\right)}{1-\nu\xi\left(1-\frac{1-\xi}{n}\right)}$$

and

$$f''(\nu) = -\frac{1}{1-\nu} - \frac{\alpha}{\nu} - (1-\alpha)\nu\left(\frac{\xi\left(1-\frac{1-\xi}{n}\right)}{1-\nu\xi\left(1-\frac{1-\xi}{n}\right)} - \frac{1}{\nu}\right)^2 < 0.$$

Moreover, we have $\lim_{\nu\to 0} f'(\nu) = \infty$ and $\lim_{\nu\to 1} f'(\nu) = -\infty$. Thus, it is straightforward to show that there exists $\hat{\nu} \in (0,1)$, where $\theta^*(\hat{\nu})$ solves Equation (33) with $\hat{\nu}$, and

$$f'(\hat{\nu}) + \xi(1-\alpha)\log\frac{\mathbf{G}(\theta^*(\hat{\nu}))}{\mathbf{F}(\theta^*(\hat{\nu}))} - (1-\alpha)\log\mathbf{H}(\theta^*(\hat{\nu})) = 0,$$

so that for $\nu \le \hat{\nu}$, we have

$$\frac{\partial\,\theta_t^*}{\partial\,\nu} = \frac{1}{\frac{\partial\,\log\mathbf{LHS}(\theta_t^*(\nu))}{\partial\,\theta_t^*}}\left(f'(\nu) + \xi(1-\alpha)\log\frac{\mathbf{G}(\theta^*(\nu))}{\mathbf{F}(\theta^*(\nu))} - (1-\alpha)\log\mathbf{H}(\theta^*)\right) \le 0,$$

where $\theta^*(\nu)$ solves Equation (33) with ν , while for $\nu > \hat{\nu}$, we have

$$\frac{\partial\,\theta_t^*}{\partial\,\nu} = \frac{1}{\frac{\partial\,\log\mathbf{LHS}(\theta_t^*)}{\partial\,\theta_t^*}}\left(f'(\nu) + \xi(1-\alpha)\log\frac{\mathbf{G}(\theta^*)}{\mathbf{F}(\theta^*)} - (1-\alpha)\log\mathbf{H}(\theta^*)\right) > 0. \;\; QED$$

B.4 Proof of Proposition 4

The **RHS** expression in Equation (B.2) is $\propto \frac{z_{t-1}^{\alpha\nu}}{a_{t-1}^{\nu}}$. Thus, the threshold for the occupation choice stays constant along the BGP. From Equations (10), (11), (12), and (19), we see that x_{jt}, r_{lt}, r_{jct}, and r_d are also constant along the BGP. Equation (26) implies that the labor supply is constant as well. Thus, Equation (1) implies that the volume of capital goods grows at the gross rate $g^{\frac{1}{\alpha}}$, while Equation (34) implies that their price grows at $g^{1-\frac{1}{\alpha}}$. It is straightforward to show that all other variables grow at a constant rate of g. QED.

C Extending the model with labor in the bank loan production function

In this section, we extend our benchmark model by allowing banks to hire labor in the first stage and show that the main properties are unchanged. Specifically, in addition to adopting capital goods, banks now need to employ labor to transform deposits into loans, as

$$B_{jt} = \gamma a_{jt}^{\nu} l_{jt}^{\omega} d_{j,t-1}^{1-\nu-\omega}, \tag{C.1}$$

where B_{jt} is total funds lent in the second stage, a_{jt} is the bank's individual level of efficiency in transforming deposits $d_{j,t-1}$ into loans, l_{jt} is the labor employed by bank j, ν and ω are the factor share, and γ is a scale parameter that captures other factors such as managerial ability, marketing expenditures, physical capital, etc. The individual bank efficiency level a_{jt} is the same as in Equation (15).

