# Banking on Creative Destruction *

Sheila Jiang    Alessandro Rebucci    Gang Zhang

First Draft: 29 August 2024
Preliminary

**Abstract**

We develop and estimate a model of endogenous growth in productivity and bank efficiency, where 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 productivity by affecting agents' occupational choices, while productivity, in turn, affects bank efficiency through the relative price of capital goods. Our findings show that greater bank technology adoption allows more able entrepreneurs to replace less able ones, increasing long-term productivity and economic growth. Empirical evidence, using U.S. bank-level and state (MSA)-level data, supports the critical mechanisms of our model.

**Keywords:** Cost of Intermediation, Endogenous growth, Firm Size Distribution, Bank efficiency, Technology Adoption, Economic Growth.
**JEL Classification:** E44; G21; G38; O33

*Sheila Jiang, Warrington College of Business, University of Florida, email: Sheila.Jiang@warrington.ufl.edu; Alessandro Rebucci, JHU Carey Business School, ABFER, CEPR and NBER, email: arebucci@jhu.edu; Gang Zhang, Cheung Kong GSB, email: gzhang@ckgsb.edu.cn (corresponding author). We are grateful to Manuel Amador, Anmol Bhandari, Gianni De Nicolo, Fabrizio Perri, Andrea Presbitero, Nicola Pierri, Qi Sun, Shengxing Zhang, and Yu Zhang, for comments and discussions. We are thankful for comments received at the ABFER-JFDS, CBCF, CEIBS, the Federal Reserve Bank of Minneapolis, FISF, PHBS, SED, and SDU. We also thank Huy Nguyen and Huajun Meng for their excellent research assistance. Zhang gratefully acknowledges financial support from the ASEAN Business Research Initiative.

# Contents

# List of Figures



# List of Tables

# 1 Introduction

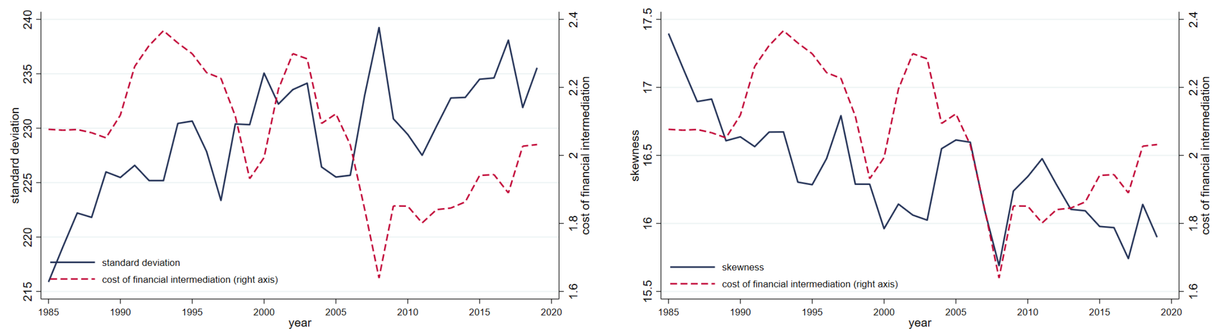
Banks and financial intermediaries, more generally, can mitigate frictions in the non-financial sector and thereby support firm innovation, investment, and growth in a so-called process of "creative destruction." Banks can also amplify economic shocks because of their own frictions and constraints. In this paper, we develop, estimate, and quantitatively evaluate a model in which banks amplify "creative destruction" by adopting technology embedded in capital goods produced by agents endowed with heterogeneous ability levels and deciding whether to be workers or entrepreneurs based on the lending terms offered by banks. Model-based counterfactual simulations match low-frequency changes in the standard deviation and the skewness of the U. S. firm size distribution in the data. Moreover, direct evidence on the cost of intermediation and bank and firm outcomes based on bank-, MSA-, and state-level U.S. data is consistent with the main positive implications of the model and its comparative statics properties.

One implication of the 'creative destruction' process on firm dynamics is that small firms tend to exit more frequently than large firms, while those that survive grow faster. As a result, firm size distribution is dispersed and highly skewed (see Aghion, Akcigit and Howitt, 2014, for a survey). In this paper, we do not take a stand on the specific drivers of the firm-size distribution.[1] Instead, we explore the dynamics of this distribution in response to improvements in individual bank efficiency or increases in aggregate productivity. When we use Bank Call Report data and the cost of financial intermediation (CFI) in Philippon (2015) as a proxy variable for bank efficiency, we find that the CFI is negatively correlated with the standard deviation and positively correlated with the skewness of the firm size distribution.

Figure 1 illustrates the evolution of the aggregate CFI, the standard deviation, and the skewness of the U.S. firm-size distribution. From an average of 218.6 employees in the 1980s, the standard deviation of this distribution increased by 4.1% in the 1990s, 1.8% in the 2000s, and 0.5% in the 2010s. In contrast, the average CFI has steadily declined since

[1] The literature has attributed the characteristics of the firm-size distribution to various factors, including entrepreneurial talent and risk-taking (Lucas, 1978), technological differences (Acemoglu and Zilibotti, 2001; Luttmer, 2007), quality ladders (Klette and Kortum, 2004), firm turnover (Foster, Haltiwanger and Syverson, 2008), (mis)allocation of resources (Hsieh and Klenow, 2009; Bartelsman, Haltiwanger and Scarpetta, 2013), financial constraint (Beck, Demirgüç-Kunt and Maksimovic, 2005), market structure (Syverson, 2004), industry characteristics (Dunne, Roberts and Samuelson, 1989), among others.

the 1990s, from 2.22% in the 1990s to 2.04% in the 2000s, declining further to 1.90% in the 2010s. Panel (b) plots the evolution of the CFI and the skewness of of the firm-size distribution over time. Starting from an average of 17.19 in the 1980s, the skewness decreased by 4.0% in the 1990s, 1.8% in the 2000s, and 0.6% in the 2010s.




(a) CFI and Standard Deviation

(b) CFI and Skewness

**Note**: The cost of financial intermediation is extended through 2019, following the definition in Philippon (2015). The standard deviation (Panel a) and skewness (Panel b) of the firm-size distribution are calculated using the Business Dynamics Statistics (BDS) dataset, as in Decker, Haltiwanger, Jarmin and Miranda (2014). First, the average employment within each size bin is calculated for the period from 1985 to 2019. Then, the share of firms in each size bin relative to the total number of firms is used to measure the density of each firm size category. Finally, the sample standard deviation and skewness of the firm-size distribution are calculated based on this density.

Figure 1
CFI and the US firm-size distribution

(**introduce the real side of the model**) Our model features endogenous growth in both bank efficiency and firms' technological progress. A continuum of agents, as in Lucas (1978), chooses between two occupations: worker or entrepreneur. This choice is based on a comparison between the wage rate and the expected profits from entrepreneurship. Entrepreneurs employ workers to produce capital goods. **In line with the standard costly-state verification framework, the realized revenues of entrepreneurs are uncertain and private information to them. As a result, they must borrow from banks to finance their wage bill upfront. The average ability of entrepreneurs in the economy determines both the relative price of capital goods and the growth of aggregate productivity.**

(**introduce the finance side of the model**) Banks provide working capital to entrepreneurs.

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 to enhance their efficiency in transforming deposits into loans. The average efficiency of individual banks determines the overall efficiency of the banking sector. This mechanism represents how firms' technological progress impacts bank efficiency. In the second stage, banks extend loans to entrepreneurs. Each bank offers an incentive-compatible loan contract to each entrepreneur, specifying the loan amount, interest rate, and monitoring terms, following the framework of Greenwood, Sanchez and Wang (2010).

(**introduce the interplay between finance and real**) The interplay between bank efficiency and firm technological progress is at the core of the model. As aggregate productivity rises, the relative price of capital goods falls, inducing banks to adopt more capital goods, thereby enhancing their efficiency in channeling funds and monitoring borrowers. This leads to higher greater growth rate in bank efficiency. Increased aggregate bank efficiency reduces borrowing costs for entrepreneurs, enabling them to expand production and demand more labor, which in turn raises wages. Furthermore, the wage rate increases relatively more than the marginal profit for entrepreneurs, resulting in the less able agents choosing to become workers rather than entrepreneurs. This reallocation raises the average ability of entrepreneurs, contributing to a higher growth rate of aggregate 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, as observed in the data shown in Figure 1.

We calibrate a small set of parameters based on values commonly used in the literature, directly estimate the critical parameter governing bank technology adoption using Call Report data from the Federal Deposit Insurance Corporation (FDIC), and estimate the model using the method of moments, targeting key stylized facts of the U.S. economy. Since a reliable measure of aggregate bank efficiency is unavailable, we use the Cost of Financial Intermediation (CFI) from Philippon (2015), defined as the ratio of value added in the financial industry to total intermediated assets, as a proxy for bank efficiency.

Next, we assess the quantitative importance of bank technology adoption in determining long-term economic growth and the standard deviation and the skewness of the firm size distribution. To do so, we increase bank technology adoption, calibrating the corresponding structural parameter change **from the average bank to the level estimated in the top half of IT-adopt banks**. In this counterfactual case, we find that the cost of funds to entrepreneurs mildly declines, but the economy's long-run growth significantly accelerates. Facing **a lower loan 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 increasing the labor share and boosting aggregate productivity growth. As the threshold for occupation choice rises, the standard deviation of the firm-size distribution, where the labor employed by entrepreneurs measures the firm size, increases in line with the average ten-year percentage changes observed in the standard deviation and skewness of the U.S. firm-size distribution between the 1980s and 2010s plotted in Figure 1.

The paper also empirically examines three model predictions with granular data. The first prediction is that as aggregate productivity advances, the relative price of capital goods declines, prompting banks to adopt more IT and increase their efficiency. To estimate this critical channel in the model's transmission mechanism, we use Call Report data combined with detailed IT spending data from the Harte Hanks Market Intelligence Computer Intelligence Technology database (He, Jiang, Xu and Yin, 2022). We proxy for bank efficiency using a bank-level value added as a share of total intermediated loans, and we refer to CFI as in Philippon (2015). Our findings show that investment in Information Technology (IT) is associated with a lower CFI after controlling for bank-level characteristics, time, and bank-fixed effects. A one standard deviation increase in IT budget, as a share of noninterest expense, is associated with a 0.044 standard deviation decrease in banks' CFI.

To establish causality, in this step of the analysis, 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 a shift-share exposure variable, which interacts 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 increased IT investment by U.S. banks leads to a lower CFI. Moreover, our results indicate that this decline in CFI is primarily driven by lower labor compensation in bank value, while profitability (measured as net income per dollar of intermediated loans) remains stable. This suggests that a substitution effect between IT expenditure and labor may be driving the data, consistent with the implication of an extension of the model we provide in the Appendix.

Second, our model predicts that banks lend more to entrepreneurs as they become more efficient. To investigate this implication, we employ U.S. bank-level data from the CRA Small Business Loan Database. We find that a lower CFI is positively associated with faster growth in small business loans issued by a bank within the same state in which the bank operates. 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, 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 test 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. We find that the state (MSA)-level CFI, measured as the deposit-weighted average of the CFI of banks operating in a particular state (or MSA), is positively correlated with the standard deviation of the firm-size distribution and negatively correlated with its skewness—consistent with our model's predictions.

To account for potential unobserved state or industry-level characteristics, we examine the relationship between state (MSA)-level CFI and the standard deviation and skewness of the firm-size distribution across sectors within a given state (MSA). In this analysis, we include state-year and sector-year fixed effects to control for such unobserved characteristics. Our results show that, within a given state (MSA), the standard deviation for sectors that rely more heavily on external finance is more negatively correlated with the state (MSA)-level CFI, while the skewness exhibits a stronger positive correlation.

## Related Literature

Our paper contributes to several strands of literature. A large body of literature has explored the theoretical and empirical relationship between financial development and economic growth (see Levine, 2005; Matsuyama, 2007, for surveys). On the theoretical front, financial intermediaries, or banks in particular, are often introduced to mitigate frictions or enhance efficiency, such as information asymmetry (Greenwood and Jovanovic, 1990; Greenwood, Sanchez and Wang, 2010), diversifying risk (Bencivenga and Smith, 1991), and alleviating creditors' financial constraints (Aghion, Howitt and Mayer-Foulkes, 2005; Buera, Kaboski and Shin, 2011; Buera and Shin, 2013; Midrigan and Xu, 2014). As a result of intermediation, in these settings, resources are allocated to more productive uses, promoting economic saving and growth. In our model, banks exist to overcome information asymmetry and a working capital constraint. Higher aggregate productivity, embedded in intermediate capital goods and reflected in their relative price, can enhance bank efficiency, which, in turn, feeds back into profitability and ultimately aggregate productivity via more lending at cheaper rates.

As in Buera and Shin (2013), our model features an occupation choice of heterogeneous agents that enable us to examine the impact of financial development not only on growth rates but also on the distribution of firm sizes. We extend their framework by allowing banks to adopt technology from entrepreneurs, thereby endogenizing financial development and enabling us to explore its feedback effects on economic growth and firm-size distribution. Buera, Kaboski and Shin (2011) investigate how financial frictions, along with sector-specific fixed costs, distort the allocation of capital and entrepreneurial talent between manufacturing and services, resulting in misallocation that reduces TFP and economic output. In our model, if banks slow their IT adoption, they negatively affect growth by extending loans to less able entrepreneurs. While the mechanism that we propose is different, the two papers share the idea that banks can affect long-run growth, affecting resource allocation in the economy.

On the empirical front, many papers have provided cross-country empirical evidence or event studies, suggesting that financial development leads to economic growth (see, for example, King and Levine, 1993; Jayaratne and Strahan, 1996; Rajan and Zingales, 1998; Kroszner and Strahan, 1999; Levine, Loayza and Beck, 2000; Beck, Levine and Loayza, 2000, among others). Although excessive credit growth can lead to financial instability and crises as stressed, for example, Kaminsky and Reinhart (1999), Ranciere, Tornell and Westermann (2008), Mian and Sufi (2009), and Schularick and Taylor (2012). While this literature focuses on cross-country comparisons, our paper focuses on the financial development of the banking industry within a closed economy.

More generally, the idea that economic growth can influence financial development, as suggested by Robinson (1954) and Lucas (1988), has received relatively less attention in the literature. This paper examines this causal link within a tractable general equilibrium (GE) model that features a two-way interaction between finance and growth. In particular, our model is closely related to the theoretical 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 bank efficiency by allowing banks to adopt capital goods from entrepreneurs, enabling us to evaluate the feedback effect of technology adoption on economic growth. Our work also relates to de la Fuente and Marín (1996) and Laeven, Levine and Michalopoulos (2015). The former study incorporates a screening cost that exogenously decreases as entrepreneurs' technology advances. The latter features an exogenously growing technology frontier in a Schumpeterian endogenous growth model from which entrepreneurs randomly adopt. Banks must innovate to efficiently monitor entrepreneurs. Our model differs in two key respects. First, both individual banks' efficiency and firm technological progress are endogenous in our setting. Second, the model allows us to assess the importance of bank IT adoption for both growth and its implications on the size distribution of firms.

A well-established literature models firm technology adoption and its impact on economic growth (see, for example, Jovanovic and Rob, 1989; Acemoglu, Aghion, Lelarge, Van Reenen and Zilibotti, 2007; Perla and Tonetti, 2014; Benhabib, Perla and Tonetti, 2021; König, Storesletten, Song and Zilibotti, 2022). We complement this literature by focusing on modeling bank technology adoption.

