Information Technology Improvement in US Commercial Bank Lending: Implications for the Declining of Small Businesses Lending

Haiyan Pang[1]

(Working in progress)

Abstract

Banks' lending to small businesses is decreasing. To combat this trend with policies, we need to know the reason behind it. I evaluate how a cost-reducing improvement in the technology of assessing hard information contributes to the declining of small business lending with a quantitative, dynamic model. The model infers that banks' costs of assessing borrowers' hard information decrease by 51% and consequently small business lending falls by 22%. This technology improvement not only discourages banks to build relationships and lend to small businesses but also increases the exit rates of smaller banks that have larger shares of small business loans. The model predicts that the first effect contributes to 51% of the decrease in small business lending and that we should subsidize small business lending rather than small banks to encourage lending to small borrowers.

Key words: Information technology, small business lending, relationship banking, innovation, fin-tech

JEL classification: G21

[1]Arizona State University. Email: Haiyan.Pang@asu.edu

Lending to small businesses (defined as C&I loans fewer than 100 million dollars) has been declining by 22% in the recent decade, from 340 billion dollars to 300 billion dollars. According to a study of OECD, small businesses "continue to face significant obstacles to fulfilling their potential to innovate, grow and create jobs, particularly when it comes to obtaining access to finance." This declining of small business lending imposes a problem for the US economy. Small businesses with employees fewer than 20 contribute to 79% of the net new jobs in the US (Edmiston, 2007) and the financial constraints of small businesses lead to higher unemployment rate and lower economic growth (Chen, Hanson and Stein, 2017). However, literatures provide little evidence for the declining of small business lending. For example, two pioneer papers (Cortés et al., 2018; Bordo and Duca, 2018)try to attribute this reduction to the increasing regulatory burdens from Dodd Franck Act, but they arrive at conflicting results. It is therefore hard to give any policy advice on how to encourage lending to these small borrowers.

This paper provides a quantitative structural framework to explain the declining of small business lending. The model shows that the declining of small business loans results from a technology improvement that reduces banks' costs of evaluating borrowers' hard information and increases banks' lending capacities. The model features a competitive banking market with commercial banks that differ in productive assets (including banks' capital and human capital used to process and evaluate hard information). Banks' productive assets, together with the technology of evaluating hard information, determine banks' lending capacities and expansion rates. In each period, banks allocate lending capacities between transaction lending and relationship lending and decide on its lending capacities of the next period. Transaction lending is an "arm-length" transaction. Relationship lending is a long-term contract with bank-borrower relationships where banks monitor borrowers' cash flow intensively along the whole lending process. As banks have increasing marginal costs of building an additional relationship, larger banks have smaller shares of relationship loans. Relationship lending in the model are small business loans. Small businesses are ex-ante risky, young and lack of audited information (Berger, Bouwman and Kim, 2017; Cortés et al., 2018); the ex-post returns from these borrowers rely on banks' monitoring (Bolton et al., 2016). Therefore, these small borrowers usually receive relationship loans.

In the model, banks' technology of assessing borrowers' hard information improves over time, but technology of building relationships stays the same. Hard information is usually numerical and soft information is usually in text. The collection and interpretation of hard information can be separated and delegated (Petersen, 2004; Liberti and Petersen, 2017). Therefore, the computer based information technological innovation, in most cases, decreases banks' costs of acquiring hard information rather than soft information.

The model suggests two mechanisms why the technology improvement can reduce small business lending. The first effect is the substituting effect. As the technology improves, banks' profits from transaction lending increases more than those from relationship lending. Banks thus increase the shares of transaction lending. In other words, banks' shares of relationship loans decrease. The second effect is the crowding effect. As the technology improvement increases banks' lending capacities, banks demand more deposits than before. The deposit interest rate increases and banks' profits decreases. Small banks, however, are constrained by their abilities of issuing more loans and earning more profits. They cannot afford the costs of staying and will exit. Their market shares are taken by large banks that have smaller shares of relationship loans. Therefore, the share of relationship loans decreases. In both situations, if banks cannot increase lending capacities enough, relationship loans to small borrowers decrease.

Distangling the two effects has great policy implications. There is large debate about how to encourage lending to small business lending in the literature. Berger et al. (2005) suggests that instead of subsidizing small business lending directly, we may subsidize the intermediaries that have comparative advantages in relationship lending. The model implies that if the substituting effect dominates, then probably, we should subsidize small business lending directly; if the crowding effect dominates, we may need to subsidize small banks. However, it is hard to distangle these two effects in a reduced form approach, because banks endogenously decide on lending and staying. Therefore, we need a structural model with technology improving and banks deciding on transaction lending, relationship lending and staying accordingly.

I calibrate the model to the U.S. individual commercial bank data from 2002 to 2007 and from 2012 to 2017. I identify a set of parameters, with which the simulated moments from the model are quantitatively consistent with the observed behaviors of the U.S. commercial banks. These moments include variations in total loans and small business loans in each year. The model shows that the costs of processing hard information of an loan application of 1 million dollars has decreased from 720 dollars in 2002 to 355 dollars in 2017. As in the model, a bank on average approves 5% of loan applications it evaluates. Therefore, per dollar transaction loan, a bank saves 0.73% dollars. This number is large if we compare this to the average loan spread, about 3%. It also means that the cost of bank transaction lending is reduced by 51%. However, for a dollar of relationship loan, the bank needs to pay about at least additionally 0.66% dollars to build relationships, so the cost of relationship lending is reduced by at most 35%. As banks have different gains from transaction lending and relationship lending, they substitute relationship loans with transaction loans. The substituting effect results in 51% of the declining in small business loans. In the model, as large banks are less constrained by their abilities of issuing more loans, large banks benefit more from the technological improvement than small banks and crowd out small banks. The quantitative model infers that a bank with additional thousand dollars of productive assets can have at most 1726 dollars of higher return from the improvement. The crowding effect contributes to 49% of the declining in small business loans.

The model does a reasonable job of fitting the data. In the model, the loan share of large banks with loans more than 1 billion dollars increases from 76% to 85% (vs 81% to 90% in the data). The share of relationship lending (small business lending) decreases from to 6.7% to 3.2% (vs from 6.6% to 3.5% in the data). The dollar amount of relationship lending decreases from 345 billion to 309 billion (vs from 340 billion to 301 billion in the data). My model also shows that loans to all borrowers with delinquency rates greater than or equal to 5% decreases from 159 billion to 78 billion dollars; while other borrowers receive more loans than before. According to the US Small Business Administration, from 2002 to 2009, more than 90% of small business loans (in dollar amount) have delinquency rates greater than 5%. Therefore, the model indicates that many risky small businesses receive fewer loans than before and this reduction of lending to risky small businesses leads to declining of small business lending.

With this quantitative model, I compare two different policies that combat the decrease in the lending to small businesses: subsidizing small banks to encourage them to stay and subsidizing lending to risky borrowers. Subsidizing lending to small businesses encourages lending to risky, small businesses. However, subsidizing small banks has negative effects on lending to small businesses. This comparison can only be done within a framework that considers how different policies can change banks' decisions about lending to small businesses. Only in this way, can I overcome "Lucas Critique"[2] and establish casual relationship between policy changes and the change of small business lending. If I subsidize banks with one percent of their loan amounts, when lending to borrowers with delinquency rates greater than or equal to 5%, a borrower with delinquency rate greater than or equal to 5% receives 4 times more loans and other borrowers also receive more loans under this policy. Thus, in the context of the model, when the U.S. Small Business Administration provides subsidized loans and loan guarantees to small businesses for start-up and expansion, risky small businesses become much less financially constrained. If I subsidize small banks (with total loans less than 100 million dollars) with 1% of their loan amounts to reduce their exit rates, loans to small borrowers stay the same as before.

1 Related Literature

This paper is first related with recent literature on the declining of small business lending. Chen, Hanson and Stein (2017) find that small business lending is declining significantly after the Great Recession and this declining contributes to slow recovery of local economy. Cortés et al. (2018) find that although stress tests make small banks' harder to survive, this test does not contribute

[2]The 'Lucas critique' is a criticism of econometric policy evaluation procedures that fail to recognize that optimal decision rules of economic agents vary systematically with changes in policy. In particular, it criticizes using estimated statistical relationships from past data to forecast the effects of adopting a new policy, because the estimated regression coefficients are not invariant but will change along with agents' decision rules in response to a new policy (Ljungqvist (2008), New Palgrave Dictionary).

to the declining of small business lending the US. My contribution to this literature is threefold: first, I provide a new reason for the declining of small business lending; second, I provide some insights to policies that could potentially encourage lending to small businesses.

This paper is related with the literature on small banks and small business lending (Berger et al., 1998; Strahan and Weston, 1998; Peek and Rosengren, 1995; **?**; Berger, Bouwman and Kim, 2017). Berger, Bouwman and Kim (2017) find that small banks still play a significant role in lending to small business, especially during economic downturns. However, other literature either finds that the exit of small banks decreases or does not affect lending to small risky borrowers using a method of reduced form regression. However, the reduced-form approach in these papers is subject to an endogeneity bias. This approach cannot possibly disentangle the local shock that affects the local market concentration as well as the small business lending from the local shock that only affects the local market concentration. In addition, the reduced form approach cannot be used for policy analysis because of being subject to the "Lucas Critique". In contrast, with a structural model, this paper is able to address "Lucas Critique" and conduct policy evaluations.

This paper is related to study about technological improvements and productivity growth in the US banking industry. Berger (2003) summarizes the difficulties of relating information technological improvements with observed productivity growth. First, firms may not adopt the best technology. Second, the productivity growth may not increase firms' profits, but benefit consumers through competition among firms. This paper tackles this challenge by a quantitative structural model that endogenizes the adoption of advanced technologies and competition among banks. By doing so, I find the productivity in the banking sector grows by 45% from 1990 to 2007 due to information technological improvements. This paper is also related with the literature on industry "shake-out." The research on industry "shake-out" suggests that with an introduction of cost-saving technology, small firms exit and large firms gain market shares (Hopenhayn, 1992; Hayashi, Li and Wang, 2017). Consistent with this paper, Hayashi, Li and Wang (2017) show that the ATM market becomes more concentrated because large firms benefit more than small firms from the introduction of ATMs that accommodate debit cards. Transaction loans to safe borrowers are similar to ATMs. When the technology of transaction lending is improving, safe borrowers are better off for sure, but risky small businesses who highly depend on relationship lending may be hurt. Therefore, I enrich the previous framework of "shake-out" with banks' choices between transaction lending and relationship lending according to borrowers' risks.

The rest of the paper is organized as follows. Section II presents key statistic features in the US commercial banking market. Section III contains the model. Section IV presents the calibration of the model. Section V shows implications of the model. Section VI concludes. Proofs and tables are in the Appendix.