Given the previous-period aggregate bank efficiency a_{t-1}, the aggregate firm productivity z_{t-1}, the relative price of capital-goods p_t, the wage w_t, the deposit rate r_d, and the amount of funds to be lent B_{jt}, bank j chooses the amount of capital goods q_{jt}, labor and deposits $d_{j,t-1}$ that minimize the total funding costs:

$$\left(1+r_{jct}\right)B_{jt} \equiv \min_{q_{jt},l_{jt},D_{jt}} p_t q_{jt} + w_t l_{jt} + (1+r_d)d_{j,t-1}, \quad s.t. \quad B_{jt} = \gamma\left(\frac{a_{t-1}}{z_{t-1}}q_{jt}\right)^{\nu} l_{jt}^{\omega} d_{j,t-1}^{1-\nu-\omega}. \tag{C.2}$$

Solving this problem, we find that the bank j's demands for capital goods, labor, and deposits are, respectively,

$$(capital\ \ good\ \ demand) \qquad p_t q_{jt} = \nu v_t B_{jt}, \tag{C.3}$$

$$(labor\ \ demand) \qquad w_t l_{jt} = \omega v_t B_{jt}, \tag{C.4}$$

$$(deposit\ \ demand) \qquad (1+r_d)\, d_{j,t-1} = (1-\nu-\omega) v_t B_{jt}, \tag{C.5}$$

where v_t is the Lagrangian multiplier on the bank's production constraint. Solving for the unit funding cost, $1+r_{jct}$, we have:

$$1+r_{jct} = \frac{1}{\gamma}\left(\frac{z_{t-1}}{a_{t-1}}\frac{p_t}{\nu}\right)^{\nu}\left(\frac{w_t}{\omega}\right)^{\omega}\left(\frac{1+r_d}{1-\nu-\omega}\right)^{1-\nu-\omega}. \tag{C.6}$$

Moreover, the labor market clearing condition in Equation (26) becomes

$$\mathbf{F}(\theta^*) = \int_{\theta^*}^{\infty} l_t(\theta)\, \mathbf{d}\, \mathbf{F}(\theta) + n l_{jt} \tag{C.7}$$

where $l_t(\theta)$ is given by Equation (3) and l_{jt} is solved from Equation (C.4). In equilibrium, the wage can be pinned down by Equation (C.7). Substituting for the unit funding cost from Equation (C.6) and the market clearing condition for the capital goods as in Equation (28) and the labor as in Equation (C.7) into the agents' arbitrage condition (32), we have that the threshold of occupation choice must satisfy the following condition:

$$\frac{\left(1-\frac{1-\xi}{n}\right)\mathbf{G}(\theta_t^*)}{\frac{1-\xi}{\xi}\mathbf{F}(\theta_t^*)\mathbf{h}(\theta_t^*)-\omega\left(1-\frac{1-\xi}{n}\right)\mathbf{H}(\theta_t^*)}=\frac{1}{\gamma}\left(\frac{z_{t-1}}{a_{t-1}}\frac{p_t}{\nu}\right)^{\nu}\left(\frac{w_t}{\omega}\right)^{\omega}\left(\frac{1+r_d}{1-\nu}\right)^{1-\nu-\omega}, \tag{C.8}$$

where the capital-good price p_t is given by

$$p_t=\alpha\left(\left(1-\xi\nu\left(1-\frac{1-\xi}{n}\right)\right)\left(\frac{\mathbf{F}(\theta_t^*)-\frac{\xi\omega}{1-\xi}\left(1-\frac{1-\xi}{n}\right)\frac{\mathbf{H}(\theta_t^*)}{\mathbf{h}(\theta_t^*)}}{\mathbf{G}(\theta_t^*)}\right)^{\xi}\mathbf{H}(\theta_t^*)z_{t-1}\right)^{-(1-\alpha)}, \tag{C.9}$$

and the wage w_t is given by

$$w_t=\frac{\alpha(1-\xi)\mathbf{h}(\theta_t^*)z_{t-1}^{\alpha}}{(\mathbf{H}(\theta_t^*))^{1-\alpha}}\left(1-\xi\nu\left(1-\frac{1-\xi}{n}\right)\right)^{-(1-\alpha)}\left(\frac{\mathbf{F}(\theta_t^*)-\frac{\xi\omega}{1-\xi}\left(1-\frac{1-\xi}{n}\right)\frac{\mathbf{H}(\theta_t^*)}{\mathbf{h}(\theta_t^*)}}{\mathbf{G}(\theta_t^*)}\right)^{\alpha\xi}. \tag{C.10}$$