Several studies explore how technology produced outside the financial system shaped the financial industry. Hannan and McDowell (1984) examine the introduction of ATMs and the use of wire transfers. Jones (2013) investigate information acquisition, computing technologies, and high-frequency trading platforms. Tufano (2003) explores software development and platforms. Other research has focused on financial innovation related to 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). In our theoretical framework, we model bank technology adoption in a general way, capturing the GE implications of specific innovations, including recent developments like large language models introduced since late 2022, on economic growth and firm-size distribution.

Lewellen and Williams (2021), Pierri and Timmer (2022), Mezzanotti and Simcoe (2023), and Branzoli, Rainone and Supino (2023) exploit bank-level data variation during the Great Recession and the COVID pandemic to estimate the causal effect of bank IT adoption on bank performance and NPLs. We quantify the effects of banks' technology adoption in a GE model and provide empirical evidence in normal and crisis times over the same period. Using patent data, Lerner, Seru, Short and Sun (2024) documents the evolution of financial innovations in the U.S. and finds that IT and non-financial firms are the key drivers of financial innovation. They also document that the geographic distribution of financial innovation is not uniformly distributed in the United States. This paper provides a model of bank IT adoption, consistent with the idea that banks primarily acquire IT embedded into intermediate goods from non-financial firms. The empirical analysis also exploits geographic variation in complementary skills needed to adopt IT, identifying the causality in the data.

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 spending and provide causal evidence that banks actively adopt different types of IT to cater to 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 some of the same data to explore the predictions of our theoretical model, and our findings are consistent with the granular evidence that these studies provide.

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 reports the results. Section 5 presents counterfactual simulations and quantitatively evaluates the model. Section 6 provides direct microeconomic evidence on the model's main implications. Section 7 concludes. Proofs and details of the analysis 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 productivity and bank efficiency.

## 2.1 Entrepreneurs, workers, and the occupation choice

There is a continuum of agents of unit mass, each of whom is assigned individual ability level $\theta$, drawn from a distribution on $\Theta = [\theta_{min}, \infty)$ with a c.d.f. $\mathbf{F}(\theta)$. The parameter $\theta$ characterizes agents as entrepreneurs who operate a firm producing capital goods or workers that inelastically supply one unit of homogeneous labor. At the beginning of each period, agents are reassigned a type. Before they are assigned their type, all individuals join a risk-sharing plan and decide on consumption and saving at the end of the period. There is no aggregate risk in the economy. Agents also own and operate consumption-good-producing firms and banks.

#### Entrepreneurs

Suppose the type-$\theta$ 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 the output, $l_t(\theta)$ is the labor input, $z_{t-1}$ is the aggregate level of productivity at $t-1$, and $\xi$ governs the returns to scale or the span of control parameter. We assume $\xi < 1$, implying that the most productive entrepreneurs cannot control all resources. We assume that the $\theta$-entrepreneurs' project will be successful or fail with probabilities $\eta$ and $1-\eta$, respectively. When projects fail, for simplicity but without loss of generality, we assume that all projects yield the common individual ability $\underline{\theta} < \theta_{min}$, where $\underline{\theta}$ is a parameter.

Entrepreneurs have no capital and must borrow to pay workers in advance. If the project succeeds, banks charge the lending rate $r_{lt}(\theta)$. Otherwise, banks require entrepreneurs to repay a fraction $x_t(\theta)$ of the loans.[2] Before learning the realization of

[2]Notably, our model nests the case where limited liability is imposed. Here, entrepreneurs produce

their projects, type-$\theta$ 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-$\theta$ entrepreneurs' problem, we have:

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

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

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

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. Expected profits decrease with the wage rate and the expected loan repayment. Thus, through the expected loan rate, bank technology adoption affects entrepreneurs' profits, agents' occupation choices, and aggregate productivity.

**Workers and the occupation choice**

The type-$\theta$ 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, the standard condition for occupational choice as in Roy (1951)

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.

and Lucas (1978). Later, we will show that the entrepreneurs' profit in equation (5) increases in $\theta$. Therefore, if the type-$\theta$ agents become entrepreneurs, so do the type-$\theta'$ ones with $\theta' > \theta$. We will see later that, under certain parameter restrictions, there exists a threshold $\theta^*$ for which the marginal agent is indifferent between being a worker and an entrepreneur. All agents who are more able than the marginal one will be entrepreneurs, while the less able ones 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 collected and redistributed equally among agents. We assume that the representative consumer in this plan has log-utility, i.e., $\mathbf{u}(c_t) = \ln c_t$, 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 their present value of their lifetime utility, subject to their budget constraint, solving

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

with $\beta$ denoting 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.[3] Banks play a 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 combine them with capital goods purchased from the entrepreneurs to produce loans. This technology adoption decision allows banks to choose the level of individual efficiency with which they transform deposits into loan,

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

giving them a competitive edge in the second stage of the game.[4] In the second stage, banks take their funding costs as given and syndicate loans to each entrepreneur with all other banks. The next two subsections describe each of these two stages in turn. The micro-founded optimal contract and its solution in the second stage are reported in the Appendix A. Readers who are not interested in the microfundations of the bank optimal contract can skip those derivations.

**The second stage: loan market equilibrium**

A type-$\theta$ entrepreneur borrows 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 loan offers from the 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-$\theta$ entrepreneur is $b_t(\theta) = \sum_j b_{jt}(\theta)$.

If the type-$\theta$ entrepreneurs' project fails, banks collectively confiscate entrepreneurs' outputs, liquidate them in the market, and recover $p_t \underline{\theta} z_{t-1} l_t^{\xi}(\theta)$.[5] 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-$\theta$ 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 in 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 $\theta$ is only known to the entrepreneurs, but not the banks. To verify the state, banks need to exert costly effort, denoted as $\mathbf{e}(\theta)$ per unit

[4]The model properties also do not change if allow banks to also use labor as an additional input in the loan production (Appendix C) or if we introduce Cournot competition in the deposit market (please see Presbitero, Rebucci and Zhang (2024) for details).

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

of fund. Once efforts are exerted, banks can always detect the realized states. In Appendix A, we design an optimal contract for banks and micro-found $\mathbf{e}(\theta)$ under stochastic monitoring as in Greenwood, Sanchez and Wang (2010). Moreover, we show that $\mathbf{e}(\theta)$ is increasing and concave in $\theta$, 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 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 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-$\theta$ entrepreneurs subject to the inverse loan demand and the resource constraint in equations (7) and (8):

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

The bank's expected profit from lending to the type-$\theta$ 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-$\theta$ 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:*

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

*and the gross lending rate for the type-$\theta$ entrepreneurs is:*

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

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

Several remarks are in order here. First, it is straightforward to show that resource constraint in equation (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 the common ability in the failed state ($\underline{\theta}$) and decreases with the expected individual ability ($\bar{\theta}$), implying that the loss given default is increasing in $\theta$. Assumption (13) requires that the common ability in the failed state ($\underline{\theta}$) is sufficiently low relative to the lower bound of the individual ability ($\theta_{min}$) so that the hair cut rate is smaller than $1 + r_{lt}(\theta)$, the gross lending rate in the successful state.

Second, 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 $\mathbf{e}(\theta)$. A more competitive banking system lends at a lower expected gross loan rate. The verification cost $\mathbf{e}(\theta)$ increases in $\theta$ as it takes more effort to verify higher $\theta$-entrepreneurs. Thus, the expected gross loan rate increases in $\theta$, and banks lend to more able entrepreneurs first. **Moreover, as we will show later, banks that adopt more capital goods and improve their efficiency experience a reduction in unit funding costs. Thus, adopting more capital goods also lowers the unit cost of verification for each borrower.**

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 $\theta$, the default premium is also increasing in $\theta$. Under Assumption (13), this default premium is larger than 1.

**The first stage: bank technology adoption**

In the first stage, banks acquire technology embedded in capital goods to manage their intermediation efficiency in the spirit of Sutton (1991) and, more generally, the IO approach to banking (Freixas and Rochet, 1997). They choose how much to invest in technology to gain an edge on their competitors before knowing the realization of the individual borrower's ability. For simplicity, the number of banks is given, and there is no equity. We assume that bank $j$ transforms deposits into loans using 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, $a_{jt}$ is the individual bank efficiency in transforming deposits $D_{j,t-1}$ into loans, $\nu$ is the factor share, and $\gamma$ is a scale parameter that captures other factors such as managerial ability, marketing expenditures, physical capital, etc.

Bank $j$ manages $a_{jt}$ by adopting new technology embedded in capital goods with an external effect from the previous period's aggregate level of bank efficiency. 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 of the bank technology adoption process 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 exists also assuming some curvature in $q_{jt}$.[6] However, as noted in Romer (1996) and others, a linear functional form ensures a well-defined balanced growth path. For the

[6] **Since bank efficiency is unobservable, we cannot directly test for the unitary elasticity of capital goods with respect to bank efficiency as specified in equation (15). Instead, we extend the Cobb-Douglas function for deposit transformation to take a CES form, represented as:** $B_{jt} = \gamma\left(\nu^{\frac{1}{\rho}} a_{jt}^{\frac{1+\rho}{\rho}} + (1-\nu)^{\frac{1}{\rho}} D_{j,t-1}^{\frac{1+\rho}{\rho}}\right)^{\frac{\rho}{1+\rho}}$. **The first order condition of the first stage problem implies** $\log q_{jt} \propto \rho \log 1 + r_{jct}$. **In Appendix D.2, we regress IT goods on the unit internal funding cost, while controlling for other bank characteristics as well as state, bank, and year fixed effects. The coefficient we find is close to one, providing supportive evidence for the assumption of unitary elasticity in equation (15).**

same reason, we enter $z_{t-1}$ at the denominator of equation (15), meaning that the higher the level of aggregate productivity, the more costly it is to originate loans and monitor borrowers.[7]

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:

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

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

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

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

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 of bank $j$ increases in the relatively price of capital goods, the deposit rate, and the last-period aggregate technology, and decreases in the last-period bank efficiency. Equation (19) is the critical channel through which firm productivity affects the banking system efficiency and its loan pricing. As the price of capital goods declines, banks adopt more capital goods and improve their ability to channel deposits into loans, lowering their funding costs and ultimately supplying funds to entrepreneurs at lower rates.

[7] 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.

## 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 using the following technology:

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

where $K$ is the capital goods purchased from entrepreneurs and $\alpha \in (0,1)$ is the capital share parameter. We further assume that the consumption good is the numeraire and normalize its price to 1. Consumption-goods producers chooses the level of capital that maximize 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 and its implications

We now discuss the market clearing conditions, assuming that, as we show next, there exists a threshold $\theta_t^*$ 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 $d_{t-1}$ balance 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

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

where $D_{j,t-1}$ is the deposit demanded by bank $j$.

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-$\theta$ entrepreneur. Thus, the loan-market clearing condition is

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

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

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

Note that $\mathbf{g}(\theta)$ summarizes 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 $Y_t^K = \int_{\theta_t^*}^{\infty} \eta y_t(\theta) + (1-\eta) y_t(\underline{\theta}) \, \mathbf{d} \, \mathbf{F}(\theta)$, where $y_t(\theta)$ is in equation

(1). Capital goods are purchased by consumption-good producers, $K_t$ in equation (22), or banks, $Q_t = nq_{jt}$, where $q_{jt}$ is 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 productivity $z_{t-1}$ and the deposit rate $r_d$, each agent is assigned an individual ability $\theta$ drawn

from a distribution on $\Theta$, 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 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 an initial deposit level $d_0$ and the sequence of the aggregate bank efficiency $a_{t-1}$, aggregate productivity $z_{t-1}$, and the deposit rates $r_d$, an intratemporal symmetric equilibrium is a sequence of wages $w_t$, capital-good prices $p_t$, bank demands of capital goods $q_{jt}$, unit cost of funds $r_{jct}$, deposit demands 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 $\theta_t^*$, labor demanded by the $\theta$-type entrepreneur $l_t(\theta)$, corresponding loan rates $r_{lt}(\theta)$, 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, for all $t$:*

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

2. *Given $p_t$, $w_t$, $r_{jct}$, and $\theta_t^*$, 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 $\theta_t^*$, the loan rate $r_{lt}(\theta)$ and the recovery rate $x_t(\theta)$ clears the loan market, $p_t$ clears the capital-good market, and $w_t$ clears the labor market.*

5. *The threshold $\theta_t^*$ 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 then 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 $\theta_t^*$ 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. We 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 $\theta_t^*$, 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 $\mathbf{h}(\theta)$ 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 $\nu$ 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*

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

*Moreover, there exist $\nu^*\in(0,1)$, where $\nu^*$ is defined in Appendix B.3, such that*

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

*Proof: see Appendix B.3.*

To provide intuition, rewrite the arbitrage condition in equation (36) as

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

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, where $\mathbf{F}(\theta_t^*)$ is the total labor supply, and $\mathbf{g}(\theta_t^*)/\mathbf{G}(\theta_t^*)$ is the share of labor employed by the type-$\theta^*$ entrepreneurs. The product of the first two terms is the marginal profit of the type-$\theta^*$ entrepreneurs. In equilibrium, the agents' occupation choice only depends on the *expected* gross loan rate, which determines the *relative* income of the marginal agent. A lower rate lowers the entrepreneurs' profits relative to workers' wage rate, inducing some less able agents to choose to be workers and increasing the threshold of occupation choice.

As the 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 $\theta^*$ increases. As aggregate 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 $\theta^*$ 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 $\theta^*$ increases.

The intuition for the comparative statics in equation (36), which drives the counterfactual simulations that we report below, is more complex. Suppose first that the price of capital goods is fixed. Increasing the factor share $\nu$ of capital goods in equations (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 $\nu$, i.e., $\Delta \ln q_{jt}/\Delta \ln \nu$, which we call adoption elasticity and is the percentage increase in capital goods adoption for one percent increase in $\nu$. If this elasticity is greater than one, a higher $\nu$ requires banks to spend more on capital goods than they save on deposits, leading to a higher unit funding cost. If this elasticity is less or equal to one, the unit funding cost decreases as $\nu$ increases.

To analyze how this adoption elasticity responds to a changing value of $\nu$. 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 $\nu$ 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 $\nu$ 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.

Lets 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 $\nu$ above which the adoption elasticity is equal to one. As we shall see below, the value of $\nu$ that we estimated from Call Report data is such that when $\nu$ 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:

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

where $\mathbf{E}(\theta|\theta \geq \theta_t^*)$ is the conditional average ability of entrepreneurs. Thus, the aggregate 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 $\tau$ 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 $\theta_t^*$ and the previous-period aggregate bank efficiency $a_{t-1}$ and 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 equations (38) and (41), respectively. Assuming that the economy starts in period 1 and the assumptions in Proposition 2 hold, for any* $\{a_0, z_0\}$*, there exists a threshold* $\theta^*$ *so that solves equation (33) evaluated at* $\{a_0, z_0\}$*, and the economy evolves along the following BGP:*

1. $g_z(\theta^*) = \eta\mathbf{E}(\theta|\theta \geq \theta_t^*) + (1-\eta)\underline{\theta}$*, and let* $g^{1/\alpha} = g_z(\theta^*)$*;*

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

3. *the occupation choice threshold* $\theta_t^*$ *is constant at* $\theta^*$*;*

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

5. *the production of capital goods $Y^K$, and the quantity of capital goods purchased by final-good producers ($K_t$) 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-$\theta$ 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 productivity increase. Proposition 3 implies that, on the one hand, higher aggregate 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 productivity, $a_t/z_t^\alpha$, 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 $\tau$ 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. Therefore, in the model estimation, $\tau$ will be anchored by the economy-wide target growth rate.