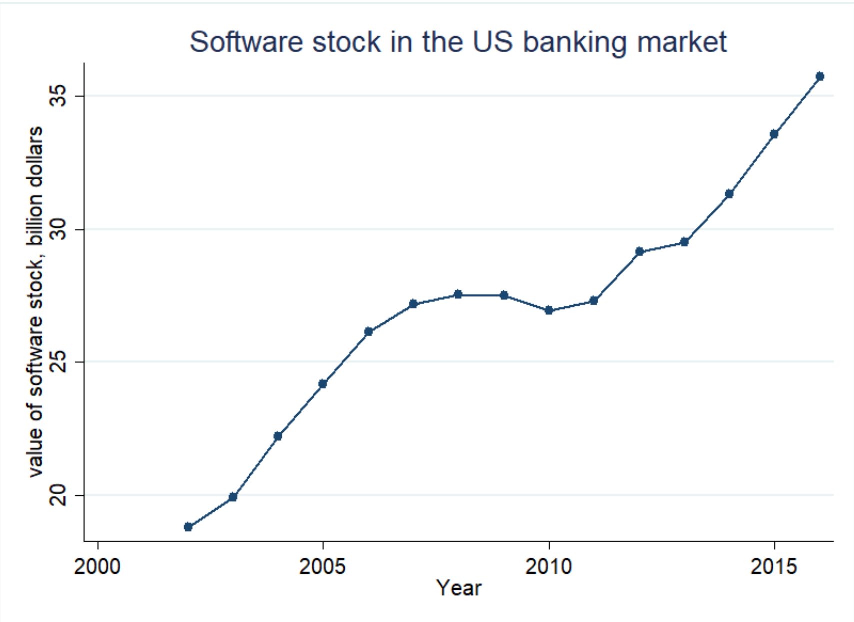
2 Motivation Facts

The following pictures show some key dynamic features in the US commercial banking industry. First, US banks have been increasingly using software. Second, US banks have reduced lending to small businesses. Third, US banking market has increasing market concentration.

2.1 The Trend of Technology Usage

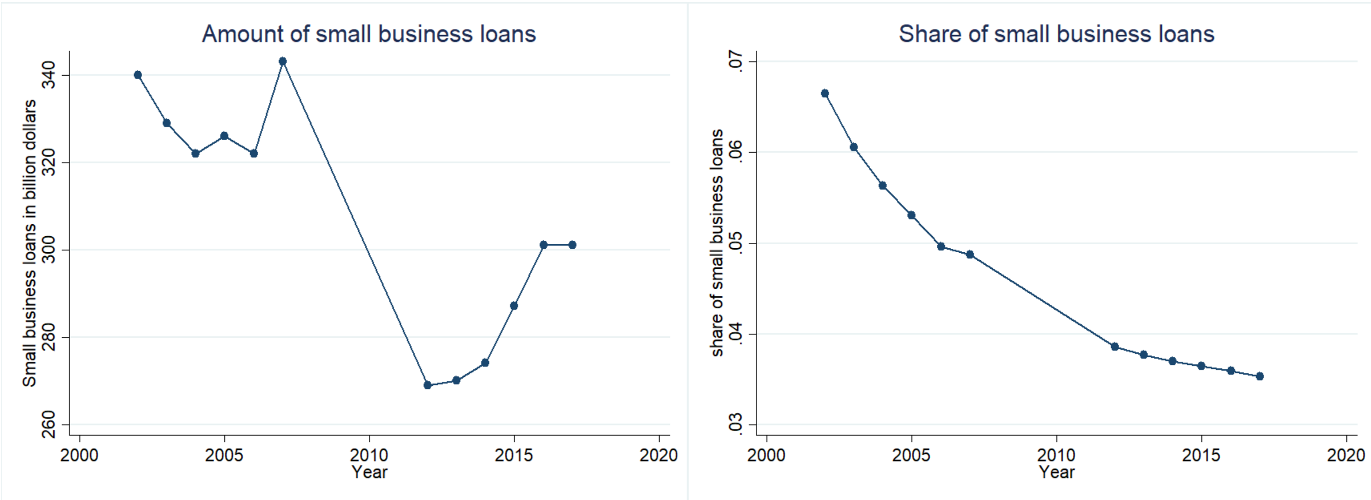
Figure.1 shows the increasing using of software in the US commercial banking sector. Banks' software stock, including prepared software (ENS1), custom software (ENS2) and own account software (ENS3) has increased from about 18 billion dollars to about 36 billion dollars in 2017. This stock has increased by 100% from 2002 to 2017. With the development of IT technology, banks have been increasingly using software and programs to evaluate borrowers' credit worthiness. The data is from the Bureau of Economic Analysis (BEA), Current-Cost Net Capital Stock of Private Nonresidential Fixed Assets Table.

Figure 1: Increasing bank software stock



Note: This figure shows banks' software stock from 2002 to 2016 in billion dollars of 2017. Banks' software stock includes prepared software (ENS1), custom software (ENS2) and own account software (ENS3).

Figure 2: Declining of Small Business Lending

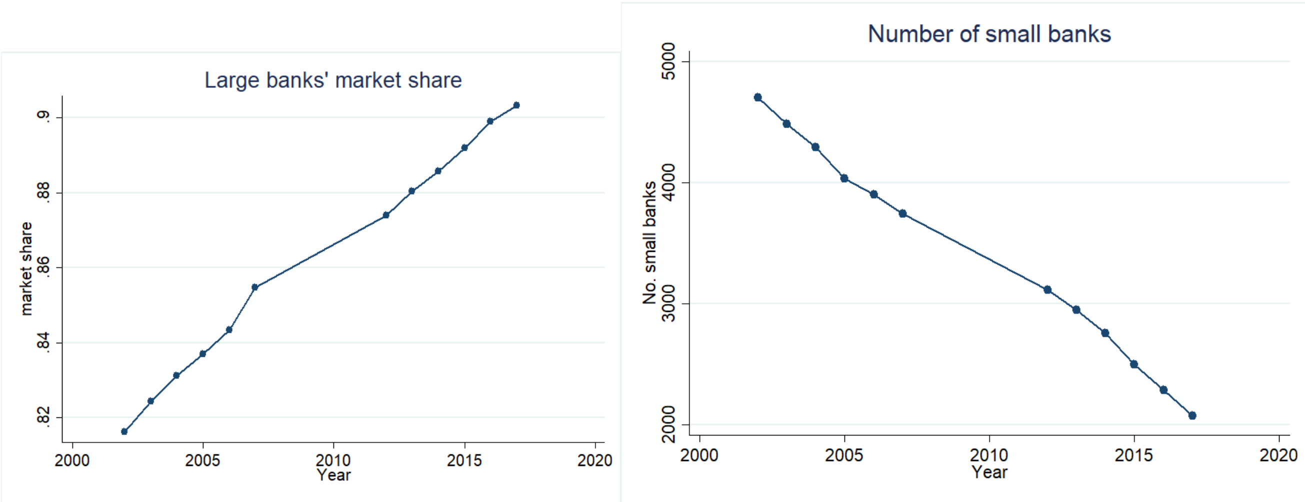


Note: The picture on the left shows that dollar amount of small business loans decreased from 340 billion dollars to 300 billion dollars with some fluctuations along this declining. The picture on the right shows that the share of small business loans to total bank loans decreased monotonically from about 6.7% to about 3.5%.

2.2 The Trend of Lending Practice

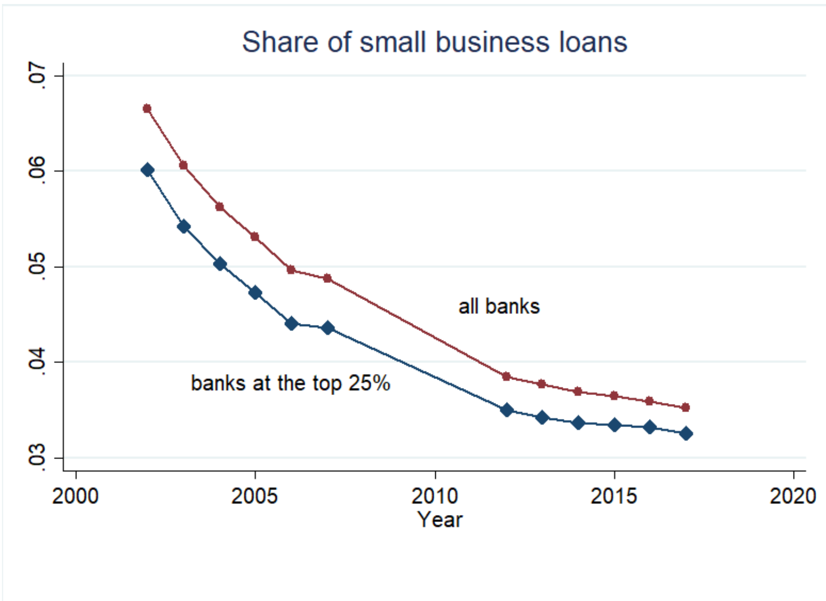
I use the data from FDIC reports on US depository institutions. I use data from 2002 to 2007 and from 2012 to 2017. All the dollar amounts are in constant 2017 US dollars. I exclude data during the recent economic recession. Figure.2 shows the declining of small business lending, in dollar amount and in share to total bank loans. The dollar amount of small business loans decreased from 340 billion dollars to 300 billion dollars with some fluctuations along this declining. The share of small business loans to total bank loans decreased monotonically from about 6.7% to about 3.5%. Figure.3 shows the increasing concentration in the US commercial banking market: the market share large banks with loans more than 1 billion dollars increased from 6782% to 90%; the number of small banks with loans fewer than 100 million dollars decreased from 4707 to 2072. Figure.4 shows that larger banks have smaller share of small business loans and their shares of small business loans decreased faster, compared to smaller banks. The average share of small business loans of banks at the top 25% (in terms of total loans) decreased from 12% to 6.5%; the average share of small business loans of banks at the bottom 25% (in terms of total loans) decreased from 15% to 12%

Figure 3: Increasing concentration



Note: The picture on the left shows that large banks with loans more than 1 billion dollars increased from 82% to 90%. The picture on the right shows that the number of small banks with loans fewer than 100 million dollars decreased from 4707 to 2072.

Figure 4: Declining of small business loans by banks of different sizes



Note: The picture shows that larger banks with loans at the top 25% have smaller shares of small business loans in each year. For example, in 2002, these large banks had 6% of small business loans while all banks have 6.7% of small business loans.

3 Model

In this section, I construct an infinite-horizon model with discrete periods. The economy is populated with borrowers and commercial banks (banks henceforth). Banks maximize expected discounted profits flows. Borrowers have no preference or behaviors in the model. There are three technologies, one for assessing borrowers' delinquency rates, one for building relationships, and one for accumulating assets. A borrower lives for one period. A borrower has a project that needs financing from a bank. He has two pieces of unobservable information. One is his delinquency rate. Another is his cash flow when his project does not pay off in the beginning. Banks take deposits and issue loans. On born, banks are endowed with assets used for assessing borrowers. The evaluation of a borrower's delinquency rate is a statistical analysis, that is based on borrowers' hard information. It happens before the lender lends to a borrower. Banks can also choose to invest in long-term relationships with borrowers to acquire borrowers' soft information. I model relationship banking following Bolton et al. (2016). Their theory emphasizes the relationship banking's ability to learn about changes in the borrower's financial condition, and to adapt lending terms to the evolving circumstances the firm is in (Rajan, 1992; Von Thadden, 1995). There are two major ways of modeling relationship lending. In Boot and Thakor (2000), relationships decrease borrowers' delinquency rates. Hence, the surplus from relationships increase in the delinquency rates of borrowers, but decrease in the cost of building relationships. If I follow Boot and Thakor (2000), I would have arrived at the same conclusion as before: banks give relationship loans to risky borrowers and transaction loans to safe borrowers.

Petersen (2004) shows that as the collecting and processing of hard information can be coded, information technological improvements are more adept at collecting, storing, and transmitting quantitative hard information than soft information. I assume that the technology of assessing borrowers improves over time, but not the technology of building relationships. When so, banks have larger comparative advantage at transaction lending over relationship lending. Banks will have smaller share of relationship loans over time.