It is now straightforward to show that the results in Proposition 2 and 3 stay the same. Using Equation (C.3), we have

$$q_{jt}=\frac{\nu\xi}{n}\left(1-\frac{1-\xi}{n}\right)\left(\frac{\mathbf{F}(\theta_t^*)-\frac{\xi\omega}{1-\xi}\left(1-\frac{1-\xi}{n}\right)\frac{\mathbf{H}(\theta_t^*)}{\mathbf{h}(\theta_t^*)}}{\mathbf{G}(\theta_t^*)}\right)^{\xi}\mathbf{H}(\theta_t^*)z_{t-1}. \tag{C.11}$$

Moreover, using the same law of motion for the aggregate bank efficiency and productivity, and substituting Equation (C.11) into Equation (39), we have

$$a_t(\theta_t^*)=\frac{\tau\nu\xi a_{t-1}}{n}\left(1-\frac{1-\xi}{n}\right)\left(\frac{\mathbf{F}(\theta_t^*)-\frac{\xi\omega}{1-\xi}\left(1-\frac{1-\xi}{n}\right)\frac{\mathbf{H}(\theta_t^*)}{\mathbf{h}(\theta_t^*)}}{\mathbf{G}(\theta_t^*)}\right)^{\xi}\mathbf{H}(\theta_t^*). \tag{C.12}$$

Equation (C.12) implies that the aggregate bank efficiency depends on the occupation choice threshold θ_t^* and the previous-period aggregate bank efficiency a_{t-1} and firm productivity z_{t-1}. We can characterize the BGP in our extended model similarly as Proposition 4.

D Additional details on model estimation

In this appendix, we provide a mapping between all estimated parameters and their targeted moments. Importantly, we also report the estimation results for ν and a robustness analysis to the assumption, in Equation (15), that individual bank efficiency is linear in the quantity of capital goods adopted by banks.

Table D.1
Model-implied Moments and Associated Parameters

Moments	equation	Associated Parameters
CFI	Equation (45)	θ^*, ξ, n, ψ, and $\underline{\theta}$
Gross growth rate of aggregate firm productivity	Equation (46)	θ^*, ψ and $\underline{\theta}$
Gross growth rate of aggregate bank efficiency	Equation (47)	θ^*, τ, ξ, n, ψ, and $\underline{\theta}$
Capital adequacy ratio	Equation (50)	θ^*, ξ, n, σ, ψ, and $\underline{\theta}$
Average recovery rate of loans	Equation (48)	θ^*, ξ, n, σ, ψ, and $\underline{\theta}$
Expected loan rate	Equation (49)	θ^*, ξ, n, σ, ψ, and $\underline{\theta}$
Share of entrepreneurs	$1-\mathbf{F}(\theta^*)$	θ^*, θ_{min}, ψ and $\underline{\theta}$
Elasticity of employment to density	$-(1+\psi)(1-\xi)$	ξ and ψ
Occupation choice	Equation (33)	θ^*, γ, ξ, n, ψ, and $\underline{\theta}$

Table D.1 reports all moments used in estimation and the structural parameters on which they depend. It clearly shows that this is an exactly identified system of simultaneous equations from which it is not evident which moment is identifying which parameter.

Table D.2 reports point estimates for ν in Equation (44) specified as described in the text. The dependent variable is a bank's loan-to-deposit ratio. The main regressor is a bank's IT-expense-to-deposit ratio. As in Section 6.2, we measure IT adoption with dollar IT budget data from the CiTDB database and assuming that the price of IT equipment is the same for all banks in year t. Column (1) is the benchmark and controls for bank characteristics and bank and year fixed effects. Column (2) adds an interaction term between the IT-expense-to-deposit ratio and a dummy variable that is equal to one if the bank's average IT expense intensity between 2010 and 2019 is in the top half of its distribution, and zero, otherwise. Column (2) of Table D.2 disciplines the change in the value of the IT share in the bank's loan production function in our counterfactual exercise.