# 4 Model estimation

In this section, we estimate the model. We first discuss two critical 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

Table 1

PARAMETER VALUES AND DATA MOMENTS

| | Calibrated parameters | | |
|---|---|---|---|
| | Name | Value | Target |
| $\alpha$ | Capital share in final-good production | 0.420 | US aggregate capital share |
| $\beta$ | Discount factor | 0.984 | $1/(1+r^d)$ |
| $\gamma$ | Parameter governing loan-to-deposit ratio | 0.771 | loan-to-deposit ratio for lowest IT-adopted banks |
| $\eta$ | Prob. of project success | 0.973 | average delinquency rate in 1987-2019 |
| $r_d$ | 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 |
| $\nu$ | share of capital goods adopted by banks in funds transformation | 0.06% |

| | Estimated parameters with method of moments | |
|---|---|---|
| | Name | Value |
| $\xi$ | Labor share in capital production | 0.801 |
| $\psi$ | Distribution curvature | 9.335 |
| $\theta_{min}$ | Lower bound of $\Theta$ | 0.754 |
| $\underline{\theta}$ | Degenerated productivity | 0.374 |
| $\sigma$ | Scalar for monitoring technology | 0.538 |
| $n$ | Number of banks | 11 |
| $\tau$ | Scalar for growth rate of bank efficiency | 3.77E(+4) |
| $a_0$ | Initial bank efficiency along BGP | 6.45E(+197) |

| Targeted moments | | |
|---|---|---|
| Moments | Model | Data |
| CFI in Philippon (2015) | 1.89% | 1.89% (average between 1965 and 2019) |
| Growth of productivity implied by BGP | 4.83% | 4.83% ($g^{1/\alpha}$ implied by BGP) |
| Growth of bank efficiency implied by BGP | 2% | 2% ($g$ implied by BGP) |
| Elasticity of firm share wrt to size | 2.06 | 2.06 as in Gabaix (2016) |
| Share of entrepreneurs | 11.2% | 11.2% as in Holter, Stepanchuk and Wang (2023) |
| Average loan recovery rate | 47.65% | 47.65% as in Altman and Kishore (1996) |
| Loan-to-deposit ratio | 97.54% | 95.24% calculated from call report |
| Expected loan rate | 5.91% | 5.73% real bank prime loan rate in 1984-2019 |

process for the remaining model parameters. The full set of model parameters is

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

Table 1 reports their estimated values together with the moments they target.

We assume that the agents' individual ability follows a geometric distribution with c.d.f. as

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

where $\psi$ governs the curvature of the density with respect to firm size. Thus, firm size roughly follows the 'Zipf's law' as in Axtell (2001) and Gabaix (2016). Consistent with the solution of the optimal contract in Appendix A, we also assume the following functional form for $\mathbf{e}(\theta)$ as

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

where $\sigma$ is a scale parameter governing the level of the verification cost. If there is no uncertainty on the project realization, i.e., $\eta = 1$, banks don't need to verify the state and $\mathbf{e}(\theta) = 0$ for $\forall\ \theta \in \Theta$. Additionally, Assumption (13) ensures that $\mathbf{e}(\theta)$ satisfies Assumption (31), and $\mathbf{h}(\theta^*)$ is increasing in $\theta^*$.

We calibrate the parameters $\{\alpha,\ \beta,\ \gamma,\ \eta,\ r_d\}$. First, we set the capital share in final goods production at 0.42 and the discount factor at 0.984, both within the typical range found in the literature. According to equation (14), if there is no IT adoption (i.e., $\nu = 0$), the loan-to-deposit ratio equals $\gamma$. Therefore, using bank-level data, we calibrate $\gamma$ to 0.77, which corresponds to the average loan-to-deposit ratio at the bottom quartile of the distribution.[8] The probability of successful project realization, $\eta$, is set at 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. We set the deposit rate, $r_d$, at 1.65%, setting it equal to the average real 3-month treasury bill rate from 1965 to 2019. Finally, we normalize initial aggregate productivity to one.

Next, we estimate $\nu$ from the bank-level data. Guided by equation (14), we estimate $\nu$ by regressing the logarithm of loan-to-deposit ratio on the logarithm of the IT-expenditure-to-deposit ratio as in the following specification:

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

[8] See Section 6 for details on the IT data and sample selection. For each bank, we calculate the average IT adoption relative to non-interest expenses (IT-to-NIE) and the average loan-to-deposit ratio from 2010 to 2019. The asset-weighted average loan-to-deposit ratios in the first, second, third, and last quartiles of the IT-to-NIE ratio distribution are 0.77, 0.79, 1.09, and 1.16, respectively. The corresponding asset-weighted averages for the IT-to-NIE ratio are 0.005, 0.013, 0.034, and 0.236, respectively.

where $\omega_t$ and $\zeta_j$ are time and bank fixed effects, respectively. We run this regression with annual data from 2010 to 2019, consistent with our other micro-economic evidence in Section 6 and find a point estimate of 0.06%, statistically significant at the 99% level—see Table D.1 in Appendix D.1 for details. This value is very close to the medium IT expenditure share of total internal funding cost, which is 0.066%.

Last, we estimate the remaining eight parameters, along with the threshold for the occupation choice from equation (33), with the method of moments. The parameters to be estimated are $\{\xi, \psi, \theta_{min}, \underline{\theta}, \sigma, n, \tau, a_0\}$. The model-implied moments and the associated parameters are summarized in Table D.2 in Appendix D.

We cannot directly observe bank efficiency in the data. As a proxy, we rely on the cost of financial intermediation (CFI) of Philippon (2015), which is defined as value added over total loans, targeting an average of 1.89% between 1950 and 2019. The model-implied CFI is given by equation (45). In the model, bank value added coincide with profits, $\Pi_t^B = \sum_j \pi_{jt}^B = n \int_{\theta_t^*}^{\infty} \pi_{jt}^B(\theta)\ \mathbf{d}\,\mathbf{F}(\theta)$. 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 $b(\theta)$ is borrowing by the type-$\theta$ entrepreneurs in equation (4), $\mathbf{G}(\theta_t^*)$ is is defined in equation (27), and $\mathbf{h}(\theta_t^*)$ is defined in equation (29). It is straightforward to show that $\phi_t$ is decreasing in the threshold of occupation choice $\theta_t^*$, as $\mathbf{G}(\theta_t^*)$ is decreasing in $\theta_t^*$ while $\mathbf{h}(\theta_t^*)$ is increasing in $\theta_t^*$ under Assumption (13). Recall also that $\phi_t$ is constant along the BGP, as the occupation choice threshold is constant. This is consistent with the observations in Philippon (2015) about the fact that the CFI for the whole US financial industry in more or less around 2% in the past century.

Using equation (38) and (41), the gross growth rate of aggregate 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 assume that the annual growth rate of GDP per capita is 2% along the BGP, where

GDP growth in our model is the same as aggregate consumption growth as in equation (20). This value is obtained by regressing log real GDP per capita on a constant and linear trend from 1950 to 2019. Proposition 4 implies that aggregate bank efficiency grows at the same rate, i.e., $g_a = 1.02$, and aggregate productivity growth in the capital goods sector is 4.83% per year, i.e., $g_z = 1.0483$, consistent with existing evidence on productivity growth in the capital goods producing sector as in Caliendo, Parro, Rossi-Hansberg and Sarte (2018).

Using equation (11) and (12), the average recovery rate and the average expected loan rate in the model are, respectively,

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

and

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

where $x(\theta)$ is solved from equation (11), $r_{lt}(\theta)$ is solved from equation (12), and $r_{jc}$ is solved in equation (19). We choose an average recovery rate of 47.65%, which is the same as the average rate for senior unsecured loans from 1982-1995 in Altman and Kishore (1996). We set the data target for the expected loan rate to 5.73%, which is the average real bank prime loan rate between 1984 and 2019 from the Board of Governors of the Federal Reserve System.

The model-implied loan-to-deposit ratio is

$$\frac{\int_{\theta^*}^{\infty} b_t(\theta)\mathbf{d}\,\mathbf{F}(\theta)}{D_{t-1}} = \frac{1-\xi}{\xi(1-\nu)}\frac{1+r_d}{1-\frac{1-\xi}{n}}\frac{\mathbf{h}(\theta^*)\mathbf{F}(\theta^*)}{\mathbf{H}(\theta^*)}. \tag{50}$$

Here, we target an asset-weighted average loan-to-deposit ratio of 95.24% for banks, excluding those in the bottom quartile of the IT-to-NIE ratio distribution.

The model implied share of agents that is entrepreneur is $1-\mathbf{F}(\theta^*)$. Given $\mathbf{F}(\theta)$ in equation (42), the logarithm of the frequency of the type-$\theta$ entrepreneur is

$$\ln(\mathbf{f}(\theta)/(1-\mathbf{F}(\theta_t^*))) = \ln\psi + \ln\theta^* - (1+\psi)\ln\theta, \tag{51}$$

where $\mathbf{f}(\theta)$ is the p.d.f. of agents' ability. Using equation (3), we can express the logarithm of the firm size, measured by employment, as

$$\ln l(\theta) = \ln \mathbf{F}(\theta^*) - \ln \mathbf{H}(\theta^*) + \frac{1}{1-\xi} \ln\left((\eta\theta + (1-\eta)\underline{\theta})/(1+\mathbf{e}(\theta)\right). \tag{52}$$

The two equations imply that the elasticity of firm employment with respect to the corresponding density is given by $-(1+\psi)(1-\xi)$. This moment targets the value of -2.06 estimated in Axtell (2001) and Gabaix (2016).

Finally, the model-implied share of entrepreneurs in the population, which is equal to $1-\mathbf{F}(\theta^*)$, targets a value of 11.2% as in Holter, Stepanchuk and Wang (2023).

To minimize the distance between the model-implied moments and their targets, we follow the following procedure. We apply the method of moments with equal weighting and choose parameters that minimize the criterion below, subject to the threshold of occupation choice solving equation (33), as

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

where $i$ indexes the $i$th moment. The model matches all data moments quite closely.[9]

# 5 Quantifying bank technology adoption

In this section, we explore the quantitative relevance of bank technology adoption with counterfactual simulations. We consider an increase in the adoption of IT equipment used in deposit transformation. We will present the sequence of intratemporal equilibria as in Proposition 2 to illustrate the model's mechanisms and the BGP comparative statics that quantifies the long-term impact of these changes in the economy. We empirically validate the critical mechanisms of the model in the last section of the paper.[10]

**In this counterfactual case, we increase the share of IT equipment used in deposit**

[9]Equation (52) suggests that the logarithm of firm size is not exactly linear in $\ln\theta$, unlike the logarithm of the firm-size density in equation (51). Nonetheless, we assume linearity for our estimation. To assess the impact of this assumption, we use the estimated parameters to compute firm size—defined as the labor employed by each type-$\theta$ entrepreneur—and the corresponding density. We then regress the logarithm of the firm-size density on a constant and the logarithm of firm size. The estimated coefficient for the logarithm of firm size is -2.11, consistent with the estimate from the linear case.

[10]We also analyze bank technology adoption in the context of higher bank funding costs, for example, as the US economy experienced in 2022-23 at the beginning of the AI revolution. See Appendix D.4 for detail.

**transformation, $\nu$, from 0.06% to 0.07%, representing a shift from the average bank to the level estimated in the top half of IT-adopting banks.**[11] Specifically, assuming that the economy is in BGP until period -1, at time $t = 0$, we permanently increase $\nu$ from 0.06% to 0.07% without any other changes. We then let the economy evolve for ten periods consistent with Proposition 2. Figure 2 reports the simulation results.

In period $t = 0$, with higher $\nu$, banks significantly increase their purchases of capital goods, as in equation (40), improving their efficiency as in equation (15) and lowering their funding costs as in equation (19).[12] Consequently, they can also offer borrowers a lower expected loan rate, also leading to a reduced CFI. The number of banks that is fixed in our model affects both their pricing power and market share. While the loan rate reflects the former, the CFI captures both effects, resulting in the CFI declining much less than the average expected loan rate in period 0.

A lower expected loan rate induces more capital goods production, leading to higher growth in loan and labor demands, and the wage rate. As a result, the labor share rises in period 0.[13] As the expected loan rate declines, expected profits of entrepreneurs at margin increases relatively less than wages, and less able agents choose to become workers, with $\theta^*$ increasing. Since the firm-size distribution at $t = -1$ is right-tailed, a higher threshold shifts the distribution further to the right, resulting in a higher standard deviation and lower skewness.[14]

[11] **In particular, we re-estimate equation (44) by adding an interaction term between the logarithm of the IT-to-deposit ratio and the indicator for banks in the top half of IT adoption. Further details are provided in Table D.1 in Appendix D.1.**

[12] Given all structural parameters calibrated or estimated in Section 4, the cutoff point of the capital-good adoption share $\nu^*$ in Proposition 3 is a very small number—4.49E(-150). Our estimated share is much larger than this cutoff point at $\nu = 0.06\% > \nu^*$. Therefore, increasing $\nu$ from this initial level results in more capital-good adoption, leading to higher bank efficiency.

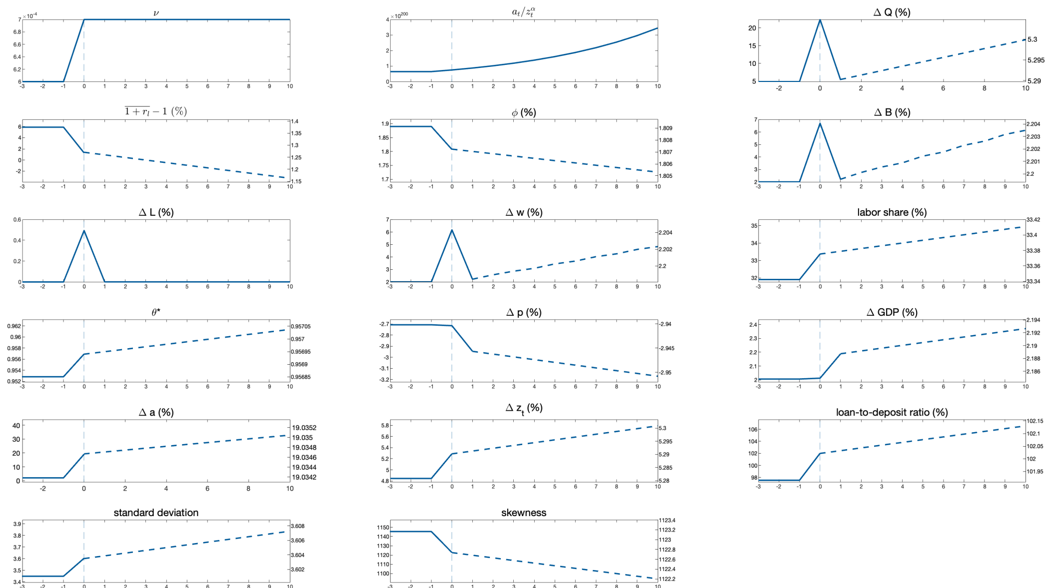
[13] The labor share is defined as labor income (before all incomes are collected and redistributed) over GDP as

$$Labor\ \ Share_t = \frac{w_t L_t}{GDP_t} = \frac{\alpha(1-\xi)\mathbf{h}(\theta^*)\mathbf{F}(\theta^*)}{\left(1-\xi\nu\left(1-\frac{1-\xi}{n}\right)\right)\mathbf{H}(\theta^*)}, \tag{54}$$

where $L_t$ is the total labor supply, and $GDP_t$ is measured by the aggregate consumption. It is straightforward to show that the labor share increases in the threshold of occupation choice.