In each period, a bank accumulates assets. When the technology for assessing borrowers improves, compared to small banks, large banks have larger returns from utilizing new technologies. Through the competition among banks in the deposit market, large banks take more market shares and small banks leave. As large banks have smaller share of lending to small businesses, lending to small businesses may decline.

I do not model borrowers' behaviors or choices. Some may argue that borrowers could search more efficiently for the best loan offers with the improvements of information technology. Therefore, advanced information technology will promote the matching between banks and borrowers. I model the efficiency improvements of matching between borrowers and banks from the perspective of banks. In the model, advanced information technology allows banks to evaluate more borrowers, which means a more efficient matching between banks and borrowers.

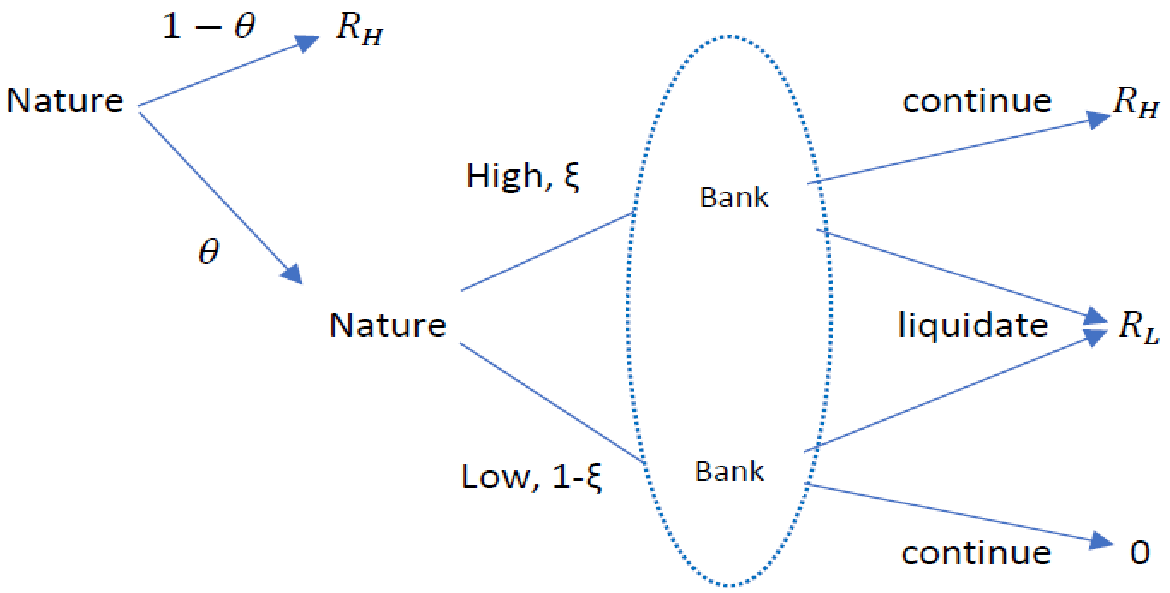
3.1 Model Details

Time Line: There are infinite periods $t = 0, 1, 2, ...$ In each period t, there are five dates, $d = 0, 1, 2, 3, 4$. On date zero, banks assess borrowers. On date 1, based on a borrower's delinquency rate, the bank decides whether to lend to him. If the bank chooses to lend to him, the bank decides to lend to him by relationship or transaction lending. On date 2, when the borrower of this project is delinquent on his debt, the bank decides whether to liquidate the project. On date 3, after the bank sees its cost of staying, the bank decides whether to stay in the market. On date 4, if the bank decides to stay, it decides its assets for the next period.

Preference and endowments: Banks are risk neutral and are endowed with assets for assessing borrowers. Borrowers have projects, but no money to invest in projects.

Types of securities: risky bank loans and riskless deposits. A bank issues a loan of $1 to finance a borrower's project. The borrower and his project exist for one period. Borrowers differ in the delinquency rates of θ, $\theta \in [0, 1]$. If the borrower repays on time, the payoff to the bank is R_H, the sum of principal and interests. If the borrower is delinquent on his debt, his project generates high cash flow with a probability of ξ and low cash flow with a probability of $1 - \xi$. If the project generates high cash flow and the bank continues its financing, the bank will receive R_H (full recovery); if the project generates low cash flow and the bank continues its financing, the bank will receive nothing. If the bank liquidates this financially distressed project, the bank receives R_L, the liquidation value of a project, $\xi R_H < R_L < 1$. Deposits are from a competitive deposit market with an increasing supply function, $r = R_H - e^{-n_r log(D)}$, where r is the deposit interest rate, D is the supply of deposits, and n_r measures the elasticity between the deposit supply and the deposit interest rate. In the model, I assume that loan rates are exogenously given. Even if I I assume that banks price loans according to borrowers' risks, the results will not change, because in reality banks cannot charge very high loan rates and their returns from lending to riskier borrowers are usually small than those from safer borrowers. The assumptions in my model capture the essence of this feature in bank lending. I could also assume that the lender will not receive full recovery when a financially distressed project will have high cash flow and the lender will have some returns when a financially distressed project will have low cash flow. However, as long as liquidation is a dominant strategy for the lender when he has no information about the future cash flow of a financially distressed project, the results in my model will hold.

Figure 5: Banks' returns from a project



Note: This figure shows banks' returns from a project with a delinquency rate of θ, given the choices of nature and the actions of a bank lender.

On date 0, measure of B newborn banks enter the market. A newborn bank has assets z^0, which is drawn from a log-normal distribution $log - gamma(\mu_z, \sigma_z)$. All borrowers apply to all banks (the incumbents and the new entrants). At this time, banks have no information about borrowers' delinquency rates or cash flow.

On date 1, banks use their assets to determine the delinquency rates of borrowers at no cost. Banks do not decide how many borrowers to evaluate. This number is determined by banks' technology and a bank's assets. The rationale behind this number is an optimal decision of the bank. The bank has decided its assets of this period in the last period and cannot make any change thereafter. Given a bank's assets and the current technology, the bank decides how many borrowers to assess. The bank will make the maximum profits if it uses all its assets to evaluate borrowers. Therefore, I abstract a bank's decision on evaluating how many borrowers by a number. A bank with assets z_t determines the delinquency rates of m_t borrowers,

$$m_t = M_t z_t^\alpha$$

, where $\alpha \in (0, 1)$ measures the return to the scale of a bank's assets and $M_t = e^{\lambda t} M_0$. The parameter M_0 measures banks' technology at period 0 and λ measures the advancement of bank's technology.

On date 2, according to the delinquency rates of borrowers, a bank chooses to whom to lend and by relationship lending or by transaction lending. If a bank lends to a borrower by relationship lending, it pays a cost c to build a relationship with the borrower. The cost of building a relationship is an increasing function of how many relationships the bank has built, where $c(L^S) = \frac{1}{F(\omega+1)}(L^S)^\omega$, L^S is the number of relationships that the bank has built, ω captures the elasticity between marginal costs of building relationships and the number of relationships, and F measures the average costs of building relationships.

The process of building relationships is as follows: the bank manager sends loan officers to collect soft information about this borrower, such as his managerial abilities, the conditions of his business and his reputation among neighbors. During the process, loan officer may shirk. Thus, the manager needs to monitor and incentivize the loan officers. Because a manager has limited time, if he monitors many loan officers, he cannot monitor all the loan officers as efficiently as managers who monitor a few loan officers. Therefore, the manager needs to incentivize these loan officers more. When a bank has many borrowers to build relationships with, it hires many loan officers. Hence, a bank has an increasing marginal cost of building relationships. Chen et al. (2004) show that financial institutions have decreasing returns to scale in managing portfolios, especially in non-routine tasks that require employees' objective judgments. Building relationships to acquire borrowers' soft information is just a task of this type.

On date 3, if a borrower repays on time, the bank receives R_H, the sum of principal and interests. If the borrower is delinquent on debt, a bank decides whether to liquidate his project or continue its financing. In relationship lending, the bank knows the cash flow from this distressed project on date 4. If the cash flow is high, the bank continues its financing and will receive full recovery, R_H; otherwise, the bank liquidates the project and receives the liquidation value, R_L. In transaction lending, the bank does not know the cash flow from this distressed project on date 4. Therefore, the bank optimally liquidates the project and receives R_L. Think about two lending: one is mortgage lending and another is lending to a high-tech start-up. In both lending, if the borrower repays on time, the lender receives the principal and interests. In a mortgage, after issuing the loan, the lender seldom contacts with the borrower; when the borrower does not repay on time, the lender will take the house over and sell it usually at a discount. In the lending to the high-tech start-up, after issuing the loan, the lender will contact with the firm CEO frequently so as to monitor the firm's cash flow, innovation activities and decisions made by the managing team. When the firm does not repay the bank on time because of lack of cash, the lender usually knows the reason behind this delinquency. If the bank and the firm CEO agree on the firm's business plan, the bank will continue its financing; otherwise, the bank will negotiate with the lender to get some money back.

On date 4, a bank earns its profits from all loans he finances. After seeing its cost of staying, the bank decides whether to stay, e_t and its assets for the next period, z_{t+1} if stays,

$$z_{t+1} = (1-\delta_z)z_t + Az_t^{1-\gamma}g_t^{\gamma}$$

where e_t is from a log-normal distribution $lnN(\mu, \sigma)$, g_t is the money used for assets accumulation, δ_z is the depreciation rate of assets, A and γ are constant parameters, and $0 < \gamma < 1$. The parameter A, the bank's assets, z_t and the technology for assessing borrowers determine the bank's return from the investment of g_t. Banks with more assets, has larger returns from this investment. As a result, when the technology of assessing borrowers is improving, the return gaps between large banks and small banks increase. Large banks benefit more from this technological improvement than small banks. The process in which banks accumulate assets can also be seen as a process of banks utilizing new technology. Large banks are thus assumed to be better at utilizing new technology than small banks. People find that large banks have generally been first to adopt advanced technologies (summarized in Berger, 2003). For example, the transaction website adoption rate varied greatly by bank size. By the end of 2001, 100% of largest banks (banks with over $10 billion in assets) had transaction websites, while 29.1% of smallest banks (with assets below $100 million) had transaction websites.

Return from a relationship loan:

$$q^R(\theta) = (1-\theta)R_H + \theta(\xi R_H + (1-\xi)R_L) - c - r$$

where c is the cost of building a relationship.

Return from a transaction loan:

$$q^T(\theta) = (1-\theta)R_H + \theta R_L - r$$

Bank's Decisions

The bank with assets z_t solves the following problem: first, based on a borrower's delinquency rate, θ, the bank decides whether to lend to him. If the bank chooses to lend to him, the bank decides to lend to him by relationship or transaction lending. Second, when the borrower of this project is delinquent on his debt, the bank decides whether to liquidate a project. Third, after it sees its cost of staying, the bank decides whether to stay in the market. Last, if the bank decides to stay, it decides its assets for the next period.

$$V_t(z_t) = \max_{\{z_{t+1}, I^R(\theta,z_t), I^T(\theta,z_t)\}} \{M_t z_t^{\alpha} \int_{\theta} [q^R(\theta)I^R(\theta) + q^T(\theta)I^T(\theta)]dU(\theta) + E_e[max\{\beta V_{t+1}(z_{t+1}) - g_t - e_t, 0\}]\}$$

s.t.

$$z_{t+1} = (1-\delta_z)z_t + Az_t^{1-\gamma}g_t^{\gamma}$$

where $I^R(\theta, z_t)$ is the indicator of relationship lending, $I^T(\theta, z_t)$ is the indicator of transaction lending, g_t is the amounts of money used for the producing new assets, e_t is the cost of staying for the next period, δ_z is the depreciation rate of assets, β is the discounting factor and $V_t(z_t)$ is the continuation value of the bank with assets z_t in period t. Banks could borrow freely and at zero interest rate from their future profits to accumulate assets and to pay the cost of staying.