To investigate robustness to the assumption that bank individual efficiency is linear in the quantity of capital goods adopted by banks as in Equation (15), we consider the following CES generalization of Equation (14):

$$B_{jt} = \gamma\left(\nu^{\frac{1}{\rho}} a_{jt}^{\frac{\rho-1}{\rho}} + (1-\nu)^{\frac{1}{\rho}} D_{j,t-1}^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}.$$

Given a_{t-1}, z_{t-1}, the relative price of capital-goods p_t, the deposit rate r_d, and the amount of funds to be lent B_{jt}, bank j chooses the amount of capital goods q_{jt} and deposits $D_{j,t-1}$ that minimize the total funding costs:

$$\left(1+r_{jct}\right)B_{jt} \equiv \min_{q_{jt},D_{j,t-1}} p_t q_{jt} + (1+r_d)D_{j,t-1}, \quad s.t. \quad B_{jt} = \gamma\left(\nu^{\frac{1}{\rho}} a_{jt}^{\frac{\rho-1}{\rho}} + (1-\nu)^{\frac{1}{\rho}} D_{j,t-1}^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}. \quad \text{(D.1)}$$

Solving this problem, we find that the bank j's demand for capital goods and deposits

Table D.2

Estimating ν and ρ

	log(Loan/Deposits)		log(IT)
	(1)	(2)	(3)
log(q/deposits)	0.0006***	0.0003**	
	(0.0002)	(0.0002)	
1[above median]		-0.0006	
		(0.0029)	
1[above median]×log(q/deposits)		0.0004**	
		(0.0003)	
log(1+r_t)			1.0483***
			(0.3364)
log(Assets)	0.4198***	0.4195***	1.3067***
	(0.0051)	(0.0051)	(0.3803)
CI loan/Total loan	0.0051	0.0052	-0.3277
	(0.0074)	(0.0075)	(0.4702)
RE loan/Total loan	-0.0135**	-0.0135**	-0.1186
	(0.0058)	(0.0059)	(0.3642)
Personal loan/Total loan	-0.0443***	-0.0443***	0.7351
	(0.0097)	(0.0097)	(0.5883)
Equity/Assets	-0.0349**	-0.0349**	1.8634*
	(0.0145)	(0.0146)	(0.9607)
Security/Assets	-0.5357***	-0.5357***	-1.2986***
	(0.0036)	(0.0036)	(0.3284)
Constant	0.5671***	0.5692***	-0.7034
	(0.0142)	(0.0143)	(1.1337)
Year FE	Y	Y	Y
Bank FE	Y	Y	Y
Obs	21,480	21,480	21,480
Adj R^2	0.93	0.97	0.82

Note: The table reports point estimates for ν in Equation (44) and ρ in Equation (D.5). In Columns (1) and (2), the dependent variable is the bank-level loan-to-deposit ratio. The main regressors are the IT-expense-to-deposit ratio and, in Column (2), its interaction with a dummy variable that equals one if the bank's average IT expense intensity between 2010 and 2019 is in the top half of its distribution, and zero, otherwise. In Column (3), the dependent variable is the log of IT expenses. The main regressor is the log of the unit funding cost, defined as the ratio of the sum of interest expenses, non-interest expenses, and deposits to total loans. Other independent variables are the bank-level characteristics as discussed in Table 3. The full sample includes 3,515 banks that remained operational for at least three consecutive years over 2010-2019 period and were incorporated in the continental states. The sample period is from 2010 to 2019. All standard errors are clustered at the bank level. $***\, p < 0.01$, $**\, p < 0.05$, $*\, p < 0.1$.

are, respectively,

$$(capital\ \ good\ \ demand) \qquad p_t q_{jt} = \nu^{\frac{1}{\rho}} \left(\frac{a_{t-1}}{z_{t-1}} q_{jt}\right)^{\frac{\rho-1}{\rho}} \left(1 + r_{jct}\right) B_{jt}^{-\frac{1}{\rho}}, \tag{D.2}$$

$$(deposit\ \ demand) \qquad (1 + r_d) D_{j,t-1} = (1-\nu)^{\frac{1}{\rho}} \left(D_{jt}\right)^{\frac{\rho-1}{\rho}} \left(1 + r_{jct}\right) B_{jt}^{-\frac{1}{\rho}}. \tag{D.3}$$

It follows that

$$p_t q_{jt} = \nu \frac{(p_t z_{t-1}/a_{t-1})^{1-\rho}}{(1 + r_{jct})^{-\rho}} B_{jt}. \tag{D.4}$$

Thus, we can estimate the following relationship between the IT expense and the unit funding cost as:

$$\log \mathbf{IT}_{bt} = \alpha_b + \alpha_t + \rho \log(1 + r_{bct}) + \gamma \mathbf{X}_{bt} + \epsilon_{bt} \tag{D.5}$$

where α_b and α_t are bank- and year-fixed effects, respectively. $\log \mathbf{IT}_{bt}$ is the log of IT expense by bank b measured as the dollar IT budget data from the CiTDB database. $1 + r_{bct}$ is bank b's unit funding cost measured by the ratio of the sum of interest expenses, non-interest expenses, and deposits scaled by total loans of a bank. $\mathbf{X}_{bt}$ is the same vector of bank-level characteristics discussed before. Column (3) of Table D.2 reports the point estimate of ρ, where the coefficient is 1.048, statistically significant at the 99% significance level, providing strong evidence for the assumption made.