[14] The model-implied standard deviation of the firm-size distribution is

$$\mathbf{sd}(\theta^*) = \sqrt{\frac{1}{1-\mathbf{F}(\theta^*)}\int_{\theta^*}^{\infty}(l(\theta)-\mathbf{avg}(\theta^*))^2\ \mathbf{d}\ \mathbf{F}(\theta)}, \tag{55}$$




**Notes**: The figure illustrates the economy's response to an increase in $\nu$. The economy is on its baseline BGP path until period -1. At $t = 0$, the value of $\nu$ increases from 0.06% to 0.07%. From this point, the economy evolves for ten periods, consistent with Proposition 2. All dashed lines after period 0 are scaled on the right axis. Aggregate productivity and bank efficiency follow the dynamics outlined in equations (38) and (41), respectively. The adoption of capital goods by banks is solved in equation (40). The expected loan rate is in equation (49). The CFI is defined 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). Labor share is defined in equation (54). The threshold for occupational choice is solved using equation (33). The price of capital is determined by equation (34). GDP is measured by aggregate consumption. The growth rates of aggregate bank efficiency and productivity are derived from equations (47) and (46), respectively. The loan-to-deposit ratio is defined in equation (50). The standard deviation and skewness of the firm-size distribution are defined in equations (55) and (56).

Figure 2
Higher $\nu$

Additionally, those who choose to be entrepreneurs borrow more and produce significantly more. However, given that their technology is constrained by previous period

---

where $\mathbf{avg}(\theta^*)$ is the average given by $\mathbf{avg}(\theta^*) = \frac{1}{1-\mathbf{F}(\theta^*)}\int_{\theta^*}^{\infty} l(\theta)\,\mathbf{d}\,\mathbf{F}(\theta)$. The model-implied skewness of the firm distribution is

$$\mathbf{skew} = \frac{1}{1-\mathbf{F}(\theta^*)}\int_{\theta^*}^{\infty}\left(\frac{l(\theta)-\mathbf{avg}(\theta^*)}{\mathbf{sd}(\theta^*)}\right)^3 \mathbf{d}\,\mathbf{F}(\theta). \tag{56}$$

aggregate productivity $z_{t-1}$, this results only in a slight acceleration in the decline of the relative price of capital goods. The latter somewhat lowers the input costs for final goods producers and also leads to only slightly higher economy-wide GDP growth in period 0.

At the end of period 0, both aggregate productivity and bank efficiency are much higher than in period $t = -1$ or what they would have been along the initial BGP. However, aggregate bank efficiency increases more than aggregate productivity at 19%, compared to 5.3%, respectively. As a result, at the end of period 0, the ratio of aggregate bank efficiency to (share-adjusted) aggregate productivity $a_0/z_0^{\alpha}$ is higher than in the initial 2% BGP or the new 2.19% BGP associated with $\nu = 0.07\%$. Moreover, as we are keeping all other parameters constant, including the unique scaling factor value for aggregate efficiency $\tau$ in equation (41), this ratio continues to steadily increase over time, 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 demand and supply factors in the banking system. On one hand, higher aggregate productivity increases loan demand, which raises the loan rate above the one in period 0. On the other hand, more efficient banks would offer borrowers a lower lending rate compared to the one in period 0. Since aggregate bank efficiency at $t = 0$ grows significantly more than aggregate 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 $a_0/z_0^{\alpha}$.

In period 1, a lower loan rate continued to stimulate production, leading to slightly faster growth in loan and labor demands, as well as in wage rates. Similarly, the labor share also continues to rise, albeit at a much slower pace than in period 0. With a lower expected loan rate, less able entrepreneurs exit and choose to become workers, and $\theta^*$ increases. Boosted by much higher previous-period aggregate 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. **Since then, we zoom in some variables using a blue dashed line, which is scaled on the right axis**.

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, and so forth. This creates a positive feedback effect that sustains the acceleration of growth. As the figure shows, these dynamics after period 1 continue indefinitely because, as we already noted, in this counterfactual the economy is not recalibrated to converge to its new BGP, to which we turn next.[15]

**Regarding the long-term impact of increased bank technology adoption along the new BGP, unlike in Figure 2, we also recalibrate $\tau$ (reducing it by 14.2% in this experiment) to achieve a new unique BGP for new $\nu = 0.07\%$, as outlined in Proposition 4. Compared to the baseline BGP, increasing the share of capital goods adopted by banks from 0.06% to 0.07% leads to an acceleration in the economy's long-run growth rate from 2% to 2.19%, a 9.5% increase, while reducing the CFI by 8 basis points, or 4.2% of its long-run value.**

Consistent with the mechanism detailed above, higher IT adoption enhances bank efficiency in transforming deposits into loans, leading to a 5.27 percentage-point increase in the loan-to-deposit ratio. Consequently, banks offer contracts with lower expected loan rates, which decrease by 4.64 percentage points, thereby also lowering the overall CFI. These 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 a result, the standard deviation of the firm-size distribution increases by 4.3% **from 15.3 in the baseline model to 16.1 in this experiment**, and the skewness decreases by 1.6% **from 86.4 in the baseline model to 84.8 in the counterfactual**. These changes 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. between the 1980s and 2010s, which are 2.2% and -2.1%, respectively, as shown in Figure 1. Moreover, as the threshold increases, more capital goods are supplied to banks and final goods producers at faster-declining prices, thereby boosting the economy-wide GDP growth rate from 2% to 2.19%.

[15] This implies that the simulation plotted in Figure 2 does not represent the transition dynamics but rather simply describes the implications of the considered counterfactual structural change through a sequence of temporary equilibria as in Proposition 2.

# 6 Empirical evidence

In this section, we empirically test three key predictions derived from our model. First, as technology advances, the relative price of capital goods declines, encouraging banks to adopt more capital goods and thereby enhancing their efficiency. Second, as banks become more efficient, they increase lending to a given type of entrepreneur. Third, more efficient banks charge lower interest rates, which leads less capable agents to opt for employment, raising the threshold for occupational choice. This implies that higher bank efficiency is linked to an increase in the standard deviation and a decrease in the skewness of the firm-size distribution, assuming a right-tailed distribution as described in equation (42). We investigate the first prediction using bank-level data, and the second and third predictions are explored using state- or MSA-level data.

## 6.1 Data and measurement

As a proxy for bank efficiency in transforming deposits into loans, we use the CFI at the individual bank level. Utilizing FDIC Call Reports data, we calculate the CFI for each bank as the ratio of its value added to the loans it intermediates.[16] 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 will also separately analyze the employee compensation and net income components of the bank-level CFI. We measure the CFI at the state (or MSA) level as a weighted average of the banks' CFI for all banks with branches operating in a given MSA, using deposit shares as weights.

We measure banks' IT adoption using the Harte Hanks Market Intelligence Computer Intelligence Technology data (CiTDB hereafter), which covers over three million establishments of firms from all industries from 2010 to 2019. CiTDB collects and sells this information to technology companies, who then use it for marketing purposes or to better serve their clients.[17] We match the name of banks in CiTDB with the name of banks in

[16] In Philippon (2015), the CFI is similarly defined, but measured for the US financial sector as a whole. With a slight abuse of notation, we continue to call this variable, which is a cost of bank intermediation, CFI.

[17] This data set 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 by several studies (see, for example, Modi, Pierri, Timmer and Peria, 2022;

Call Reports as in Cuesta, Jiang, Jorring and Xu (2023).

Following Decker, Haltiwanger, Jarmin and Miranda (2014), to construct the firm-size distribution across states (MSAs) or by sector across states (MSAs), we use the Business Dynamics Statistics (BDS) dataset, which aggregates the number of firms and employees within specific employee size bins.[18] We then calculate the average size of each bin within each group (state, MSA, state by sector, and MSA by sector).[19] For each bin, we then measure the density of a specific firm size by calculating the share of firms in that size bin over the total number of firms within the group and compute the sample standard deviation and skewness of the firm-size distribution.

We follow the standard two-step procedure in Rajan and Zingales (1998) to calculate the external finance dependence (EFD) for publicly listed firms using the CompuStat dataset. Then, we take the average EFD 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 2 reports summary statistics for the bank-level CFI, its two components, IT expenditure intensity, and bank characteristics. The average CFI at the bank level is 1.83%, which is similar to the CFI for the whole financial system in Philippon (2015) over the same sample period, which is 1.89%. There is also considerable heterogeneity in the CFI at the bank level and its two components. The average intensity of IT adoption, measured by IT budget scaled by total non-interest expenses, is 14%, and the standard deviation is 28%. In terms of bank characteristics, we consider the log of assets as a proxy of a bank's

Charoenwong, Kowaleski, Kwan and Sutherland, 2022; He, Jiang, Xu and Yin, 2021; Kwan, Lin, Pursiainen and Tai, 2023, among others) to explore the patterns and consequences of IT adaptation in the financial sector. He, Jiang, Xu and Yin (2021) provides a detailed comparison of IT investment in CiTDB with FR Y-9C voluntary disclosure of bank IT expenses at the bank-holding company level (when the expenses are greater than the threshold of $100K or 7% of total noninterest expenses). In Appendix E.3, we conduct similar empirical test using the IT expense reported in the Call report from FDIC (we thank Modi, Pierri, Timmer and Peria (2022) to construct this data and make it publicly available). All main results are robust.

[18]Specifically, BDS reports state-level firm sizes, both aggregate and by sector, using bins of 1-4, 5-9, 10-19, 20-99, 100-499, 500-999, 1000-2499, 2500-4999, 5000-9999, and 10,000+, while MSA-level firm sizes, both aggregate and by sector, are reported with coarser bins of 1-19, 20-499, and 500+, respectively.

[19]If the average number of employees within a particular size bin for different groups (state, MSA, state by sector, and MSA by 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.

size, the equity-to-asset ratio as a proxy of a bank's capital structure, the ratio of securities as a share of total assets as a proxy of banks' liquidity condition. Finally, we consider using the shares of C&I loans, real estate loans and personal loans in the total loans to proxy for banks' lending profile or lending specialization.

## 6.2 Bank technology adoption and the CFI

We start by first exploring the prediction that as technology advances, the relative price of capital goods declines, leading banks to adopt more capital goods and, in turn, increase their efficiency. Consider first conditional correlations between IT intensity and the bank-level CFI, using the following specification:

$$\mathbf{CFI}_{b,t} = \beta \mathbf{IT}_{b,t-1} + \gamma \mathbf{X}_{b,t-1} + \alpha_b + \alpha_t + \epsilon_{b,t} \tag{57}$$

where $\alpha_b$ and $\alpha_t$ are bank and year fixed effects, respectively. **IT** is IT expense intensity (measured by IT budget scaled by total noninterest expenses), 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 3 reports the point estimate for equation (57). Column (1) reports the benchmark result, showing that the coefficient on the IT adoption intensity variable 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 CFI. Increasing "IT/noninterest" expense from 14% by 25.3 percentage points is associated with 11.44 basis points decrease in CFI. Comparing with the mean of CFI (1.8%), this is equivalent to 6.35% (0.001144/0.018= 6.35%) decrease in CFI. In dollar terms, this amounts to \$742.14K decrease in the annual cost of financial intermediation.[20]

In columns (3) and (5), we examine how the two components of the bank-level CFI,

[20]The calculation of this magnitude is as follows: using the coefficient of Column (1) of Table 3, a one standard deviation increase in the dependent variable leads to 0.0444 standard deviation decrease in the dependent variable, and since the standard deviation of the dependent variable is 0.026, we will have the 0.0444×0.026=0.001144. In our sample, the average total dollar amount of intermediated assets is \$649 million, which means the average dollar amount of cost of financial intermediation is 1.8%×\$649 million=\$11.68 million. A 6.35% decrease from \$11.68 million translates into \$742.14K decrease in cost of financial intermediation.

Table 2
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/Total expense | 0.117 | 0.253 | 0.003 | 0.017 | 0.104 |
| 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 |
| Real estate 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 banks' balance sheets and IT spending profiles in the sample. "CFI" represents the cost of financial intermediation at the bank level, calculated as the ratio of value added to intermediated loans. $salary/Int.;loans$ and $net;income/Int.;loans$ represent the ratio of employee compensation and net income to intermediated loans and leases, respectively. "IT/Non-interest expense" refers to the 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, come from the US Call Reports, while IT budget data are sourced from the CiTDB. The sample includes 3,515 banks that were in operation for at least three consecutive years and are incorporated in the continental United States over the 2010-2019 period. All data are winsorized at the top and bottom 2.5%, and expressed in percentage terms, except for the logarithm of assets. $\mathbf{sd}_{i,s(m)}$ and $\mathbf{skewness}_{i,s(m)}$ 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 $m$. **EFD** measures external finance dependence, computed using the two-step procedure outlined in Rajan and Zingales (1998).

employee compensation, and net income, correlate with the change in IT expense. A one standard deviation increase in IT adoption intensity is associated with 0.0342 stan-

Table 3
IT Adoption and Cost of Financial Intermediation: OLS

| | 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) |
| CI loan/Total loan | | 0.0385 | | 0.0154 | | 0.0311 |
| | | (0.0246) | | (0.0147) | | (0.0221) |
| Real estate 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) |
| 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) |
| Bank FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| N | 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 $\beta$ from equation (57). The dependent variables include the bank-level CFI and the ratios of employee compensation or net income to intermediated loans and leases. The control variables are IT expense intensity and various bank-level characteristics, such as the log of assets, the equity-to-asset ratio, the ratio of securities to total assets, and the shares of C&I loans, real estate loans, and personal loans in total loans. The full sample consists of 3,515 banks that remained operational for more than three consecutive years and were incorporated in the continental United States. The sample period spans from 2010 to 2019. Bank and year fixed effects are included. All standard errors are clustered at the bank level. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

dard deviation decrease in "Salary/Intermediated assets," and a one standard deviation increase in IT adoption intensity is associated with 0.01 standard deviation decrease in "Net income/Intermediated assets." In column (2), (4), and (6), we estimate the regression equation (57) with bank-year level control variables included and the results are qualitatively and quantitatively similar.[21]

Next, we now want to establish a causal link between technology adoption and bank

[21] **In Appendix E.1, we test the relationship using the IT sub-component, specifically software, which is considered more relevant for loan transformation. Our results remain robust. In Appendix E.2, we 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.**

efficiency. We instrument technology adoption using a shift-share variable that interacts an aggregate measure of the change in the cost 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 (measured by the mile distance between a bank's headquarter county centroid and the nearest land-grant college). In other words, the shift-share variable is the product of the log difference in the quality-adjusted relative price of capital in Eichengreen (2015) with the bank's distance to the nearest land-grant colleges, following Moretti (2004) and Pierri and Timmer (2022). 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.[22] The specification of the two-stage regression model is as follows.

$$\mathbf{IT}_{bt} = \beta\Delta\mathbf{CP}_{t-1} \times \mathbf{LGC}_b + \delta'\mathbf{X}_{bt} + \alpha_b + \alpha_t + \epsilon_{b,t} \tag{58}$$

$$\mathbf{CFI}_{bt} = \tilde{\beta}\widehat{\mathbf{IT}}_{b,t-1} + \gamma'\mathbf{X}_{b,t-1} + \tilde{\alpha}_b + \tilde{\alpha}_t + \tilde{\epsilon}_{b,t}. \tag{59}$$

where $\alpha_b$ and $\tilde{\alpha}_b$ are the bank fixed effects, and $\alpha_t$ and $\tilde{\alpha}_t$are the year fixed effects. **IT** is the IT expense intensity. $\Delta$**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 banks characteristics used in the correlation analysis. We cluster standard errors at the bank level.