Competitive Equilibrium

A competitive equilibrium is a deposit interest rate r_t^*, a distribution of bank's assets Ω_t, a set of bank's decisions $\{z_{t+1}, I^R(\theta, z_t), I^T(\theta, z_t)\}$, and the induced valuation process $V_t(z_t)$, such that:

A bank's decision $\{z_{t+1}, I^R(\theta, z_t), I^T(\theta, z_t)\}$ solves the problem of the bank with assets z_t at the given deposit interest rate r_t^*,

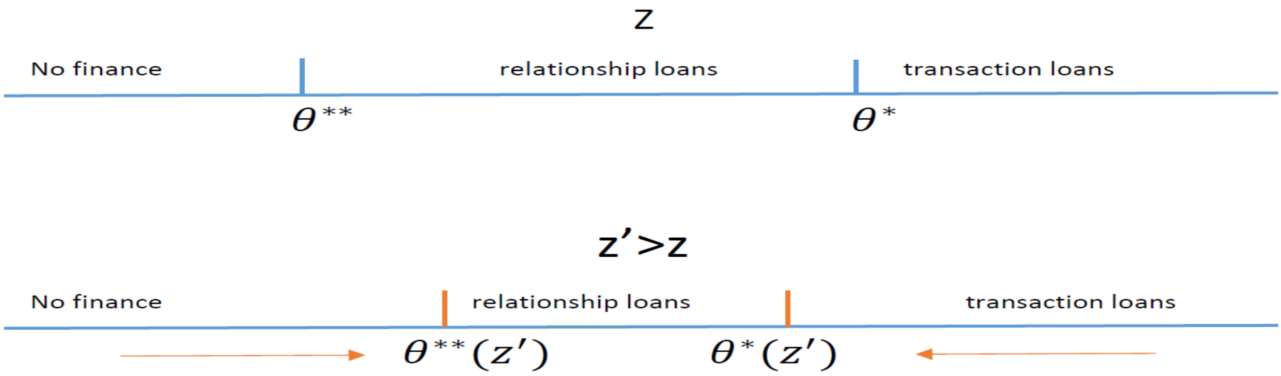
The deposit market is cleared at the market rate r_t^*,

$$\int_{z_t}\int_{\theta} M_t z_t^{\alpha}(I^R(\theta, z_t) + I^T(\theta, z_t))dU(\theta)d\Omega_t = S^{-1}(r_t^*)$$

Proposition: *For the bank with assets z, there exists two thresholds $\theta^* < \theta^{**}$, such that if the borrower is with delinquency rate of θ that $\theta < \theta^*$, the bank finances him with transaction lending; if the borrower is with delinquency rate of θ that $\theta^* \leq \theta \leq \theta^{**}$, the bank finances him with relationship lending; and if the borrower is with delinquency rate of θ that $\theta > \theta^{**}$, the bank will not finance him. Also,*

$$\frac{\partial\theta^*}{\partial z} < 0, \frac{\partial\theta^{**}}{\partial z} > 0$$

Figure 6: Shifts of two thresholds



Note: This figure shows that there are two thresholds that determine a bank's transaction lending and relationship lending and that when a bank has more assets than before, it increases its risk tolerance for transaction loans and decreases its risk tolerance for relationship loans. From the left to the right, borrowers become safer with lower delinquency rates.

Intuitions: The additional expected return from a relationship, $\xi\theta(R_H - R_L) - c$, is increasing in the delinquency rate of the project, θ. Therefore, if a project is too safe, the additional return from a relationship exceeds the cost of building a relationship. So, there is a θ^* such that the cost and the return equal. On the other hand, when a project is too risky, the expected return from this project is less than the cost of financing it, so there is a θ^{**} such that the bank will not finance projects with delinquency rate of $\theta > \theta^{**}$. When a bank has more assets, it could evaluate more borrowers and if the bank chooses to build more relationships, the bank's cost of building a relationship increases. This increase reduces the surplus from relationships, and the bank extend transaction loans to riskier borrowers who received relationship loans before, which makes θ^* shift to the left. In addition, the banks' return from the riskiest borrowers, who received relationship loans before, becomes negative now. Therefore, the bank will now not lend to these borrowers, which makes θ^{**} shift to the right.

The proposition qualitatively implies that as information technology improves and banks become more efficient to evaluate borrowers, high risk borrowers will receive fewer loans and transaction loans are extended to risky borrowers.

4 Calibration

I calibrate my model to the U.S. individual commercial bank data. I identify a set of parameters, with which the simulated moments from the model are quantitatively consistent with the observed behaviors of the U.S. commercial banks. Banks differ in assets and therefore differ in total loans, relationship loans and shares of relationship loans. Cross-sectionally, banks with more assets have more total loans and relationship loans, but smaller shares of relationship loans. Overtime, banks make more loans, but the share and the dollar amount of small business lending decline. Large banks grow faster than small banks. These large banks take more market shares and small banks exit. The variations in banks' total loans increases. These cross-sectional and overtime variations allow me to identify the parameters in the technology of assessing borrowers and building relationships and the technology of accumulating assets.

In the calibration, I find that in 2002, a bank pays1750 thousand dollars in 2002 to evaluate one million dollars of loan applications and 810 thousand dollars in 2017. I may overestimate the technology improvement in processing borrowers' hard information. The advances in banks technology are multidimensional. For example, some technologies, like online banking and mobile banking, may also allow banks to collect deposits at cheaper price and therefore, banks could make more loans over time. However, in this paper, I attribute all the effects from banking technology improvements to the one that increase banks efficiency of collecting and processing borrowers' hard information. This can be justifiable when information collection and process is the key step of making loans. Banks are never lack of loan applications. To whom to lend to is a real problem. The decision is based on banks' information about their borrowers. The recent computer based technological improvements have greater effects on the collection and process of hard information than soft information. As is in Liberti and Petersen (2017),

> "Hard information is quantitative, easy to store and transmit in impersonal ways, and its information content is independent of the collection process. Technology has changed and continues to change the way we collect, process, and communicate information. This has fundamentally transformed the way financial markets and institutions operate. One of these changes is a greater reliance on hard relative to soft information in financial transactions. This has altered the design of financial institutions by moving decisions outside the traditional boundaries of organization."

4.1 Data

The data is from the Federal Deposit Insurance Corporation (FDIC), Statistics on Depository Institutions (SDI). The data are all reported in June in each year. I use data from 2002 to 2017 while excluding data from 2008 to 2011 when is the Subprime Crisis. First, I do not introduce economic fluctuation in the model. Therefore, I cannot explain the data during crisis using this model. Second, the market for small business lending is far from securitized compared to t mortgage lending. The collapse of loan securitization market may not have effects on lending to small businesses. Third, the declining of lending to small businesses may not come from the demand side. Although during the crisis, many small firms exit, the demand for loans from small businesses are always not satisfied. According to the statistics from a financial service company, Behalf, in 2012, 43% of small businesses said that they were unable to find sources for the business financing they needed (NSBA 2012) and only 13% of applicants were approved for a small business loan in 2013 (Ventury Capital 2015). I exclude banks that have zero amount of small business loans. These banks usually are small and specialized on a type of lending, such as mortgages, agricultural loans.

A bank's total loans in the model are measured by total loans and leases net of unearned income[3]. I assume implicitly that the loan size distribution does not change much. Some people may argue that compared to jumbo mortgage loan, non-jumbo mortgage loans become more liquid than before because of the development of securitization market, so banks issue more non-jumbo mortgage loans and fewer jumbo mortgages. Therefore, the average loan size may become smaller than before. However, this change will not have large effect on the loan size distribution, as jumbo mortgages only consist less than 2% of all mortgages. Relationship loans are measured by loans to small businesses. Small business loans are loans with an original amount of $1 million or less that are reported as C&I loans to U.S. addresses. Banks build relationships when they lend small firms because small firms are usually informationally opaque (Berger and Udell, 1995, 2002). Transaction loans are defined as a bank's total loans minus its relationship loans. They are car loans, consumption loans, mortgages and large C&I loans. Because of the development of securitization market, these loans can be easily securitized and sold. They are transaction loans. The delinquency loans are loans that are past due more than 30 days, unacrrual and charged-off. The Table. 1 shows the definition of each variable. Table. 2 shows the summary of statistics.

Table.1 inserted here.

Table.2 inserted here.

4.2 Calibration Method and Results

I calibrate the model by method of moments. I select the values of parameters to match the key moments in the data with the simulated ones from the model. With the assumed values of every group of parameters, I compute the optimal choices of each bank and the deposit interest rate in the equilibrium in each period. The solution to the banks' problems is provided in the Appendix 2. I then compute the moments from the model and compare them with the moments from the data. The search will stop until distance between the moments in the model and the moments in the data is small enough. The weight put on each moment is normalized to 1. The moments

[3] Unearned revenue is money received by an individual or company for a service or product that has yet to be fulfilled. Unearned revenue can be thought of as a "prepayment" for goods or services that a person or company is expected to produce for the purchaser. As a result of this prepayment, the seller has a liability equal to the revenue earned until delivery of the good or service. Source: http://www.investopedia.com/terms/u/unearnedrevenue.asp

include the dollar amounts of total loans, the standard variations of total loans, the loan shares of banks with loans more than 1 billion dollars, the number of small banks with loans fewer than 100 million dollars, the average of banks' total loans for banks the at the top 25% percent (in terms of total loans), the average of banks' total loans for banks the at the bottom 25% percent (in terms of total loans), the the dollar amount of small business loans, the average share of small business loans for the top 25% banks, the loan delinquency rates and the average amount and standard variations of total loans of entry banks from 2002 to 2007 and from 2012 to 2017. There are 92 moments. I put three restrictions in the calibration. First, the average bank productive assets must increase over time because the values of bank software increase over time. Second, the ratio of the standard deviations of bank loans to the sum of loans and the average of loans of banks at the top 25% to the average of loans of banks at the bottom 25% increase over time. These two specifications are consistent with the data observations.

The calibration is to estimate the parameters in bank's technology of evaluating borrowers' delinquency rates, M_0, λ, α, the parameters in bank's technology of building relationships, F, ω, the parameter in deposit supply function, n_r, the parameter in the technology used by banks to accumulate assets, $\delta_z, A, -\gamma$, the distribution of the staying costs, μ, σ , the parameter in the deposit supply function, n_r and the parameters that characterize the returns from the projects, R_H, R_L, ξ. I calibrate period 0 in the model to the year of 2002. I additionally assume that in the first period, incumbent banks have assets z that are from the distribution of $log-gamma(\mu_0, \sigma_0)$. The parameter R_H is calculated as the ratio of incomes from loans to total loans. Assets depreciating rate δ_z is set to 0.004. The discounting factor β is set to 0.996. The number of newly entered banks are calculated as total de nova banks from 2003 to 2007 and from 2012 to 2017 to the number of years. Figure.7-15 shows the comparison of moments from the model and from the data. Table.3 shows the value for each parameter and the corresponding moments used to identify them.