E Robustness checks on the empirical analysis

In this section, we report some robustness checks of our main empirical results.

E.1 Robustness check with respect to using subcomponents of IT expenditure

First, we only consider IT expense sub-components that are more directly related to transform deposit into loans. Thus, we re-estimate Equation (55) using the ratio of software to non-interest-expense, instead of IT expense intensity. As Table E.1 shows, our main results are intact.

E.2 Additional bank dependent variables

We then re-estimate Equation (55) using alternative measures of bank performance, such as the lending rate and loan-to-deposit ratio. Our model predicts that with increased adoption of capital goods, banks' lending rates decrease, while the loan-to-deposit ratio rises. Column (1) and (2) of Table E.2 present the results for the lending rate, while Column (3) and (4) show the results for the loan-to-deposit ratio. All findings align with our model's predictions.

Table E.1

Robustness: Alternative Measure of IT Spending (Software Budget Only)

	CFI	
	(1)	(2)
Software/Non-interest expense	-0.0444***	-0.0420***
	(0.0072)	(0.0074)
log(Assets)		-0.6513***
		(0.0525)
Equity/Assets		0.0781***
		(0.0211)
Security/Assets		-0.0461***
		(0.0163)
CI loan/Total loan		0.0387
		(0.0247)
RE loan/Total loan		0.0318
		(0.0315)
Personal loan/Total loan		0.0873***
		(0.0276)
Constant	-0.0573***	0.7709***
	(0.0001)	(0.0708)
Year FE	Y	Y
Bank FE	Y	Y
Controls	N	Y
Obs	24,625	24,625
Adj R^2	0.68	0.69

Note: The table presents the point estimates for β from Equation (55), using the ratio of software budget to the non-interest-expense instead of IT expense intensity. The dependent variable is the bank-level CFI. The control variables are the same as in Table 3. The full sample consists of 3,515 banks that remained operational for at least three consecutive years over 2010-2019 period and were incorporated in the continental states. The sample period is from 2010 to 2019. Bank and year-fixed effects are included. All standard errors are clustered at the bank level. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

Table E.2

Robustness: Alternative Outcome Variables (Interest Rate and Loan-to-deposit Ratio)

	Interest rate		Loan/Deposits	
	(1)	(2)	(3)	(4)
IT/Non-interest expense	-0.00004***	-0.00005***	0.0076*	0.0076***
	(0.0000)	(0.0000)	(0.0043)	(0.0028)
log(Assets)		-0.0001***		0.2065***
		(0.0000)		(0.0298)
Equity/Assets		0.0001***		0.1086***
		(0.0000)		(0.0132)
Security/Assets		0.0005***		-0.7406***
		(0.0000)		(0.0115)
CI loan/Total loan		0.0000		-0.0322*
		(0.0000)		(0.0181)
RE loan/Total loan		0.0001		-0.0334
		(0.0000)		(0.0251)
Personal loan/Total loan		0.0001***		-0.0553***
		(0.0000)		(0.0202)
Constant	-0.0041***	-0.0038***	0.6707***	0.0643
	(0.0000)	(0.0001)	(0.0000)	(0.0412)
Bank FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Obs	24,625	24,625	24,625	24,625
Adj R^2	0.79	0.81	0.88	0.94

Note: The table presents the point estimates for β from Equation (55). The dependent variables are the lending rate (Column 1 and 2) and the the loan-to-deposit ratio of a bank (Column 3 and 4). The control variables are the same as in Table 3. The full sample consists of 3,515 banks that remained operational for at least three consecutive years over 2010-2019 period and were incorporated in the continental states. The sample period is from 2010 to 2019. Bank and year-fixed effects are included. All standard errors are clustered at the bank level. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.