Column (1) of Table 4 reports the point estimate for the first stage. The F-statistics for the first-stage regression is 51.416, which is 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 large declines in capital prices, the more a bank will need to spend on IT in dollar terms to catch up the IT adoption.[23] Column (2) reports the estimation results from the second stage. The coefficient in the second-stage is qualitatively and quantitatively consistent with our OLS estimation, estimated coefficient in the IV framework is negative and statistically significant at the 95% significance level. Similarly, consistent with the analysis in panel regression, column (3)

[22] 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. This gives rich variation in the exposure to IT progress and availability of high-skilled human capital.

[23] Note that the quality-adjusted relative price of capital always declines throughout our sample periods.

and (4) suggest that the investment in IT mainly replaces the labor with no significant effects on net income per unit of intermediated loans. Column (5) to column (8) reports the IV estimation results with bank level control variables. Notice that our IV estimation coefficients are slightly larger in absolute magnitude compared with our OLS estimation, this could be due to omitted-variable bias in the OLS specification.

### 6.3 CFI and small business loan growth

Next, we check whether banks that become more efficient lend more to entrepreneurs. Specifically, we examine the dynamism of entrepreneurial activities, measured by the growth of small business loans, in response to changes in bank CFI or IT expenditure, leveraging bank location and *state-level data*. In particular, we estimate the following regression equation at the *bank-state-year* level and the state-year level:

$$Y_{b,s,t} \quad = \quad \beta \mathbf{CFI}_{b,t-1} \; or \; \mathbf{IT}_{b,t-1} + \gamma \mathbf{X}_{b,t-1} + \alpha_b + \alpha_{st} + \epsilon_{b,s,t} \qquad (60)$$

where $\alpha_b$ represents bank fixed effects and $\alpha_{st}$ denotes state-by-year fixed effects, included to control for unobserved, time-varying state-level factors such as shifts in demand, regulatory changes, and other influences. The outcome variable $Y$ is the annual log difference in the dollar amount of small business loans made by bank $b$ in state $s$. Data on small business loans is obtained from the CRA Small Business Loan Database, which tracks the total dollar amount of lending by banks to small businesses with annual revenues below one million dollars. The main explanatory variable is either the bank's CFI or its IT expense intensity in year $t-1$. $\mathbf{X}$ is a vector of bank characteristics as outlined in Section 6.2. Standard errors are clustered at the bank level. Table 5 presents the results.

Table 5 shows that a lower CFI is significantly correlated 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 loans (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 as expected, again in line with the model's prediction.

Table 4
IT ADOPTION AND COST OF FINANCIAL INTERMEDIATION: IV

| | First-stage | Second-stage | | | First-stage | Second-stage | | |
|---|---|---|---|---|---|---|---|---|
| | | CFI | $\frac{Salary}{Int.\ loans}$ | $\frac{Net\ income}{Int.\ loans}$ | | CFI | $\frac{Salary}{Int.\ loans}$ | $\frac{Net\ income}{Int.\ loans}$ |
| | (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) |
| $\frac{CI\ loan}{Total\ loan}$ | | | | | -0.1090*** | -0.0001 | -0.0050 | 0.0103 |
| | | | | | (0.0400) | (0.0108) | (0.0112) | (0.0157) |
| $\frac{Real\ estate\ loan}{Total\ loan}$ | | | | | -0.0065 | 0.0277* | 0.0184 | 0.0349 |
| | | | | | (0.0655) | (0.0165) | (0.0171) | (0.0238) |
| $\frac{Personal\ loan}{Total\ loan}$ | | | | | 0.1063** | 0.0189* | 0.0052 | 0.0392** |
| | | | | | (0.0435) | (0.0114) | (0.0119) | (0.0166) |
| $\frac{Equity}{Assets}$ | | | | | -3.3716*** | 1.5293*** | 0.8481*** | 2.2701*** |
| | | | | | (0.9299) | (0.2604) | (0.2701) | (0.3770) |
| $\frac{Security}{Assets}$ | | | | | 0.0657*** | -0.0153** | -0.0423*** | 0.0484*** |
| | | | | | (0.0252) | (0.0067) | (0.0070) | (0.0098) |
| Dep HHI | | | | | -0.2850 | -0.0626 | -0.0974 | 0.0390 |
| | | | | | (0.2907) | (0.0748) | (0.0776) | (0.1082) |
| 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 | | | |
| N | 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 $\beta$ from the first-stage estimation in equation (58). Column (2)-(4) and (6)-(8) report the point estimates $\tilde{\beta}$ from the second-stage estimation in equation (59). In the first stage, the dependent variable is IT expense intensity, defined as the IT budget scaled by total noninterest expenses. The instrumental variable used is a shift-share variable, calculated as the product of the log difference in the quality-adjusted relative price of capital from Eichengreen (2015) and the bank's proximity to the nearest land-grant colleges, following the methods of Moretti (2004) and Pierri and Timmer (2022). In the second stage, the dependent variables include the bank-level CFI and the ratios of employee compensation or net income to intermediated loans and leases. Other control variables in both stages are various bank-level characteristics, such as the log of assets, the equity-to-asset ratio, the ratio of securities to total assets, and the shares of C&I loans, real estate loans, and personal loans in total loans. The full sample consists of 3,515 banks that remained operational for more than three consecutive years and were incorporated in the continental United States. The sample period spans from 2010 to 2019. Bank and year fixed effects are included. All standard errors are clustered at the bank level. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

## 6.4 CFI and atandard deviation and skewness of firm-size distribution

Finally, we explore whether higher bank efficiency, given a right-tailed distribution as described in equation (42), is associated with greater standard deviation and lower skewness in the firm-size distribution.

Table 5
CFI, IT Expenditure and Small Business Loan

| | 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) |
| CI loan/Total loan | | -0.0010 | | 0.0382 |
| | | (0.0635) | | (0.0923) |
| Real estate loan/Total loan | | -0.0670 | | -0.0946 |
| | | (0.0767) | | (0.1556) |
| Personal loan/Total loan | | -0.0769 | | -0.1668 |
| | | (0.0569) | | (0.1285) |
| Equity/Asset | | -0.0525 | | 0.0016 |
| | | (0.0366) | | (0.0609) |
| Security/Asset | | 0.0245 | | -0.0077 |
| | | (0.0365) | | (0.0488) |
| State × year FE | Y | Y | Y | Y |
| Bank FE | Y | Y | Y | Y |
| N | 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 $\beta$ in equation (60). The outcome variable is the log difference in the dollar amount of small business loans, sourced from the CRA Small Business Loan Database. The main explanatory variable is either CFI or IT expense intensity of the corresponding bank in year $t-1$. Other control variables are various bank-level characteristics, such as the log of assets, the equity-to-asset ratio, the ratio of securities to total assets, and the shares of C&I loans, real estate 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. $***\ p<0.01$, $**\ p<0.05$, $*\ p<0.1$.

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

$$Y_{s(m),t} = \beta \mathbf{CFI}_{s(m),t-1} + \mathbf{X}_{s,t-1} + \alpha_{s(m)} + \alpha_t + \epsilon_{s(m),t} \quad (61)$$

where $\alpha_{s(m)}$ and $\alpha_t$ represent state (MSA) and year-fixed effects, respectively. The outcome variable, $Y_{s(m),t}$, is the standard deviation or 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 affect the firm-size distribution. **X** includes state-level characteristics such as the logarithm of real GDP per capita, the logarithm of real income, the unemployment rate, and the logarithm of the consumer price index. The sample covers 50 states and District of Columbia and 917 MSAs, spanning from 1985 to 2019. We cluster standard errors at the state (MSA) level.

Columns (1) and (2) of Table 6 report the test results at the state level, suggesting that a lower state-level CFI (more efficient banks in that state) is significantly correlated with the higher standard deviation and lower skewness of the firm-size distribution. Columns (5) and (6) display point estimates at the MSA level. The results are robust.

Since unobserved state (MSA) characteristics may influence both CFI and the firm-size distribution, we further investigate sector variation within a given state (MSA) to examine how the firm-size distribution across different sectors is associated with bank efficiency. Unfortunately, due to the lack of bank-firm linkage data, we cannot directly construct a sector-specific measure of bank efficiency. Instead, we interact the state (MSA) level CFI with the external finance dependence (EFD) measure, developed by Rajan and Zingales (1998), to assess how the firm-size distribution in sectors that rely more heavily on external finance correlates with more efficient banks. Specifically, we estimate the following regression equation at the state (MSA)-sector-year level:

$$Y_{i,s(m),t} = \beta \mathbf{CFI}_{s(m),t-1} \times \mathbf{EFD}_i + \alpha_{i,s(m)} + \alpha_{s(m),t} + \alpha_{i,t} + \epsilon_{i,s(m),t}. \tag{62}$$

Here, the outcome 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 the deposit-weighted CFI at the state or MSA level, while **EFD** is the EFD, constructed using the standard two-step procedure from Rajan and Zingales (1998). $\alpha_{i,s(m)}$ captures state (MSA)-sector fixed effects, controlling for time-invariant characteristics of a sector in a given state (MSA), such as any endowment advantages of sector $i$. $\alpha_{s(m),t}$ represents state (MSA)-year fixed effects, which control for time-varying state (MSA) characteristics, such as business cycles or regulatory changes. Finally, $\alpha_{i,t}$ accounts for sector-year fixed effects, controlling for any time-varying sector-specific characteristics, such as technological advancements or outsourcing. The sample includes 15 sectors across 50 states, the District of Columbia, and 917 MSAs, covering the period from 1985 to 2019.

Columns (3) and (4) of Table 6 present the test results at the state level, indicating

Table 6
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**: Columns (1), (2), (5), and (6) of the table report the point estimates for $\beta$ from equation (61). Columns (3), (4), (7), and (8) present the point estimates for $\beta$ from equation (62). The outcome variables in Columns (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 outcome variables in Columns (2), (4), (6), and (8) reflect the skewness of the firm-size distribution for the same corresponding regions. The state (MSA) level CFI is the weighted average of the CFI of banks operating in the state (MSA), with deposit share used as weights. The EFD measures the extent to which a sector depends on external finance, following the two-step procedure outlined in Rajan and Zingales (1998). State characteristics include the logarithm of real GDP per capita, the logarithm of real income, the unemployment rate, and the logarithm of the consumer price index. The sample consists of 15 sectors, covering 50 states, the District of Columbia, and 917 MSAs, spanning the years 1985 to 2019. State (MSA) and year fixed effects are included in Columns (1)-(2) and (5)-(6). State (MSA)-by-sector, state (MSA)-by-year, and sector-by-year fixed effects are included in Columns (3)-(4) and (7)-(8). Standard errors are clustered at the state level in Columns (1) and (2), at the state-by-sector level in Columns (3) and (4), at the MSA level in Columns (5) and (6), and at the MSA-by-sector level in Columns (7) and (8). $*** \; p < 0.01$, $** \; p < 0.05$, $* \; p < 0.1$.

that within a given state, a lower state-level CFI is significantly correlated with a higher standard deviation and lower skewness in the firm-size distribution for sectors that are more dependent on external financing. Columns (7) and (8) provide the point estimates at the MSA level, where the results remain robust.

## 7 Conclusions

In this paper, we build and estimate a model of growth and finance in which banks adopt technology embedded in capital goods produced by entrepreneurs, and 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 by fitting moments of the US economy, we find that increasing adoption of banking technology adoption significantly boosts the economy's rate of growth. We then estimate the impact of IT expenditure on the cost of bank intermediation with FIDC Call Report bank-level data. The microeconomic evidence that we report is consistent with the bank technology adoption mechanism at the model's core.

# References

Acemoglu, D. (2009). *Introduction to modern economic growth*. Princeton university press.

—, Aghion, P., Lelarge, C., Van Reenen, J. and Zilibotti, F. (2007). Technology, information, and the decentralization of the firm. *The Quarterly Journal of Economics*, **122** (4), 1759–1799.

— and Zilibotti, F. (2001). Productivity differences. *The Quarterly Journal of Economics*, **116** (2), 563–606.

Aghion, P., Akcigit, U. and Howitt, P. (2014). What do we learn from schumpeterian growth theory? In *Handbook of economic growth*, vol. 2, Elsevier, pp. 515–563.

—, Howitt, P. and Mayer-Foulkes, D. (2005). The effect of financial development on convergence: Theory and evidence. *The quarterly journal of economics*, **120** (1), 173–222.

— and Howitt, P. W. (2009). *The economics of growth*. MIT press.

Altman, E. I. and Kishore, V. M. (1996). Almost everything you wanted to know about recoveries on defaulted bonds. *Financial Analysts Journal*, **52** (6), 57–64.

Axtell, R. L. (2001). Zipf Distribution of U.S. Firm Sizes. *Science*, **293** (5536), 1818–1820.

Bartelsman, E., Haltiwanger, J. and Scarpetta, S. (2013). Cross-country differences in productivity: The role of allocation and selection. *American economic review*, **103** (1), 305–334.

Bartram, S. M., Branke, J. and Motahari, M. (2020). *Artificial intelligence in asset management*. CFA Institute Research Foundation.

Beck, T., Demirgüç-Kunt, A. and Maksimovic, V. (2005). Financial and legal constraints to growth: does firm size matter? *The journal of finance*, **60** (1), 137–177.

—, Levine, R. and Loayza, N. (2000). Finance and the sources of growth. *Journal of financial economics*, **58** (1-2), 261–300.

Bencivenga, V. R. and Smith, B. D. (1991). Financial intermediation and endogenous growth. *The review of economic studies*, **58** (2), 195–209.

Benhabib, J., Perla, J. and Tonetti, C. (2021). Reconciling models of diffusion and innovation: A theory of the productivity distribution and technology frontier. *Econometrica*, **89** (5), 2261–2301.

Berg, T., Burg, V., Gombović, A. and Puri, M. (2020). On the rise of fintechs: Credit scoring using digital footprints. *The Review of Financial Studies*, **33** (7), 2845–2897.

Bloom, N., Garicano, L., Sadun, R. and Reenen, J. V. (2014). The distinct effects of information technology and communication technology on firm organization. *Management Science*, **60** (12).

Branzoli, N., Rainone, E. and Supino, I. (2023). The role of banks' technology adoption in credit markets during the pandemic. *Bank of Italy Temi di Discussione (Working Paper) No*, **1406**.

Buera, F. J., Kaboski, J. P. and Shin, Y. (2011). Finance and development: A tale of two sectors. *American economic review*, **101** (5), 1964–2002.

— and Shin, Y. (2013). Financial frictions and the persistence of history: A quantitative exploration. *Journal of Political Economy*, **121** (2), 221–272.

Caliendo, L., Parro, F., Rossi-Hansberg, E. and Sarte, P.-D. (2018). The impact of regional and sectoral productivity changes on the us economy. *The Review of economic studies*, **85** (4), 2042–2096.

Charoenwong, B., Kowaleski, Z. T., Kwan, A. and Sutherland, A. (2022). RegTech. *Working Paper*.

Chen, J. and Roth, J. (2023). *Logs with zeros? Some problems and solutions*. Tech. rep., Working Paper.

Cohn, J. B., Liu, Z. and Wardlaw, M. I. (2022). Count (and count-like) data in finance. *Journal of Financial Economics*, **146** (2), 529–551.