The model does a reasonable job of fitting the data. In the model, the loan share of large banks with loans more than 1 billion dollars increases from 76% to 85% (vs 81% to 90% in the data). The share of relationship lending (small business lending) decreases from to 6.7% to 3.2% (vs from 6.6% to 3.5% in the data). The dollar amount of relationship lending decreases from 345 billion to 309 billion (vs from 340 billion to 301 billion in the data). My model also shows that loans to all borrowers with delinquency rates greater than or equal to 6% decreases from 159 billion to 78 billion dollars; while other borrowers receive more loans than before. According to the US Small Business Administration, from 2002 to 2009, more than 90% of small business loans (in dollar amount) have delinquency rates greater than 6% and in the model, all relationship loans have delinquency rates greater than 4.9%. Therefore, the model indicates that many risky small businesses receive fewer loans than before and this reduction of lending to risky small businesses leads to declining of small business lending. The mean of loans of newly entered bank is 613 million dollars in the model (vs 675 million dollar in the data); the standard variations of loans of newly entered bank is 5.3 billion dollars in the mode (vs 5.1 billion dollars in the data).

Figure.7-15 inserted here.

Table.3 inserted here.

The model shows that the costs of processing hard information of an loan application of 1 million dollars has decreased from 720 dollars in 2002 to 355 dollars in 2017. As in the model, a bank on average approves 5% of loan applications it evaluates. Therefore, per dollar transaction loan, a bank saves .73% dollars (that is, $\frac{720-355}{1000000} \div 5\%$). This number is large if we compare this to the average loan spread, about 3%. It also means that the cost of bank transaction lending is reduced by 51%. However, for a dollar of relationship loan, the bank needs to pay about at least additionally 0.66% (that is, $\frac{1}{F(1+\omega)}$) dollars to build relationships in relationship lending, so the cost of relationship lending is reduced at most 35%. The difference of effects on transaction lending and relationship lending makes banks to substitute relationship loans with transaction loans. In the model, as large banks are less constrained by their abilities of issuing more loans, large banks benefit more from the technological improvement than small banks and crowd out small banks. The quantitative model infers that a bank with additional thousand dollars of productive assets can have at most 1726 (that is, $(0.05\alpha(M_{12}-M_1)+0.05\alpha(M_{12}-M_1)A\gamma(1-\gamma))(R_H-r))$ dollars of higher return from the improvement.

4.3 Comparative Analysis

The comparative analysis provides intuitions how I identify each parameters. I group the parameters in three categories. Group one includes parameters whose increase will increase total loans but reduce relationship loans, including, $M_0, \alpha, \mu_0, \sigma_0$. Group two includes parameters whose increase will increase total loans and relationship loans, including, $F, -\omega, \xi, -n_r$. Group three includes parameters whose increase will increase the growth rate of total loans, including, $\lambda, A, -\gamma$. The common features among parameters in the same group create a problem for identifying them.

To identify the parameters in the first group, I need to use the ratio of loan standard variation to total loans, defined as r_{1t} and the ratio of average loans of large banks (banks at the top 25%) and the average loans of small banks (banks at the bottom 25%), defined as r_{2t}, where $t = 1, ..., 12$. I increase M_0 from 1339 to 1636, increase α from .89 to .9, decreases from 1.09 to .88, increase

μ_0 from 21 to 21.2, and increase σ_0 from .4 to .42 (Table.4). Only the increase of μ_0 can increase $\frac{r_{2,12}}{r_{2,1}}$ and only the increase of σ_0 can increase $\frac{r_{1,12}}{r_{1,1}}$.

To identify the parameters in the second group, I need to use the moments of loan delinquency rates, the number of small banks with loans fewer than 100 million dollars and the loan share of banks with loans more than 1 billion dollars. I increase F from 148 to 181, decrease ω from .0279 to .0259, increase ξ from .3 to .31, and I decrease n_r from .152 to .15 (Table.5). Only the increase of $-n_r$ can increase the loan delinquency rate; only the increase of F can decrease the loan share of large banks with loans more than 1 billion dollars; the increase of ξ decreases the number of banks with loans fewer than 100 million dollars.

To identify the parameters in the third group, I need to use r_{1t} and r_{2t} again. I increase λ from .042 to .043, decrease γ from .31 to .29, and increase A from .36 to .38 (Table.6). Only the decrease of γ can increase $\frac{r_{1,12}}{r_{1,1}}$ and only the increase of A can increase $\frac{r_{2,12}}{r_{2,1}}$.

Table.4-6 inserted here.

5 Counterfactual and Policy Experiments

In this section, I will conduct one decomposing analysis and two policy experiments. I decompose the effects from the substituting mechanisms and the crowding mechanisms. I find that the first mechanism contributes to 99.7% of the declining of small business loans. Consistent with the results from decomposing analysis, the policy experiment shows that to encourage lending to small businesses, we should subsidize lending to small businesses rather than small banks.

5.1 Decomposing the Effects from the Two Mechanisms

In this experiment, I keep the substituting effect and shut down the crowding effects between large and small banks. To decompose the effects from two mechanisms, I first assume that banks do not accumulate asset, exit, enter or look forward. In this way, banks solve a static problem in each period. In this experiment, small business loans decrease by 15 billion dollars, rather than 35.5 billion dollars in the benchmark model. I thus conclude that the substituting effect accounts for at least 43% of the declining. In then allow banks to look forward but I do not allow banks' entry or exit. I find small business loans decrease by 18 billion dollars, rather than 35.5 billion dollars in the benchmark model. I thus conclude that the substituting effect accounts for at least 51% of the declining. This result implies that as the substituting effect dominates, we may subsidize lending to small borrowers directly, not subsidize small banks. Hence, I compare these two policies in the next subsection.

5.2 Policy Experiments

Using the quantitative model, I experiment with two policies to encourage lending to small borrowers and compare their effects on small business loans of 2017.

In the first policy experiment, I subsidize banks with one percent of their loan amounts, when lending to borrowers with delinquency rates greater than or equal to 5%, because in the model, only these borrowers receive fewer loans over time. Compared to the benchmark model, a borrower with delinquency rate greater than or equal to 5% receives 4 times more loans and other borrowers also receive more loans under this policy. Thus, in the context of the model, when the U.S. Small Business Administration provides subsidized loans and loan guarantees to small businesses for start-up and expansion, risky small businesses become much less financially constrained.

In the second policy experiment, I subsidize small banks (with total loans less than 100 million dollars) with 1% of their loan amounts to reduce their exit rates. Compared to the benchmark model, this policy does not increases relationship loans. Berger et al. (2005) suggests that instead of subsidizing small business lending directly, we may subsidize the intermediaries that have comparative advantages in relationship lending. My paper shows that within the context of information improvements, this policy may not have the positive effects as expected.

6 Conclusions and Implications

I present a framework for analyzing how information technological improvements affect the U.S. commercial banks. Over time, banks build up their abilities of evaluating borrowers. Advanced technology improves these abilities of large banks more than those of small banks and thus changes the size distribution of the U.S. banks. The technological improvements also increase banks' advantage in transaction lending over relationship lending. Therefore, borrowers who depend on transaction lending benefit from these improvements, but some risky small borrowers who depend on relationship lending are suffering.

This paper has implications on policies that encourage efforts to meet the credit needs of small businesses. This paper predicts that decreasing the cost of acquiring soft information and subsidizing lending to small businesses may encourage lending to risky, small businesses. However, subsidizing small banks has negative effects on the lending to the riskiest small businesses.

Reference

Aghion, Philippe, and Peter Howitt. 1990. "A model of growth through creative destruction." National Bureau of Economic Research.

Baumol, William J. 1968. "Entrepreneurship in Economic Theory." *The American Economic Review*, 58(2): 64–71.

Berger, Allen N. 2003. "The economic effects of technological progress: Evidence from the banking industry." *Journal of Money, credit, and Banking*, 35(2): 141–176.

Berger, Allen N, and Gregory F Udell. 1995. "Relationship lending and lines of credit in small firm finance." *Journal of business*, 351–381.

Berger, Allen N, and Gregory F Udell. 2002. "Small business credit availability and relationship lending: The importance of bank organisational structure." *The economic journal*, 112(477).

Berger, Allen N, and Robert DeYoung. 2006. "Technological Progress and the Geographic Expansion of the Banking Industry." *Journal of Money, Credit, and Banking*, 38(6): 1483–1513.

Berger, Allen N, Anthony Saunders, Joseph M Scalise, and Gregory F Udell. 1998. "The effects of bank mergers and acquisitions on small business lending." *Journal of financial Economics*, 50(2): 187–229.

Berger, Allen N, Christa HS Bouwman, and Dasol Kim. 2017. "Small bank comparative advantages in alleviating financial constraints and providing liquidity insurance over time." *The Review of Financial Studies*, 30(10): 3416–3454.

Berger, Allen N, Nathan H Miller, Mitchell A Petersen, Raghuram G Rajan, and Jeremy C Stein. 2005. "Does function follow organizational form? Evidence from the lending practices of large and small banks." *Journal of Financial economics*, 76(2): 237–269.

Berger, Allen N, Richard J Rosen, and Gregory F Udell. 2007. "Does market size structure affect competition? The case of small business lending." *Journal of Banking & Finance*, 31(1): 11–33.

Berger, Allen N, W Scott Frame, and Nathan H Miller. 2005. "Credit scoring and the availability, price, and risk of small business credit." *Journal of money, credit and banking*, 191–222.

Bernanke, Ben S, Mark Gertler, and Simon Gilchrist. 1999. "The financial accelerator in a quantitative business cycle framework." *Handbook of macroeconomics*, 1: 1341–1393.

Bharath, Sreedhar T, Sandeep Dahiya, Anthony Saunders, and Anand Srinivasan. 2009. "Lending relationships and loan contract terms." *The Review of Financial Studies*, 24(4): 1141–1203.

Birch, David L. 1979. *The job generation process.* Cambridge, Mass. : M.I.T. Program on Neighborhood and Regional Change.

Black, Sandra E., and Philip E. Strahan. 2002. "Entrepreneurship and Bank Credit Availability." *The Journal of Finance*, 57(6): 2807–2833.

Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J Terry. 2012. "Really uncertain business cycles." National Bureau of Economic Research.

Bolton, Patrick, Xavier Freixas, Leonardo Gambacorta, and Paolo Emilio Mistrulli. 2016. "Relationship and transaction lending in a crisis." *The Review of Financial Studies*, 29(10): 2643–2676.

Boot, Arnoud WA, and Anjan V Thakor. 2000. "Can relationship banking survive competition?" *The journal of Finance*, 55(2): 679–713.

Bordo, Michael D., and John V. Duca. 2018. "he Impact of the Dodd-Frank Act on Small Business." *No. w24501. National Bureau of Economic Research.*

Campello, Murillo, John R Graham, and Campbell R Harvey. 2010. "The real effects of financial constraints: Evidence from a financial crisis." *Journal of financial Economics*, 97(3): 470–487.

Chen, Brian S, Samuel G Hanson, and Jeremy C Stein. 2017. "The decline of big-bank lending to small business: Dynamic impacts on local credit and labor markets."

Chen, Joseph, Harrison Hong, Ming Huang, and Jeffrey D Kubik. 2004. "Does fund size erode mutual fund performance? The role of liquidity and organization." *The American Economic Review*, 94(5): 1276–1302.

Cole, Rebel A, Lawrence G Goldberg, and Lawrence J White. 2004. "Cookie cutter vs. character: The micro structure of small business lending by large and small banks." *Journal of financial and quantitative analysis*, 39(2): 227–251.

Corbae, Dean, Pablo Dâerasmo, et al. 2011. "A quantitative model of banking industry dynamics."

Cortés, Kristle, Yuliya Demyanyk, Lei Li, Elena Loutskina, and Philip E Strahan. 2018. "Stress Tests and Small Business Lending." National Bureau of Economic Research.