Cong, L. W., Tang, K., Wang, J. and Zhang, Y. (2021). Alphaportfolio: Direct construction through deep reinforcement learning and interpretable ai. *Available at SSRN 3554486*.

Cuesta, J. I., Jiang, S., Jorring, A. and Xu, D. (2023). Bank technology adoption and loan production in the u.s mortgage market. *Working Paper*.

de la Fuente, A. and Marín, J. (1996). Innovation, bank monitoring, and endogenous financial development. *Journal of Monetary Economics*, **38** (2), 269–301.

De Ridder, M. (2024). Market power and innovation in the intangible economy. *American Economic Review*, **114** (1), 199–251.

Decker, R., Haltiwanger, J., Jarmin, R. and Miranda, J. (2014). The role of entrepreneurship in us job creation and economic dynamism. *Journal of Economic Perspectives*, **28** (3), 3–24.

Dunne, T., Roberts, M. J. and Samuelson, L. (1989). The growth and failure of us manufacturing plants. *The Quarterly Journal of Economics*, **104** (4), 671–698.

Eichengreen, B. (2015). Secular stagnation: the long view. *American Economic Review*, **105** (5), 66–70.

Forman, C., Goldfarb, A. and Greenstein, S. (2012). The internet and local wages: A puzzle. *American Economic Review*, **102** (1), 556–75.

Foster, L., Haltiwanger, J. and Syverson, C. (2008). Reallocation, firm turnover, and efficiency: Selection on productivity or profitability? *American Economic Review*, **98** (1), 394–425.

Freixas, X. and Rochet, J.-C. (1997). *Microeconomics of Banking*. MIT press.

Fuster, A., Plosser, M., Schnabl, P. and Vickery, J. (2019). The role of technology in mortgage lending. *The Review of Financial Studies*, **32** (5), 1854–1899.

Gabaix, X. (2016). Power Laws in Economics: An Introduction. *Journal of Economic Perspectives*, **30** (1), 185–206.

Goldstein, I., Jiang, W. and Karolyi, G. A. (2019). To fintech and beyond. *The Review of Financial Studies*, **32** (5), 1647–1661.

Gopal, M. and Schnabl, P. (2022). The rise of finance companies and fintech lenders in small business lending. *The Review of Financial Studies*, **35** (11), 4859–4901.

Greenwood, J. and Jovanovic, B. (1990). Financial development, growth, and the distribution of income. *Journal of political Economy*, **98** (5, Part 1), 1076–1107.

—, Sanchez, J. M. and Wang, C. (2010). Financing Development: The Role of Information Costs. *American Economic Review*, **100** (4), 1875–1891.

Hannan, T. H. and McDowell, J. M. (1984). The determinants of technology adoption: The case of the banking firm. *The RAND Journal of Economics*, pp. 328–335.

He, Z., Jiang, S., Xu, D. and Yin, X. (2021). Investing in lending technology: It spending in banking. *Working Paper*.

—, —, — and — (2022). *Investing in Lending Technology: IT Spending in Banking*. Working Paper 30403, National Bureau of Economic Research.

Holter, H. A., Stepanchuk, S. and Wang, Y. (2023). Taxation and entrepreneurship in the united states. *Available at SSRN 4341843*.

Hopenhayn, H. A. (1992). Entry, exit, and firm dynamics in long run equilibrium. *Econometrica: Journal of the Econometric Society*, pp. 1127–1150.

Hsieh, C.-T. and Klenow, P. J. (2009). Misallocation and manufacturing tfp in china and india. *The Quarterly journal of economics*, **124** (4), 1403–1448.

Jayaratne, J. and Strahan, P. E. (1996). The finance-growth nexus: Evidence from bank branch deregulation. *The Quarterly Journal of Economics*, **111** (3), 639–670.

Jermann, U. and Quadrini, V. (2012). Macroeconomic effects of financial shocks. *American Economic Review*, **102** (1), 238–271.

Jiang, S., Jørring, A. and Xu, D. (2023). Bank technology adoption and loan production in the u.s. mortgage market. *working paper*.

Jones, C. I. and Vollrath, D. (2013). *Introduction to economic growth*. New York: WW Norton & Company, Inc.

Jones, C. M. (2013). What do we know about high-frequency trading? *Columbia Business School Research Paper*, (13-11).

Jovanovic, B. and Rob, R. (1989). The growth and diffusion of knowledge. *The Review of Economic Studies*, **56** (4), 569–582.

Kaminsky, G. L. and Reinhart, C. M. (1999). The twin crises: the causes of banking and balance-of-payments problems. *American economic review*, **89** (3), 473–500.

King, R. G. and Levine, R. (1993). Finance and growth: Schumpeter might be right. *The quarterly journal of economics*, **108** (3), 717–737.

Klette, T. J. and Kortum, S. (2004). Innovating firms and aggregate innovation. *Journal of political economy*, **112** (5), 986–1018.

König, M., Storesletten, K., Song, Z. and Zilibotti, F. (2022). From imitation to innovation: Where is all that chinese r&d going? *Econometrica*, **90** (4), 1615–1654.

Kroszner, R. S. and Strahan, P. E. (1999). What drives deregulation? economics and politics of the relaxation of bank branching restrictions. *The Quarterly Journal of Economics*, **114** (4), 1437–1467.

Kwan, A., Lin, C., Pursiainen, V. and Tai, M. (2023). Stress testing banks' digital capabilities: Evidence from the covid-19 pandemic. *Journal of Financial and Quantitative Analysis*, p. 1–29.

Laeven, L., Levine, R. and Michalopoulos, S. (2015). Financial innovation and endogenous growth. *Journal of Financial Intermediation*, **24** (1), 1–24.

Lerner, J., Seru, A., Short, N. and Sun, Y. (2024). Financial innovation in the twenty-first century: Evidence from us patents. *Journal of Political Economy*, **132** (5), 1391–1449.

Levine, R. (2005). Finance and growth: theory and evidence. *Handbook of economic growth*, **1**, 865–934.

—, Loayza, N. and Beck, T. (2000). Financial intermediation and growth: Causality and causes. *Journal of monetary Economics*, **46** (1), 31–77.

Lewellen, S. and Williams, E. (2021). Did technology contribute to the housing boom? evidence from mers. *Journal of Financial Economics*, **141** (3), 1244–1261.

Lucas, R. E. (1978). On the size distribution of business firms. *The Bell Journal of Economics*, pp. 508–523.

— (1988). On the mechanics of economic development. *Journal of monetary economics*, **22** (1), 3–42.

Luttmer, E. G. (2007). Selection, growth, and the size distribution of firms. *The Quarterly Journal of Economics*, **122** (3), 1103–1144.

Matsuyama, K. (2007). Aggregate implications of credit market imperfections. *NBER macroeconomics annual*, **22**, 1–81.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *econometrica*, **71** (6), 1695–1725.

Mezzanotti, F. and Simcoe, T. (2023). *Research and/or Development? Financial Frictions and Innovation Investment*. Tech. rep., National Bureau of Economic Research.

Mian, A. and Sufi, A. (2009). The consequences of mortgage credit expansion: Evidence from the us mortgage default crisis. *The Quarterly journal of economics*, **124** (4), 1449–1496.

Midrigan, V. and Xu, D. Y. (2014). Finance and misallocation: Evidence from plant-level data. *American economic review*, **104** (2), 422–458.

Modi, K., Pierri, N., Timmer, Y. and Peria, M. S. M. (2022). The anatomy of banks' it investments: Drivers and implications. *IMF Working Papers*, **2022** (244).

Moretti, E. (2004). Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data. *Journal of econometrics*, **121** (1-2), 175–212.

Perla, J. and Tonetti, C. (2014). Equilibrium imitation and growth. *Journal of Political Economy*, **122** (1), 52–76.

Philippon, T. (2015). Has the US Finance Industry Become Less Efficient? On the Theory and Measurement of Financial Intermediation. *American Economic Review*, **105** (4), 1408–1438.

Pierri, N. and Timmer, Y. (2022). The importance of technology in banking during a crisis. *Journal of Monetary Economics*, **128**, 88–104.

Presbitero, A., Rebucci, A. and Zhang, G. (2024). Bank technology adoption and productivity. *Available at SSRN 4688583*.

Rajan, R. and Zingales, L. (1998). Financial development and growth. *American economic review*, **88** (3), 559–586.

Ranciere, R., Tornell, A. and Westermann, F. (2008). Systemic crises and growth. *The Quarterly Journal of Economics*, **123** (1), 359–406.

Robinson, J. V. (1954). The rate of interest and other essays. *MacMillan*.

Romer, D. (1996). *Advanced macroeconomics*. A Dzz˜ zszon of The McGraw. Hil1˜ ompante.

Roy, A. D. (1951). Some thoughts on the distribution of earnings. *Oxford economic papers*, **3** (2), 135–146.

Schularick, M. and Taylor, A. M. (2012). Credit booms gone bust: monetary policy, leverage cycles, and financial crises, 1870–2008. *American Economic Review*, **102** (2), 1029–1061.

Stock, J. and Yogo, M. (2005). *Testing for Weak Instruments in Linear IV Regression*, New York: Cambridge University Press, pp. 80–108.

Sutton, J. (1991). *Sunk costs and market structure: Price competition, advertising, and the evolution of concentration*. MIT press.

Syverson, C. (2004). Market structure and productivity: A concrete example. *Journal of political Economy*, **112** (6), 1181–1222.

Tufano, P. (2003). Financial innovation. *Handbook of the Economics of Finance*, **1**, 307–335.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

# A Micro structure for function $\mathbf{e}(\theta)$

In this section, we provide some micro structure for function $\mathbf{e}(\theta)$. As banks only observe the entrepreneur's type but not whether his project succeeds (S) or fails (F), banks must exert a costly verification effort $e_{jt}^{k}(\theta)$ of the state $k \in \{S, F\}$, with per unit of fund lent cost $e_{jt}^{k}(\theta)(1+r_{jct})b_{jt}(\theta)$. Unlike the benchmark case, where banks can detect the true state for sure after 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). Also, suppose that this probability is increasing, twice-differentiable, and concave in efforts $e_{jt}(\theta)$ with $\mathbf{Pr}(0) = 0$.

To avoid free-riding and coordination issues, we assume that all banks exert effort and verify the state. When misreporting is detected, banks can recover $m_{jt}^{kk'}(\theta)$ with $k, k' \in \{S, F\}$ and $k \neq k'$, where the entrepreneur realizes $k$ but reports $k'$. The penalty $m_{jt}^{FS}(\theta)$ and $m_{jt}^{FS}(\theta)$ charged by bank $j$ cannot exceed the fair share of the syndicate, which leads 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. This specification implies that the more efforts banks exert, the more likely they detect the true state, but the marginal benefit of exerting effort is diminishing. Thus, bank $j$ designs the offer in the way that the repayment is incentive-compatible as:

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

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

equation (A.3) is the incentive-compatible constraint (ICC) of a successful entrepreneur. It states that if a successful entrepreneur truthfully reports, the scheduled payment, $(1 + r_{lt}(\theta))\, b_{jt}(\theta)$, is at most as much as the expected payment when cheating, which is the right-hand size of equation (A.3). The entrepreneur has a probability of $\mathbf{Pr}\left(e_{jt}^{F}(\theta)\right)$ to be detected when cheating and penalized with $m_{jt}^{SF}(\theta)$, and a probability $1 - \mathbf{Pr}\left(e_{jt}^{F}(\theta)\right)$ being able to escape the bank's verification only paying the amount in the failed state, i.e., $x_{jt}(\theta) b_{jt}(\theta)$, which we call escape payoff. Analogously, equation (A.4) is 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 fraction $x_{jt}(\theta)$, the penalties $m_{jt}^{SF}(\theta)$ and $m_{jt}^{FS}(\theta)$, and the verification efforts $e_{jt}^{S}(\theta)$ and $e_{jt}^{F}(\theta)$ to maximize its expected profit from lending to the type-$\theta$ entrepreneur while inducing truthful reporting as follows

$$\max \quad \Big(\eta\,(1+r_{lt}(\theta))+(1-\eta)x_{jt}(\theta)\Big)b_{jt}(\theta)-\left(1+r_{jct}\right)b_{jt}(\theta)$$
$$-\left(\eta e_{jt}^{S}(\theta)+(1-\eta)\eta e_{jt}^{F}(\theta)\right)\left(1+r_{jct}\right)b_{jt}(\theta), \tag{A.5}$$
$$s.t. \qquad (7),\ (8),\ (A.1),\ (A.2),\ (A.3),\ \text{and}\ (A.4). \tag{A.6}$$

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

**Proposition 5 (Loan market equilibrium solution for symmetric banks)** *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 of bank j for the type-$\theta$ entrepreneur is given by:*

$$e_{jt}^{S}(\theta)=0, \tag{A.7}$$
$$e_{jt}^{F}(\theta)=\mathbf{e}(\theta)=\mathbf{Pr}^{-1}\left(\xi-\frac{(1-\xi)\underline{\theta}}{\eta(\theta-\underline{\theta})}\right), \tag{A.8}$$
$$x_{jt}(\theta)=\frac{\underline{\theta}}{\xi\,(\eta\theta+(1-\eta)\underline{\theta})}\,\frac{1+(1-\eta)\mathbf{e}(\theta)}{1-\frac{1-\xi}{n}}\left(1+r_{jct}\right), \tag{A.9}$$
$$b_{jt}(\theta)=\frac{1}{n}\left(\frac{\eta\theta+(1-\eta)\underline{\theta}}{1+(1-\eta)\mathbf{e}(\theta)}\,\frac{\left(1-\frac{1-\xi}{n}\right)p_t\xi z_{t-1}}{\left(1+r_{jct}\right)w_t^{\xi}}\right)^{\frac{1}{1-\xi}}, \tag{A.10}$$
$$m_{jt}^{SF}(\theta)=\frac{\theta}{\xi n}\left(\left(\frac{\eta\theta+(1-\eta)\underline{\theta}}{1+(1-\eta)\mathbf{e}(\theta)}\,\frac{1-\frac{1-\xi}{n}}{\left(1+r_{jct}\right)w_t}\right)^{\xi}p_t\xi z_{t-1}\right)^{\frac{1}{1-\xi}}, \tag{A.11}$$
$$m_{jt}^{FS}(\theta)=\frac{\underline{\theta}}{\xi n}\left(\left(\frac{\eta\theta+(1-\eta)\underline{\theta}}{1+(1-\eta)\mathbf{e}(\theta)}\,\frac{1-\frac{1-\xi}{n}}{\left(1+r_{jct}\right)w_t}\right)^{\xi}p_t\xi z_{t-1}\right)^{\frac{1}{1-\xi}}, \tag{A.12}$$

*where $\mathbf{Pr}^{-1}(\cdot)$ is the inverse function of $\mathbf{Pr}(\cdot)$. Moreover, the effort function $\mathbf{e}(\theta)$ is increasing and twice-differentiable in $\theta$. The equilibrium loan rate for the type-$\theta$ entrepreneur is given by:*

$$1+r_{lt}(\theta)=\frac{\xi\eta\theta-(1-\xi)(1-\eta)\underline{\theta}}{\eta\xi\,(\eta\theta+(1-\eta)\underline{\theta})}\,\frac{1+(1-\eta)\mathbf{e}(\theta)}{1-\frac{1-\xi}{n}}\left(1+r_{jct}\right). \tag{A.13}$$

**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 negative. Thus, $x$, $m^{FS}$, and $m^{SF}$ can be solved with equation (8), (A.2) and (A.1), respectively. Thus, the ICC for successful reporting is not binding. As the 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 $\mathbf{Pr}\left(e^F_{jt}(\theta)\right) = \xi - \frac{(1-\xi)\underline{\theta}}{\eta(\theta-\underline{\theta})}$. Thus, the efforts in this case is solved as in equation (A.8). 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.13). Using (A.10), we obtain equation (A.11) and (A.12). QED.

Next, suppose the banker $j$'s probability of detecting the true state of the tyep–$\theta$ entrepreneur is given by the following increasing and concave function in $e_j$:

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

Thus, using equation (A.8), we can solve for the verification effort per unit of loan as

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

# B Proofs

In this Appendix, we provide the proofs of the lemmas, propositions, and corollaries stated in the 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 $x_{jt}(\theta) = \frac{\underline{\theta}}{\xi\bar{\theta}}(1 + r_{lt}(\theta))$. Thus, using equation equation (10), we have the lending rate in the successful state

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

## 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 $\theta$. Thus, under assumption that the function $\mathbf{h}(\theta)$ is increasing in $\theta$, it is straightforward to show that the $\mathbf{LHS}(\theta)$ is decreasing in $\theta$. Moreover, $\lim_{\theta\to\theta_{min}} \mathbf{LHS}(\theta) \to \infty$ and $\lim_{\theta\to\infty} \mathbf{LHS}(\theta) = 0$. Notably, $\pi^E(\theta)$ is increasing in $\theta$. Therefore, for any finite $z_{t-1}$, $a_{t-1}$, and $r_d$, there exists a unique $\theta^*$ 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 $\theta < \theta_t^*$. Notably, $\mathbf{LHS}(\theta_t^*) = \mathbf{RHS}$ implies that equation (33) holds. QED.

## B.3 Proof of Proposition 3

We define $\mathbf{LHS}(\theta)$ and $\mathbf{RHS}$ 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,

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

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

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

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

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 $\nu^* \in (0,1)$, where $\theta^*(\nu^*)$ solves equation (33) with $\nu^*$, and

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

so that for $\nu \leq \nu^*$, we have

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

where $\theta^*(\nu)$ solves equation (33) with $\nu$ , while for $\nu > \nu^*$, we have

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

### B.4 Proof of Proposition 4

We have **RHS** defined in equation (B.2) as $\mathbf{RHS} \propto \frac{z_{t-1}^{\alpha\nu}}{a_{t-1}^{\nu}}$. Thus, the threshold for the occupation choice stays constant along the BGP. Using equation (10), (11), (12), and (19), we have that the recovery rate $x_{jt}$, the loan rate $r_{lt}$, the unit funding cost $r_{jct}$, and the deposit rate $r_d$ are also constant along the BGP. Equation (26) implies that the labor is constant as well. Thus, equation (1) implies that the capital goods grow 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 Extended model with labor in banks

Now, we extend our benchmark model by allowing banks to hire labor in the first stage and show that our main results stay the same with this extension. Specifically, in addition to adopt capital goods from entrepreneur, banks 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 the 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 $j$,

$\nu$ and $\omega$ are the factor share, and $\gamma$ is a scale parameter that captures other factors such as managerial ability, marketing expenditures, physical capital, etc. Here, we define the individual efficiency $a_{jt}$ the same as in equation (15).

Given the last-period aggregate bank efficiency $a_{t-1}$, the aggregate 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 demand for capital goods 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 in 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:

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

where the capital-good price $p_t$ is given by

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

and the wage $w_t$ is given by

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

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

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

Moreover, we use the same law of motion for the aggregate bank efficiency and productivity. Substituting equation (C.11) into equation (39), we have

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

equation (C.12) implies that the aggregate bank efficiency depends on the occupation choice threshold $\theta_t^*$ and the previous-period aggregate bank efficiency $a_{t-1}$ and firm productivity $z_{t-1}$. We can now characterize the BGP in our extended model.

**Proposition 6 (Balanced growth path existence and uniqueness)** *Denote the gross rate of growth of aggregate firm productivity and bank efficiency as $g_{zt}\left(\theta_t^*\right)=z_t\left(\theta_t^*\right)/z_{t-1}$ and $g_{at}\left(\theta_t^*\right)=a_t\left(\theta_t^*\right)/a_{t-1}$, respectively, where $z_t\left(\theta_t^*\right)$ and $a_t\left(\theta_t^*\right)$ are defined in equations (38) and (41), re-*

*spectively. Assuming that the economy starts in period 1, for any $\{z_0, a_0\}$, there exists a deposit rate $r_d$ and a threshold $\theta^*$ so that $\theta^*$ solves equation (33) evaluated at $\{a_0, z_0, r_d\}$, and the economy then evolves along the following unique balanced growth path:*

1. *Let $g_a = g^{1+\omega/\nu}$, and then $g_z(\theta^*) = \eta \mathbf{E}(\theta|\theta \geq \theta_t^*) + (1-\eta)\underline{\theta} = g^{1/\alpha}$;*
2. *The occupation choice threshold $\theta_t^*$ is constant at $\theta^*$;*
3. *The unit funding cost $r_{jct}$, the loan rate $r_{lt}(\theta)$, and the loan-recovery rate $x_{jt}(\theta)$ for any type-$\theta$ entrepreneur are constant;*
4. *The production of capital goods $Y^K$, and the quantity of capital goods purchased by final-good producers ($K_t$) and banks ($Q_t$) grow at the gross rate $g^{1/\alpha}$, while the price of capital goods contracts at the gross rate $g^{1-1/\alpha}$;*
5. *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-$\theta$ 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 $g$.*

# D Quantitative analysis details

## D.1 Estimating $\nu$

In this section, we estimate $\nu$ using equation (44). Column (1) of Table D.1 presents the point estimate from our benchmark regression, which includes bank characteristics as well as state, bank, and year fixed effects.

Furthermore, we re-estimate equation (44), by incorporating the interaction term between the IT-to-deposit ratio and an indicator for banks in the top half of IT adoption. Specifically, we measure IT adoption using the average IT budget from 2010 to 2019. Banks in the top half of the IT adoption distribution are classified as IT-intensive. Column (2) of Table D.1 reports the point estimates used to guide the change in parameter of our counterfactual exercise.

Table D.1

ESTIMATE $\nu$ AND $\rho$

| | 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) |
| Real estate 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) |
| N | 21,480 | 21,480 | 21,480 |
| State FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| Bank FE | Y | Y | Y |
| Adj $R^2$ | 0.93 | 0.97 | 0.82 |

**Note**: The table reports the point estimates for $\nu$ in equation (44) and $\rho$ in equation (D.5). In column (1) and (2), the outcome variables are the bank-level loan-to-deposit ratio. The main regressor is the IT expense intensity, and its interaction with the indicator for banks in the top half of IT adoption is added in column (2). In column (3), the dependent variable is the natural log of total IT budget of a bank in a given year, the main regressor is the natural log of the ratio between interest income, non-interest income, and deposits scaled by total loans of a bank. Other independent variables are the bank-level characteristics as discussed in Table 2. The full sample includes 3515 banks that survive more than three consecutive years and are incorporated in the continental states. The sample period is from 2010 to 2019. All standard errors are clustered at the bank level. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

## D.2 Estimating $\rho$

Since bank efficiency is unobservable, we cannot directly test for the unitary elasticity of capital goods with respect to bank efficiency as specified in equation (15). Instead, we extend the Cobb-Douglas function for deposit transformation to take a CES form, represented as:

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

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:

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

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

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

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

We have

$$q_{jt} = \nu \left( \frac{p_t}{1 + r_{jct}} \right)^{-\rho} B_{jt} \quad \text{(D.4)}$$

Thus, we test the relationship between IT goods and the unit funding cost using the following strategy:

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

where $\alpha_b$ and $\alpha_t$ are bank and year fixed effects, respectively. $1 + r_{bct}$ is the measure for bank $b$'s unit funding cost, which is measured by the ratio of the sum of interest income, non-interest income, and deposits scaled by total loans of a bank. $\mathbf{X}_{bt}$ is the vector of bank-level characteristics discussed above. Column (3) of Table D.1 reports the point estimate, where the coefficient is 1.048 and statistically significant at the 99% significance level.

## D.3 Model-implied moments and structural parameters

In Table D.2, we list all moments used for estimation and parameters that is associated with each moment.

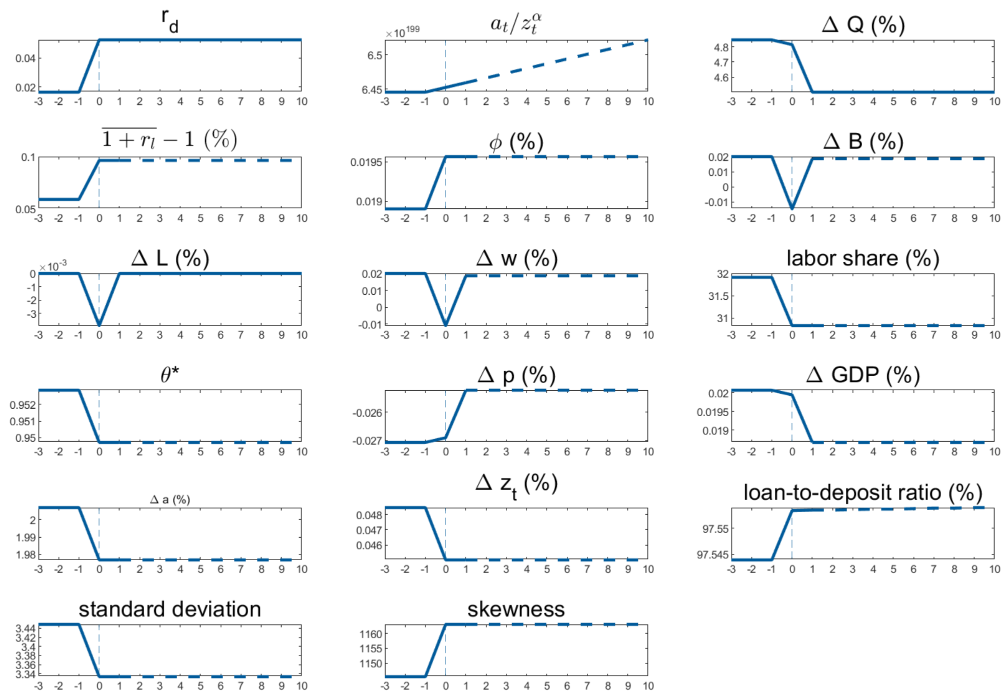
Table D.2
MODEL-IMPLIED MOMENTS AND ASSOCIATED PARAMETERS

| Moments | equation | Associated Parameters |
|---|---|---|
| CFI | equation (45) | $\theta^*$, $\xi$, $n$, $\psi$, and $\underline{\theta}$ |
| Gross growth rate of aggregate productivity | equation (46) | $\theta^*$, $\psi$ and $\underline{\theta}$ |
| Gross growth rate of aggregate bank efficiency | equation (47) | $\theta^*$, $\tau$, $\xi$, $n$, $\psi$, and $\underline{\theta}$ |
| Average recovery rate of loans | equation (48) | $\theta^*$, $\xi$, $n$, $\sigma$, $\psi$, and $\underline{\theta}$ |
| Average loan rate | equation (49) | $\theta^*$, $\xi$, $n$, $\sigma$, $\psi$, and $\underline{\theta}$ |
| Loan-to-deposit ratio | equation (50) | $\theta^*$, $\xi$, $n$, $\psi$, and $\underline{\theta}$ |
| Share of entrepreneurs | $1 - \mathbf{F}(\theta^*)$ | $\theta^*$, $\theta_{min}$, $\psi$ and $\underline{\theta}$ |
| Elasticity of employment to density | $-(1+\psi)(1-\xi)$ | $\xi$ and $\psi$ |
| Occupation choice | equation (33) | $\theta^*$, $\gamma$, $\xi$, $n$, $\psi$, and $\underline{\theta}$ |

## D.4 Higher funding costs

In this section, we analyze bank technology adoption in the context of higher bank funding costs, for example, as the US economy experienced in 2022-23 at the beginning of the AI revolution. We assume that, in period -1, the economy is at its initial BGP and, at time $t = 0$, the deposit rate $r_d$ permanently increases from 1.65% to 5.24%, which matches the average 3-month US Treasury bill rate in 2023. Then, the economy evolves for ten periods as in the previous counterfactual. Figure **??** reports the simulation results.

When $r_d$ increases at $t = 0$, the banks' unit funding cost in equation (19) rises. Banks pass these higher funding costs onto borrowers by raising the expected loan rate, which, in turn, increases the CFI. This higher expected loan rate slows the growth of capital goods output, loan demand, labor demand, and the wage rate, ultimately reducing the labor share. As the expected loan rate rises, less able entrepreneurs enter the labor market as workers, leading to a decrease in $\theta^*$. Since the firm-size distribution at $t = -1$ is right-tailed, a lower threshold shifts the distribution to the left, resulting in a lower standard




**Notes**: The figure illustrates the economy's response to an increase in $r_d$. The economy is on its baseline BGP path until period -1. At $t = 0$, the value of $r_d$ increases from 1.65% to 5.24%. From this point, the economy evolves for ten periods, consistent with Proposition 2. Aggregate productivity and bank efficiency follow the dynamics outlined in equations (38) and (41), respectively. The adoption of capital goods by banks is solved in equation (40). The expected loan rate is in equation (49). The CFI is defined 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). Labor share is defined in equation (54). The threshold for occupational choice is solved using equation (33). The price of capital is determined by equation (34). GDP is measured by aggregate consumption. The growth rates of aggregate bank efficiency and productivity are derived from equations (47) and (46), respectively. The loan-to-deposit ratio is defined in equation (50). The standard deviation and skewness of the firm-size distribution are defined in equations (55) and (56), respectively, respectively.

Figure D.1
Higher $r_d$

deviation and higher skewness. However, since they produce with aggregate technology from the previous period $z_{-1}$, the relative price of capital goods declines only slightly. This small increase in the input costs of final goods producers results in a slightly lower economy-wide GDP growth in period 0. Additionally, the slower decline in the price of capital goods starts to hinder banks from adopting new technology, reducing individual bank efficiency and slowing the overall growth in aggregate bank efficiency.

By the end of period 0, the decline in bank efficiency growth is less pronounced than the decline in productivity growth. Consequently, the ratio of bank efficiency to share-adjusted productivity $a_0/z_0^{\alpha}$ is higher than it was along the initial BGP. Leaving all other structural parameters unchanged, the economy does not converge to a new BGP. In period 1, a higher $a_0/z_0^{\alpha}$ partially offsets the negative impact of the higher loan rate on production. As a result, the growth rates of labor and loan demand, as well as wages, bounce back, although they remain below the levels observed along the previous BGP (not visible in Figure **??**). The labor share remains depressed, and the high expected loan rate discourages less able agents from becoming entrepreneurs, keeping the threshold for occupation choice at its lower level reached period 0. Due to the significantly lower aggregate productivity in the previous period $z_0$, the supply of capital goods now contracts more sharply, and the relative price of capital goods declines more slowly. This, in turn, raises production costs in the final goods sector, leading to a marked slowdown in economy-wide GDP growth.

Starting from period 1, both aggregate bank efficiency and productivity grow at a slower pace, with bank efficiency growing at a slightly higher rate than productivity, and $a_0/z_0^{\alpha}$ steadily rises, which leads to a gradual decrease in the expected loan rate. As a result, growth in production, loan demand, labor demand, and wage rate start to recover at a limited rate, causing the labor share to increase. With a lower expected loan rate, less able entrepreneurs exit the market and choose to become workers, leading to an increase in $\theta^*$. The increased production of capital goods drives down their price, which contributes to higher GDP growth due to somewhat lower input costs.