Edmiston, Kelly D. 2007. "The role of small and large businesses in economic development."

Evans, David S., and Boyan Jovanovic. 1989. "An Estimated Model of Entrepreneurial Choice under Liquidity Constraints." *Journal of Political Economy*, 97(4): 808–827.

Gennaioli, Nicola, Andrei Shleifer, and Robert Vishny. 2012. "Neglected risks, financial innovation, and financial fragility." *Journal of Financial Economics*, 104(3): 452–468.

Gertler, Mark, and Simon Gilchrist. 1994. "Monetary policy, business cycles, and the behavior of small manufacturing firms." *The Quarterly Journal of Economics*, 109(2): 309–340.

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

Hayashi, Fumiko, Bin Grace Li, and Zhu Wang. 2017. "Innovation, Deregulation, and the Life Cycle of a Financial Service Industry." *Review of Economic Dynamics*, 26: 180–203.

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

Hopenhayn, Hugo Andrés. 1993. "The shakeout."

Keeton, William R. 1996. "Do bank mergers reduce lending to businesses and farmers? New evidence from tenth district states." *Economic Review-Federal Reserve Bank of Kansas City*, 81(3): 63.

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

Krusell, Per, and Anthony A Smith, Jr. 1998. "Income and wealth heterogeneity in the macroeconomy." *Journal of political Economy*, 106(5): 867–896.

Liberti, Jose M, and Atif R Mian. 2009. "Estimating the effect of hierarchies on information use." *The Review of Financial Studies*, 22(10): 4057–4090.

Liberti, José María, and Mitchell A Petersen. 2017. "Information: Hard and soft." *Rev. Corporate Finance Stud.*

Myler, Larry. 2015. "Face Interactions Can Never Be Replaced By Technology." *https://www.forbes.com/sites/larrymyler/2015/11/21/.*

Nadiri, M Ishaq, and Ingmar R Prucha. 1996. "Estimation of the depreciation rate of physical and R&D capital in the US total manufacturing sector." *Economic Inquiry*, 34(1): 43–56.

Nguyen, Hoai-Luu Q. 2014. "Do bank branches still matter? The effect of closings on local economic outcomes."

OECD. 2014. *Financing SMEs and Entrepreneurs 2014.*

Peek, Joe, and Eric S Rosengren. 1995. "Small business credit availability: How important is size of lender?"

Petersen, Mitchell A. 2004. "Information: Hard and soft."

Petersen, Mitchell A, and Raghuram G Rajan. 1994. "The benefits of lending relationships: Evidence from small business data." *The journal of finance*, 49(1): 3–37.

Rajan, Raghuram G. 1992. "Insiders and outsiders: The choice between informed and arm's-length debt." *The Journal of Finance*, 47(4): 1367–1400.

Rajan, Raghuram G. 2006. "Has finance made the world riskier?" *European Financial Management*, 12(4): 499–533.

Romer, Paul M. 1990. "Endogenous technological change." *Journal of political Economy*, 98(5, Part 2): S71–S102.

Stein, Jeremy C. 2002. "Information production and capital allocation: Decentralized versus hierarchical firms." *The journal of finance*, 57(5): 1891–1921.

Stiglitz, Joseph E. 2000. "Capital market liberalization, economic growth, and instability." *World development*, 28(6): 1075–1086.

Strahan, Philip E, and James P Weston. 1998. "Small business lending and the changing structure of the banking industry." *Journal of Banking & Finance*, 22(6): 821–845.

Sullivan, Richard J, and Zhu Wang. 2013. "Internet Banking: An Exploration in Technology Diffusion and Impact."

Sullivan, Richard, Zhu Wang, et al. 2005. "Internet banking: An exploration in technology diffusion and impact." *Federal Reserve Bank of Kansas City Payments System Research Working Paper*, 05–05.

Townsend, Robert M. 1979. "Optimal contracts and competitive markets with costly state verification." *Journal of Economic theory*, 21(2): 265–293.

Triplett, and Bosworth. July 2002. "'Baumol's Disease' has been cured: It and multifactor productivity in us services industries." *Brookings Institution working paper.*

Von Thadden, Ernst-Ludwig. 1995. "Long-term contracts, short-term investment and monitoring." *The Review of Economic Studies*, 62(4): 557–575.

A Mathematical Appendix

A.1 Proof of Theorem 1

The the bank with assets z solves:

$$\max_{I_j, I_j^S}\{m(z)(\int_{\theta^*}^{\theta^{**}}((1-\theta)R_H+\theta(\xi R_H+(1-\xi)R_L)-r)d\theta+\int_0^{\theta^*}((1-\theta)R_H+\theta R_L-r)d\theta)-L^s c(L^s)\}$$

where $L^s=m(z)(\theta^{**}-\theta^*)$, $c(L^S)=\frac{1}{F(\omega+1)}(L^S)^\omega$

Take the first order conditions of θ^{**},θ^* :

$$F((1-\theta^{**})R_H+\theta^{**}(\xi R_H+(1-\xi)R_L)-r)=[m(z)(\theta^{**}-\theta^*)]^\omega \tag{A.1}$$

$$F\xi\theta^*(R_H-R_L)=[m(z)(\theta^{**}-\theta^*)]^\omega \tag{A.2}$$

Solve θ^{**} from equation (6),

$$\theta^{**}=\theta^*+\frac{1}{m(z)}[F\xi\theta^*(R_H-R_L)]^{1/\omega} \tag{A.3}$$

From (5) and (6):

$$\xi\theta^*(R_H-R_L)=(1-\theta^{**})R_H+\theta^{**}(\xi R_H+(1-\xi)R_L)-r \tag{A.4}$$

Take (7) into (8),

$$\theta^*(R_H-R_L)=R_H-\frac{1}{m(z)}[F\xi(1-\theta^*)(R_H-R_L)]^{1/\omega}(1-\xi)(R_H-R_L)-r \tag{A.5}$$

from (9) we see that when z increases, θ^* is larger. Similarly, I solve θ^{**} and I find that when z increases, θ^{**} is smaller.

A.2 Model Computation

Banks' choice of relationship and transaction loans in each period is a static problem. In the first step, I compute banks' choices of relationship loans and transaction loans at the assumed deposit interest rate. In the second step, I compute the deposit interest rate that clears the deposit market. In the third step, I update the deposit interest rate and in the last step, I iterate step 1-3 until the deposit interest rate converge.

The computation of dynamic programming takes four steps. In the first step, I compute banks' value function at the initial assumed deposit interest rates, $\{r_t\}_{t=1,2,...,}$. I apply the contraction mapping theorem (CMT). I start by making an initial guess for the value function at each assets point (an initial guess of zero at each point). I compute the first iteration of the value function by considering the future value as the initial guess. This will yield a new value (the sum of the current payoff and the discounted (expected) future payoff). I use this value as the future value in the next iteration to produce a new value, etc.[4] In the second step, I solve banks' problems and compute the deposit interest rate that clears the deposit market in each period. In the third step, I update the deposit interest rates, $\{r_t\}_{t=1,2,...}$, and in the last step, I iterate step 1-3 until the deposit interest rates converge.

[4] The computation of value function is referred to http://home.uchicago.edu/hickmanbr/uploads/chapter5_2.pdf

B Tables and Figures

Table 1: Definitions of variables

definitions	*variables*
total loans and leases	total loans
loans to small businesses and small farms	relationship loans, L^S
sum of loans past due, unacrual and charged off/ total loans	delinquency rate

Table 2: Summary of statistics

2002-2007, 2012-2017, No.banks= 78190

variables	*mean*	*std*	*min*	*max*
total loans	1052	16800	9	940000
small businesses loans	47	447	0	29800
delinquent loans	31	759	0	82300
total interest and fee income on loans	37	593	0	38400

Note: All the numbers are in constant million US dollars of 2017.

Table 3: Values of parameters and targeted moments

parameter	*description*	*value*	*moments*
M_0	parameters in the technology	339	total loans: mean
α	of evaluating borrowers' credit	.88	market concentration
F	parameters in the technology	157	log(small business loans): mean, std
ω	of building relationships	.0303	share of small business loans: mean, std
R_L	liquidation value	.5	share of small business loans: mean, std
ξ	possibility of high cash flow	.3	delinquency rate: mean
R_H	sum of principal and interest rate	1.037	interest incomes from loan/accrual loans
λ	measure of technological improvement	.0809	annual loan growth rate
γ	parameter in assets accumulation technology	.29	market concentration
A		.29	
μ	mean of the log of the staying costs	5	number of small banks
σ	std of of the log of the staying costs	7.8	
B	measure of new born banks	89	number of newly entered banks
μ_z	mean of the log of assets of new born banks	6.3	mean of loans of new born banks
σ_z	std of of the log of assets of new born banks	3.4	std of of loans of new born banks
μ_0	mean of the log of assets of incumbent banks	7	
σ_0	std of of the log of assets of incumbent banks	3.3	
n_r	parameter in deposit supply function	.152	

Note: This table shows the values for each parameter.

Table 4: Moments Comparison I

parameter	$\frac{r_{1,12}}{r_{1,1}}$	$\frac{r_{2,12}}{r_{2,1}}$
$M_0 = 1636$	.94	.96
$\alpha = .9$	.5	.88
$\mu_0 = 21.2$	1.11	1.17
$\sigma_0 = .42$	1.1	1.08
baseline	1.14	1.09

Note:In the table, the ratio of loan standard variation to total loans, is defined as r_{1t} and the ratio of average loans of large banks (banks at the top 25%) and the average loans of small banks (banks at the bottom 25%), is defined as r_{2t}, where $t = 1, ..., 12$.

Table 5: Moments Comparison II

parameter	delinquency rate	number of small banks	loan share of large banks
$F = 181$	.0208	3541	80.7%
$\omega = .0259$	.0227	3224	81.3%
$\xi = .31$	.0226	2771	84.3%
$n_r = .15$	.0233	2514	80.9%
baseline	.023	2790	80.8%

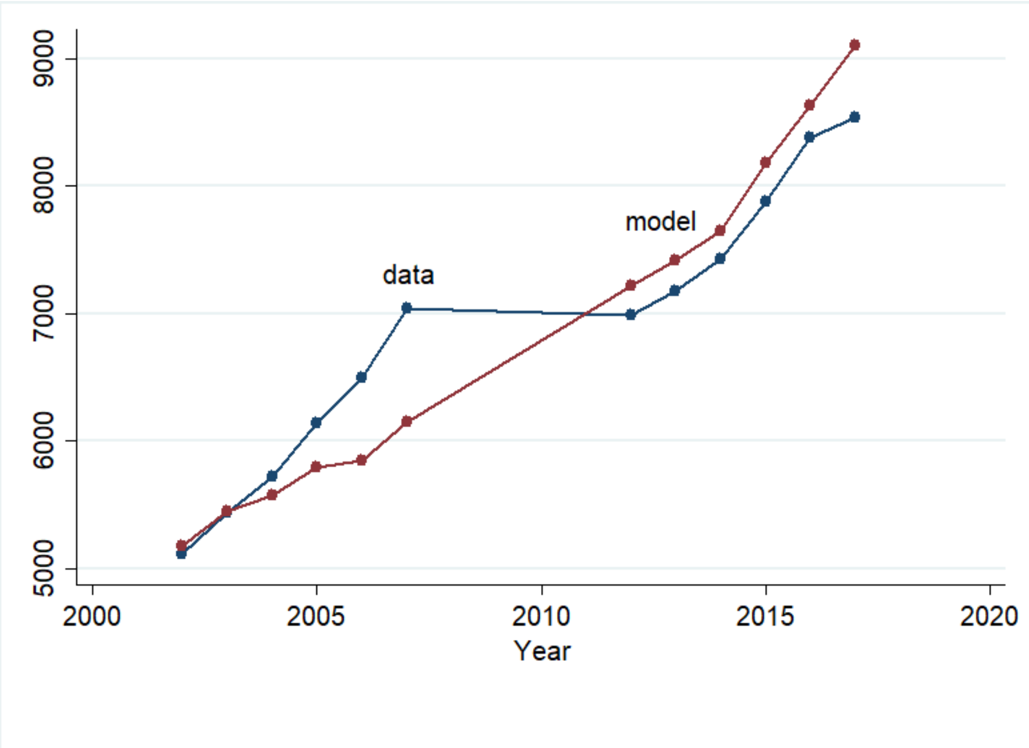
Note:In the table, the delinquency rate, the number of small banks and the loan share of large banks are the average of these moments of each year. Small banks are banks with loans fewer than 100 million dollars and large banks are banks with loans more than 1 billion dollars.