Column (3) of Table D.3 reports the moments for selected variables in the new BGP in which we increase $r_d$ and decrease $\tau$ by 0.1%. As shown in column (3) of Table D.3, compared to the initial BGP in column (1), the GDP growth rate declines by 6.5%, from 2% to 1.87%, while the CFI increases by 7 basis points or 3.7%. When banks pass their higher funding costs on to borrowers, entrepreneurs' output growth and the decline in capital goods prices slows. This also increases input costs in final goods production and lowers the economy's GDP growth rate. Additionally, higher loan rates prompt less-able agents to become entrepreneurs. As a result, the standard deviation of the firm-size distribution decreases by 3.2%, and the skewness increases by 1.2%. A slower decline in capital goods prices also discourages banks from purchasing capital goods, resulting in a lower long-run growth rate in aggregate bank efficiency.

Table D.3

Comparative statics along the balanced growth path

| | Baseline (1) | Higher $\nu$ (2) | Higher $r_d$ (3) | Higher $\nu$ and $r_d$ (4) |
|---|---|---|---|---|
| Growth rate of GDP | 2.00% | 2.19% | 1.87% | 2.05% |
| **CFI** | 1.89% | 1.81% | 1.96% | 1.87% |
| Average expected loan rate | 5.91% | 1.27% | 9.64% | 4.84% |
| Loan-to-deposit ratio | 97.67% | 102.02% | 97.55% | 102.03% |
| St. Dev. of firm-size distribution | 15.26 | 16.05 | 14.76 | 15.53 |
| Skew. of firm-size distribution | 86.43 | 84.79 | 87.49 | 85.84 |

**Note**: The table reports critical moments in four BGPs. The only structural parameters that change are those listed in the columns heading. Column (1) is the baseline BGP as estimated in Section 4. In column (2), we increase $\nu$ from 0.06% to 0.07%. In column (3), we increase the target deposit rate, $r_d$, from 1.65% to 5.24%. In column (4), we increase $\nu$, from 0.06% to 0.07%, and $r_d$, from 1.65% to 5.24%. GDP is measured by aggregate consumption. The CFI is defined in equation (45). The average expected loan rate $\overline{1+r_l}-1$ is defined in equation (49). The loan-to-deposit ratio is defined in equation (50). The standard deviation and skewness of the firm-size distribution are defined in equations (55) and (56), respectively.

Last, we examine how the long-run moments of the economy change when we permanently increase the share of of capital goods in loan production in the context of. In this counterfactual, we increase $\nu$ from 0.06% to 0.07% and $r_d$ from 1.65% to 5.24%, decreasing $\tau$ by 14.3%. Table D.3 shows that the higher funding costs tend to offset the efficiency and productivity gains associated with the technological improvement on the bank side of the economy, suggesting faster bank technology adoption in the context of higher funding costs might not yield the same economy-wide growth gains as under more normal funding circumstances.

# E Robustness for empirical test

In this section, we conduct some robustness check for our first results.

## E.1 Robustness check with IT subcomponent

First, we only consider more relevant sub-component of IT adoption by banks for transforming loans. Thus, we reestimate equation (57) using the software-to-NIE ratio, instead of IT-to-NIE ratio. As Table E.1 shows, our main results remain.

## E.2 Robustness check with other bank performance

We then re-estimate equation (57) 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. Columns (1) and (2) of Table **??** present the results for the lending rate, while Columns (3) and (4) show the results for the loan-to-deposit ratio. All findings align with our model's predictions.

## E.3 Bank technology adoption and CFI–Evidence from Call Report Data

In this section, we report additional empirical tests with alternative source of IT expense. We measure bank IT adoption with the IT expenses measure constructed by Modi, Pierri, Timmer and Peria (2022) available from 2002 to 2017. In the Call Reports, banks are not specifically required to report IT investments and expenses separately. However, they report up to three most important non-interest expenses that are not otherwise itemized and represent at least 10% of the unclassified non-interest expenses. Typically, bank non-interest expenses are operating expenses that are separate from interest expense and provisions for credit losses. They include employee salaries, equipment rental or leasing, ITC expenses, office rent, amortization of intangible assets, taxes and licenses, among others. Modi *et al.* (2022) use textual analysis of the verbal description of these top three noninterest expenses to identify them as "IT expense" if the description contains any IT-related keyword such as "software", "computer", or "internet". We then divide this

Table E.1

ROBUSTNESS: ALTERNATIVE MEASURE OF IT SPENDING USING SOFTWARE BUDGET ONLY

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

**Note**: The table presents the point estimates for $\beta$ from equation (57), 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 2. The full sample consists of 3,515 banks that remained operational for more than three consecutive years and were incorporated in the continental United States. The sample period spans 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: Interest rate and loan-to-deposit ratio versus IT Spending

| | 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) |
| CI loan/Total loan | | 0.0000 | | -0.0322* |
| | | (0.0000) | | (0.0181) |
| Real estate loan/Total loan | | 0.0001 | | -0.0334 |
| | | (0.0000) | | (0.0251) |
| Personal loan/Total loan | | 0.0001*** | | -0.0553*** |
| | | (0.0000) | | (0.0202) |
| Equity/Assets | | 0.0001*** | | 0.1086*** |
| | | (0.0000) | | (0.0132) |
| Security/Assets | | 0.0005*** | | -0.7406*** |
| | | (0.0000) | | (0.0115) |
| 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 |
| N | 24,625 | 24,625 | 24,625 | 24,625 |
| $AdjR^2$ | 0.79 | 0.81 | 0.88 | 0.94 |

**Note**: The table presents the point estimates for $\beta$ from equation (57). The dependent variables are 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 2. The full sample consists of 3,515 banks that remained operational for more than three consecutive years and were incorporated in the continental United States. The sample period spans from 2010 to 2019. Bank and year fixed effects are included. All standard errors are clustered at the bank level. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

measure of IT expenses by noninterest expenses and call this variable *IT expense intensity*. Obviously, banks may also invest in IT when this category does not make up the top three expenditure items. We deal with this data limitation explicitly below. The sample period is from 2002 to 2017. The sample includes 5,815 banks that are alive at least half of the sample periods (over eight consecutive years) and are incorporated in the continental United States. The results are robust to changing these restrictions.

### Conditional correlations

We first consider conditional correlations between IT intensity and the bank-level CFI, using the following specification:

$$\mathbf{CFI}_{bt} = \alpha \mathbf{IT}_{b,t-1} + \gamma' \mathbf{X}_{b,t-1} + \beta \mathbf{V}_{b,t-1} + \eta' \mathbf{V}_{b,t-1} \otimes \mathbf{X}_{b,t-1} + \nu_b + \omega_t + \epsilon_{bt} \tag{E.1}$$

where $\otimes$ is the Kronecker product, $b$ and $t$ index individual banks and years, respectively, **IT** is the IT expense intensity (lagged by one year since installing new IT equipment and training employees may take some time), and $\nu$ and $\omega$ are bank and year fixed effects, respectively. $\mathbf{X}$ is the vector of (lagged) bank-level characteristics discussed above.

The vector $\mathbf{V}_{bt} = [\mathbf{1}_b^{no\,IT}, \mathbf{1}_{bt}^{zero}, \mathbf{1}_t^{RC}]$ includes three dummy variables. The first dummy, $\mathbf{1}_b^{no\,IT}$, is equal to one if bank $b$ never reports IT expenses as a top-three item throughout the sample period and zero otherwise. The second one, $\mathbf{1}_{bt}^{zero}$, is equal to one if bank $b$ reports IT expense as a top-three item at least once during the sample period, but is not listed in year $t$, and zero otherwise. The last one is a dummy for the Great Recession years, $\mathbf{1}_t^{RC}$, taking value one if the year is 2008 or 2009 and zero otherwise. Following Wooldridge (2010), the term $\mathbf{V}_{b,t-1} \otimes \mathbf{X}_{b,t-1}$ controls for the differential behavior of banks that may invest in IT even though IT is not listed as a top three non-interest expense and also for unobserved factors during the Great Recession years.

Table E.3 reports the point estimate for equation (E.1). Column (1) reports the benchmark result, showing that the coefficient on the IT adoption intensity variable is negative and statistically significant. In columns (2) and (3), we examine how the two components of the bank-level CFI, employee compensation, and net income, correlate with the change in IT expense.

Next, we want to establish causation by taking an instrumental variable approach. However, this approach is feasible only for a subset of banks (called IT-intensive banks) that report IT expense as one of their top three non-interest items at least once during the sample period. Therefore, before proceeding, we want to compare this sub-sample of IT-intensive banks with the full sample used in the correlation analysis above. Column (4), (5), and (6) of Table E.3 show the point

Table E.3
Panel regression results

| | Full Sample | | | Subsample (IT-intensive banks) | | |
|---|---|---|---|---|---|---|
| | **CFI** | $\frac{salary}{Int.\,loans}$ | $\frac{net\,income}{Int.\,loans}$ | **CFI** | $\frac{salary}{Int.\,loans}$ | $\frac{net\,income}{Int.\,loans}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\mathbf{IT}_{b,t-1}$ | -0.0012** | -0.0011*** | -0.0001 | -0.0013** | -0.0011*** | -0.0002 |
| | (0.001) | (0.000) | (0.001) | (0.001) | (0.000) | (0.001) |
| Obs | 81,980 | 81,980 | 81,980 | 32,775 | 32,775 | 32,775 |
| $R^2$ | 0.625 | 0.788 | 0.586 | 0.603 | 0.770 | 0.560 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| $\mathbf{1}_b^{no\,IT} \times X_{bt}$ | Yes | Yes | Yes | No | No | No |
| $\mathbf{1}_{bt}^{zero} \times X_{bt}$ | Yes | Yes | Yes | Yes | Yes | Yes |
| $\mathbf{1}_t^{RC} \times X_{bt}$ | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Note**: The table reports the point estimates for $\alpha$ in equation (E.1). The outcome variables are the bank-level CFI, the ratio of employment compensation to intermediated assets, and the ratio of net income to intermediated assets. Independent variables are the IT expense intensity and the bank-level characteristics as in Table 2. Three types of heterogeneous effects of bank characteristics on CFI are considered. $\mathbf{1}_b^{no\,IT} \times X_{bt}$ controls for the heterogeneous effects of banks that never report IT expense among the top three non-interest expenses. $\mathbf{1}_{bt}^{zero} \times X_{bt}$ controls for the heterogeneous effects of banks that report IT expense at least once during the sample period but do not report it in year $t$. $\mathbf{1}_t^{RC} \times X_{bt}$ control for the heterogeneous effects of the Great Recession years. Bank-specific and year fixed effects are included in all regressions. The full sample includes 5815 banks that survive more than eight years and are incorporated in the continental states. The subsample that of IT-intensive banks includes 2306 banks that report IT expense at least once as a top-three non-interest expense items throughout the sample period. The sample period is from 2002 to 2017. All standard errors are clustered at the bank level. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

estimates of the IT expense intensity coefficient in equation (E.1) estimated with the sub-sample of IT-intensive banks are essentially the same.

### Instrumental variable regressions

Motivated by the robust correlation between more IT adoption and lower CFI, we now want to establish a causal link between technology adoption and bank efficiency.

We instrument IT adoption using a shift-share variable that interacts an aggregate measure of the change in the cost of capital goods with a bank-specific measure of the availability of skilled human capital needed for technology adoption. The shift-share variable is the product of the log

Table E.4
IV REGRESSION RESULTS

| | First-stage | Second-stage | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\Delta\mathbf{CP}_{t-1} \times \mathbf{LGC}_{b1}$ | 3.661*** | | | |
| | (1.393) | | | |
| $\widehat{\mathbf{IT}}_{b,t-1}$ | | -0.0016** | -0.0011*** | -0.0004 |
| | | (0.0008) | (0.0005) | (0.0007) |
| Obs | 31,252 | 30,483 | 30,483 | 30,483 |
| $R^2$/psuedo $R^2$ | 0.920 | 0.612 | 0.779 | 0.569 |
| Wald test | 9.71 | | | |
| Controls | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

**Note**: The table reports the point estimates for the first and second stage estimation of equation (E.2) and (E.3). $\Delta\mathbf{CP}_t$ is the log difference in the relative price of capital, $\mathbf{LGC}_b$ is the distances to the closest land-grant colleges, and $\widehat{\mathbf{IT}}_{bt}$ is the fitted value from the first stage. Independent variables are the IT expense intensity and the bank-level characteristics, including the logarithm of assets, the capital-to-asset ratio, the share of liquidity assets of total assets. Two types of heterogeneous effects of bank characteristics on CFI are considered. Bank-specific and year fixed effects are included in all regressions. The sample is restricted to IT-intensive banks. The sample period is from 2002 to 2017. The first stage is estimated with the Poisson pseudo-maximum likelihood method, where standard errors are clustered at the bank level. The standard errors of the second-stage regression are bootstrapped with 1000 draws. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$.

difference in the quality-adjusted relative price of capital in Eichengreen (2015) with the bank's distance to the nearest five land-grant colleges, following Moretti (2004) and Pierri and Timmer (2022). 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. The specification of the two-stage regression model is as follows.

$$\mathbf{IT}_{bt} = \beta\Delta\mathbf{CP}_{t-1} \times \mathbf{LGC}_b + \delta'\mathbf{X}_{bt} + \phi\mathbf{V}_{bt} + \rho'\mathbf{V}_{bt} \otimes \mathbf{X}_{bt} + \mu_b + \theta_t + \zeta_{bt} \tag{E.2}$$

$$\mathbf{CFI}_{bt} = \alpha\widehat{\mathbf{IT}}_{b,t-1} + \gamma'\mathbf{X}_{b,t-1} + \psi\mathbf{V}_{b,t-1} + \eta'\mathbf{V}_{b,t-1} \otimes \mathbf{X}_{b,t-1} + \nu_b + \omega_t + \epsilon_{bt}. \tag{E.3}$$

Here, $\mathbf{IT}_{bt}$ is the IT expense intensity of bank $b$ in year $t$, $\Delta\mathbf{CP}_t$ is the log difference in the relative price of capital, $\mathbf{LGC}_b$ is the distance to the nearest land-grant colleges, $\widehat{\mathbf{IT}}$ is the fitted value from the first stage, $\mathbf{X}$ is the vector of banks characteristics used in the correlation analysis, $\mathbf{V}_{bt} =$

$[\mathbf{1}_{bt}^{zero}, \mathbf{1}_{t}^{RC}]$ is a subset of the dummy variables used before to control for heterogeneous effects of bank characteristics, $\mu_b$ and $\nu_b$ are the bank fixed effects, and $\theta_t$ and $\omega_t$ are the year fixed effects. As we include bank fixed effects in the second stage, we need to incorporate them also in the first stage. Therefore, we must restrict our sample to IT-intensive banks. Furthermore, in some years, IT investment is not large enough to be listed as one of the top-three non-interest expense items. Therefore, we apply the Poisson pseudo maximum likelihood method, as per Cohn, Liu and Wardlaw (2022) and Chen and Roth (2023), to estimate the first stage.

Column (1) of Table E.4 reports the point estimate for the first stage. The interaction term is positive and statistically significant. Column (2) reports the estimation results from the second stage, with standard error bootstrapped with over 1000 draws. The estimated coefficient is negative and statistically significant at the 95% significance level. Consistent with the analysis in panel regression, Column (3) and (4) suggest that the investment in IT mainly replaces the labor with no significant effects on net income per unit of intermediate asset.