Table 6: Moments Comparison III

parameter	$\frac{r_{1,12}}{r_{1,1}}$	$\frac{r_{2,12}}{r_{2,1}}$
$\lambda = .043$	.72	1.03
$\gamma = .29$	1.18	1.12
$A = .38$	1.13	1.16
baseline	1.14	1.09

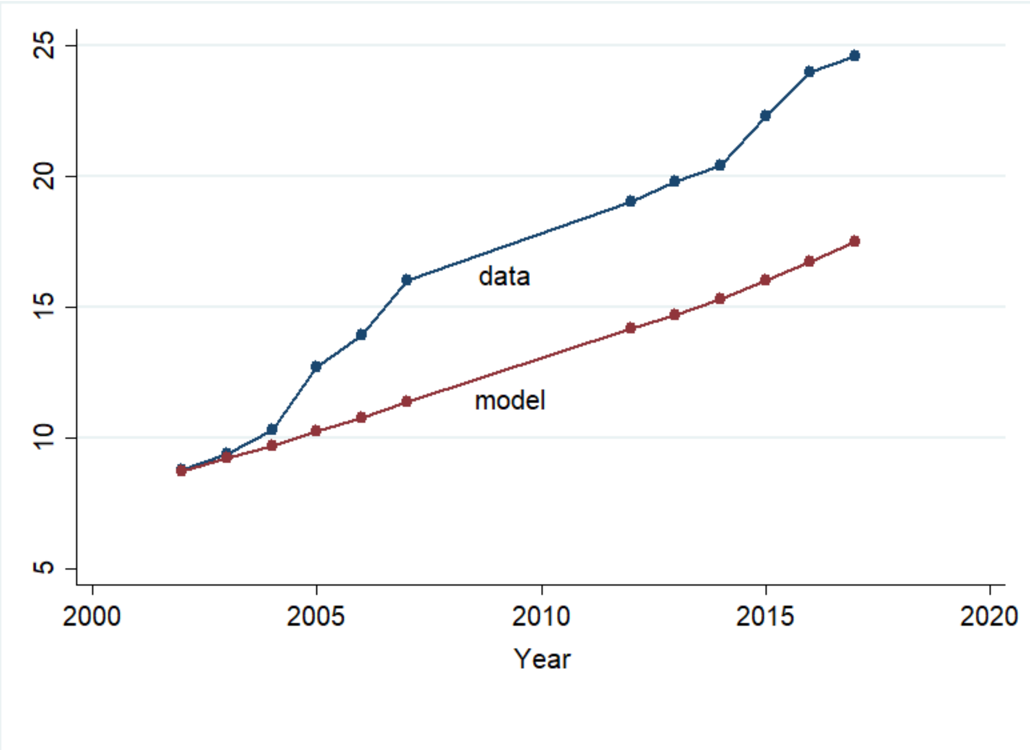
Note:In the table, the ratio of loan standard variation to total loans, is defined as r_{1t} and the ratio of average loans of large banks (banks at the top 25%) and the average loans of small banks (banks at the bottom 25%), is defined as r_{2t}, where $t = 1, ..., 12$.

Figure 7: Total loans in billion dollars



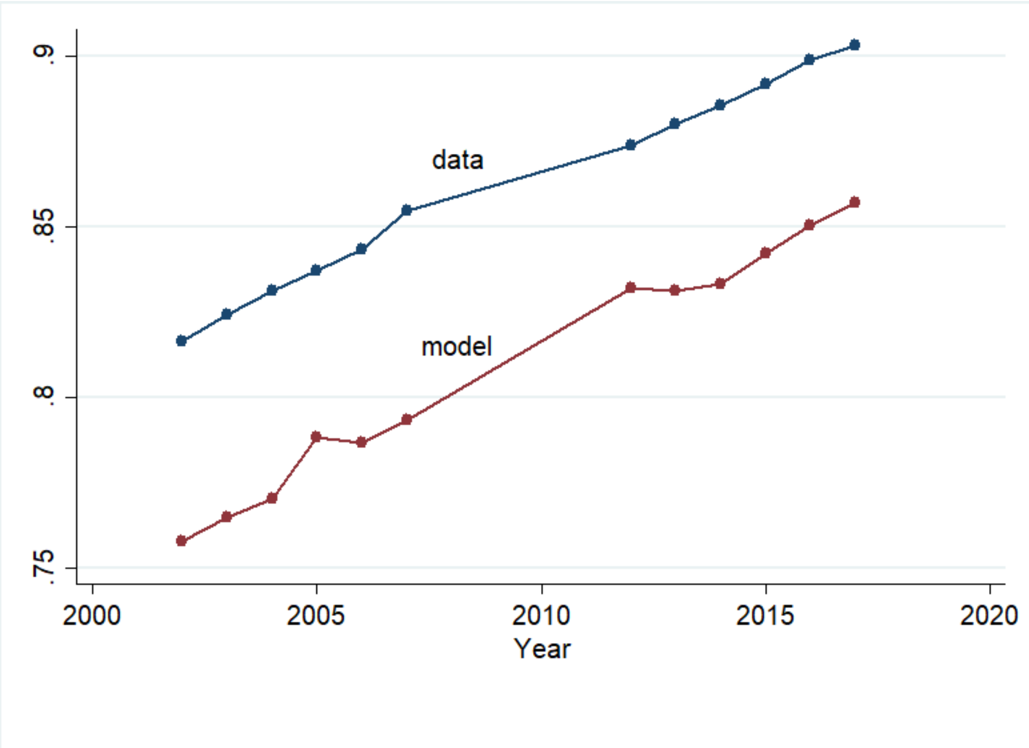
Note: This figure shows that the model does a reasonable work in explaining the increasing loan amounts in the US commercial banking market from 2002 to 2017.

Figure 8: Standard variations of total loans



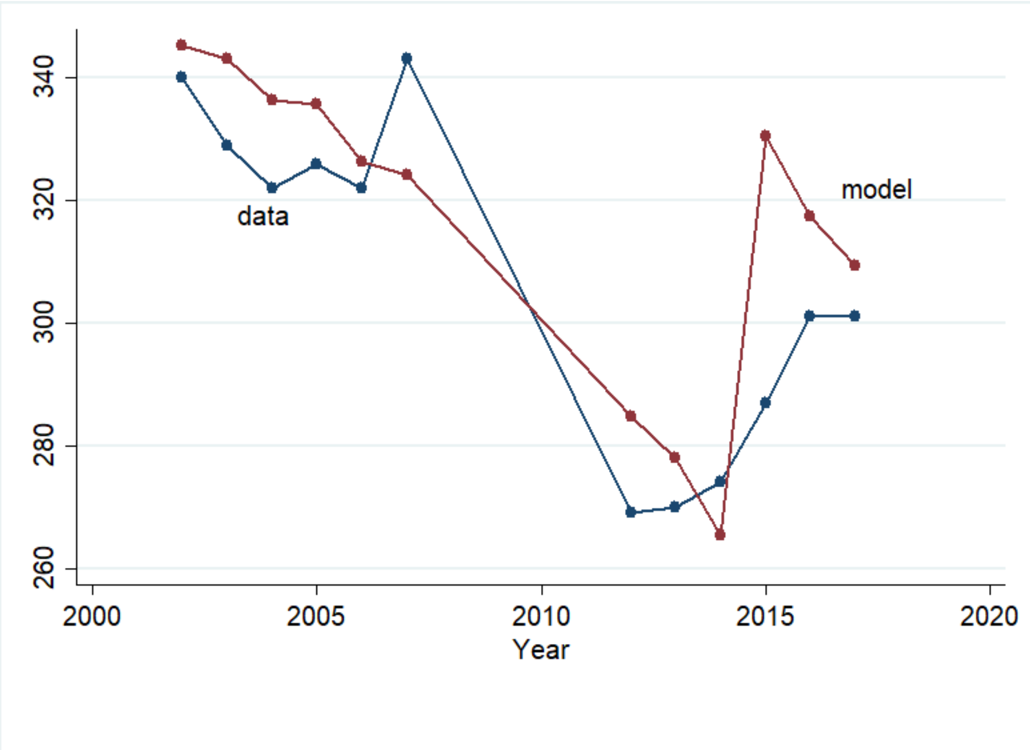
Note: This figure shows that the model does a reasonable work in explaining the increasing variations of loan amounts in the US commercial banking market from 2002 to 2017.

Figure 9: Market shares of banks at the top 25%



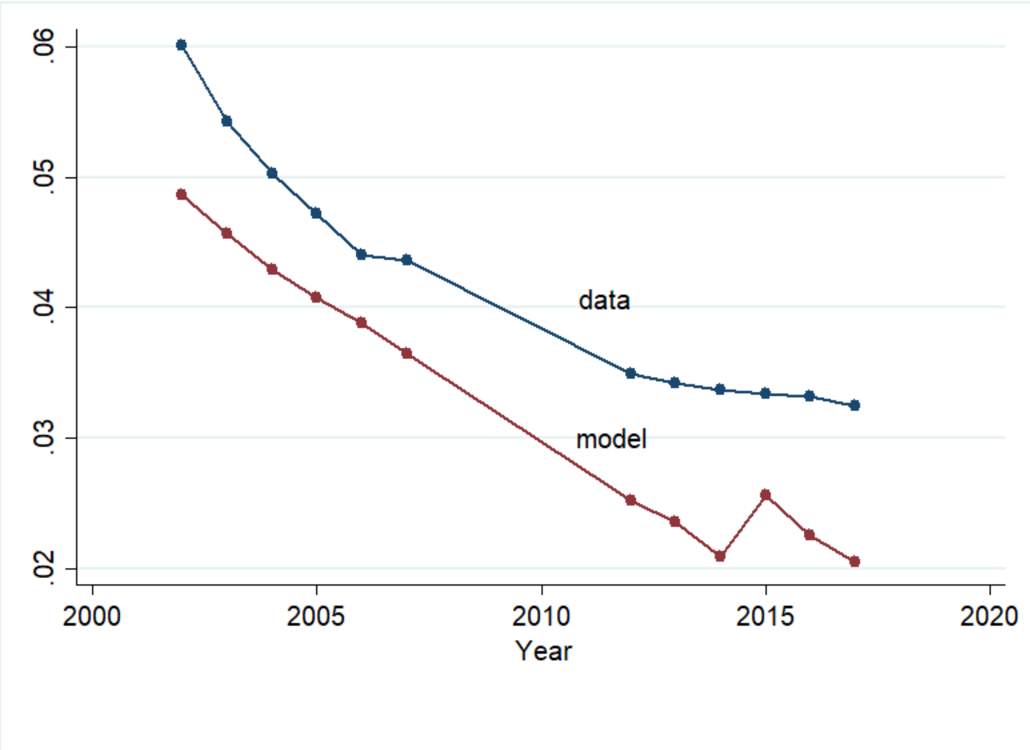
Note: This figure shows that the model does a reasonable work in explaining the increasing concentration in the US commercial banking market from 2002 to 2017.

Figure 10: Decreasing small business loans



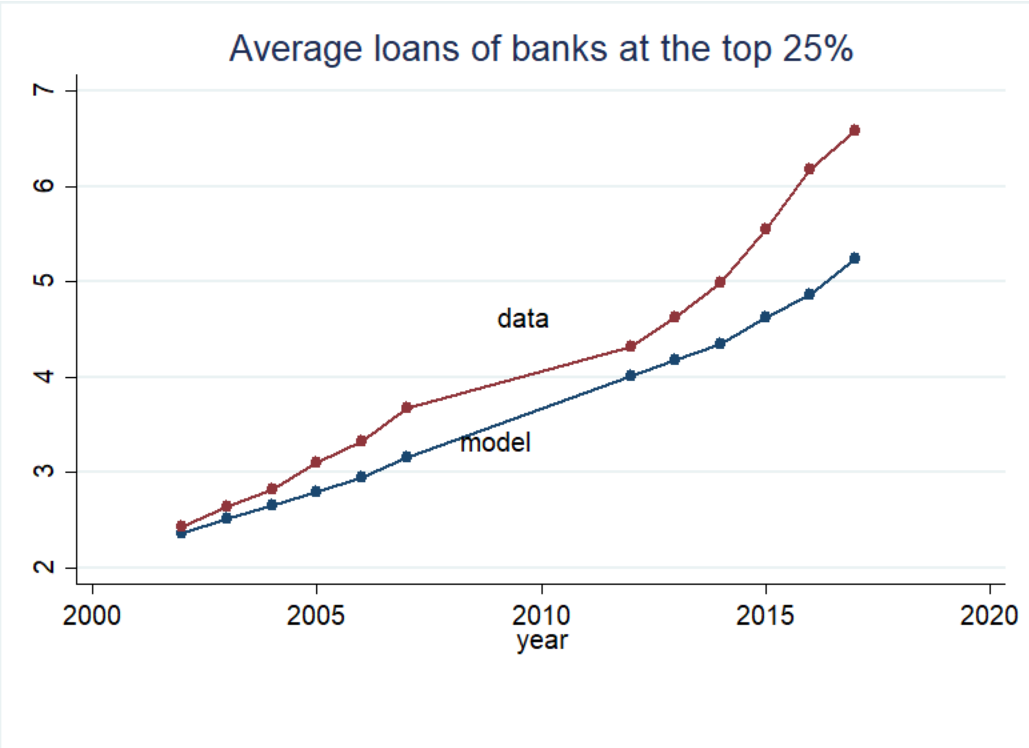
Note: This figure shows that the model does a reasonable work in explaining the decreasing small business loan in the US commercial banking market from 2002 to 2017.

Figure 11: Share of small business loans of large banks



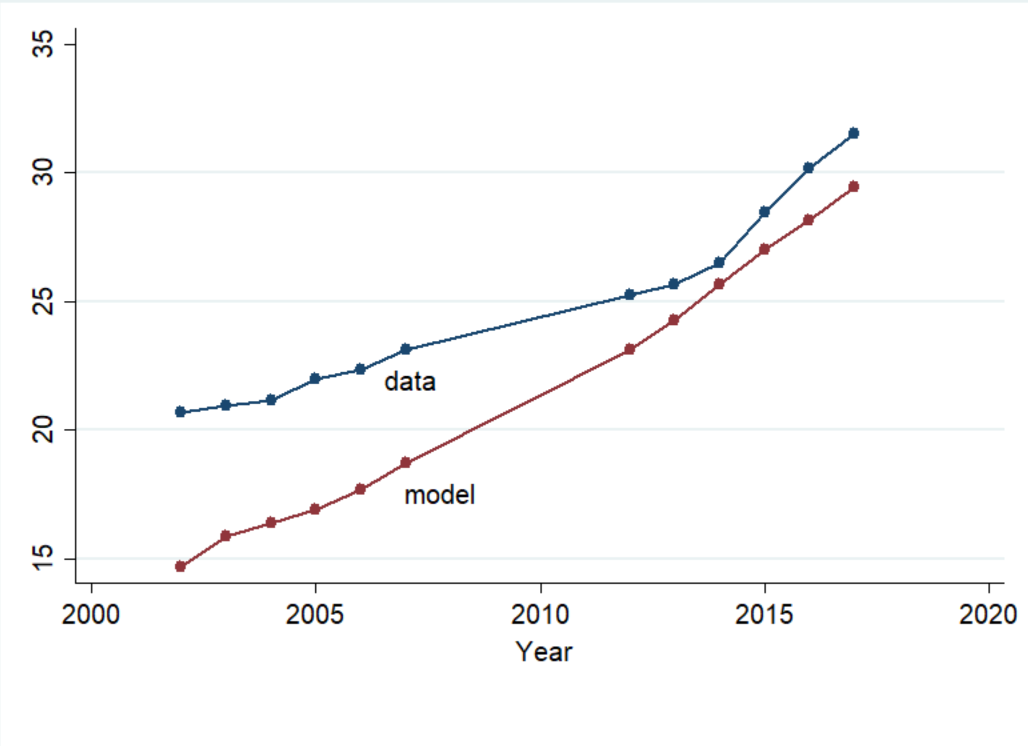
Note: This figure shows that the model does a reasonable work in explaining the decreasing share of small business loans of the banks at the top 25% in terms of total loans in the US commercial banking market from 2002 to 2017.

Figure 12: Decreasing small business loans



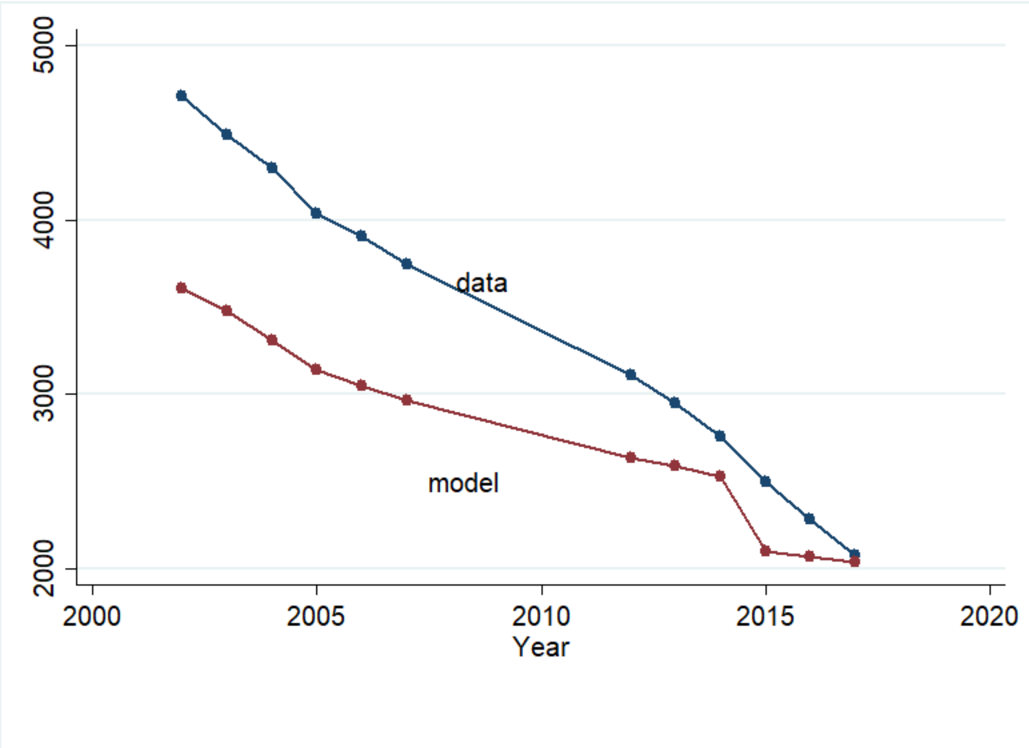
Note: This figure shows that the model does a reasonable work in explaining the decreasing small business loan in the US commercial banking market from 2002 to 2017.

Figure 13: Average loans of small banks



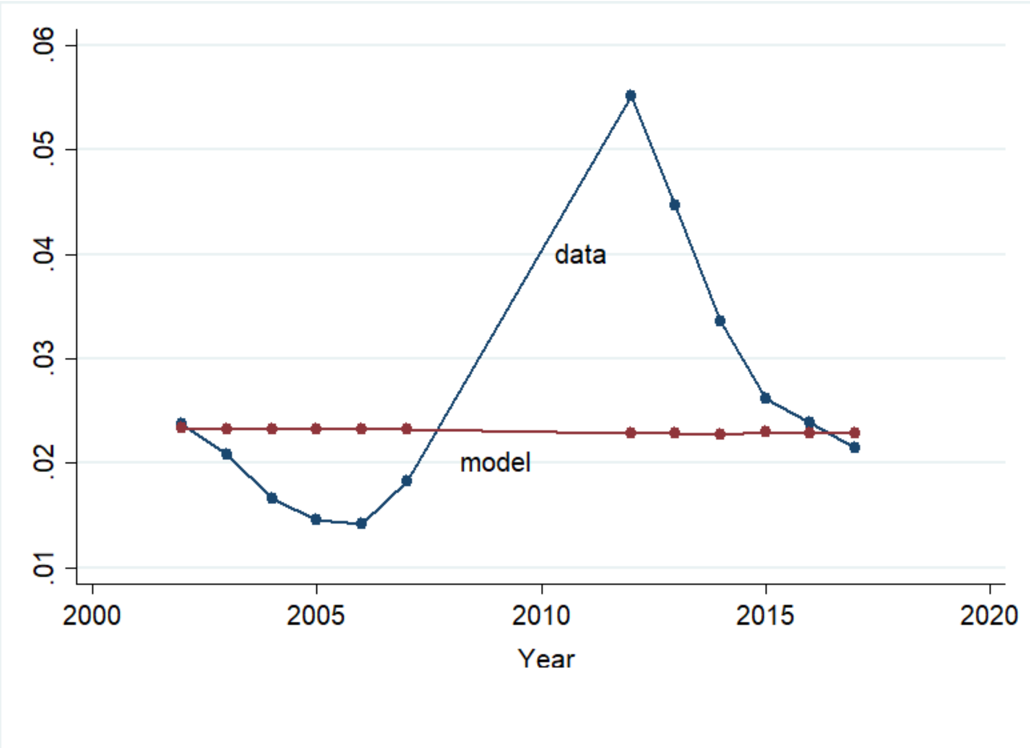
Note: This figure shows that the model does a reasonable work in explaining the average loans of banks at the bottom 25% in the US commercial banking market from 2002 to 2017.

Figure 14: Number of small banks



Note: This figure shows that the model does a reasonable work in explaining the decreasing number of small banks with total loans fewer than 100 million dollars in the US commercial banking market from 2002 to 2017.

Figure 15: Loan delinquency rate



Note: This figure shows that the model does a reasonable work in explaining the loan delinquency rate of the banks in the US commercial banking market from 2002 to 2017.