**Information Technology Improvements 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. I evaluate how information technology improvements contribute to the decline of small business lending with a quantitative, dynamic model. The model infers that banks' costs of assessing borrowers' hard information decrease by 50% and consequently, small business lending falls by 12% from 2002 to 2017. 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 declined by 12% from 2002 to 2017, from 340 billion dollars to 300 billion dollars (measured in 2017 US dollars). This decline 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 33% of decline in small business lending in a US county lead to a 0.7% increase in the local unemployment rate (Chen, Hanson and Stein, 2017). However, literature provides little explanation for the decline 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 decline of small business lending. The model suggests two mechanisms how information technology (IT) improvement can reduce small business lending: substitution effects between transaction and relationship lending and crowding-out effect between large and small banks. The first effect is the substitution effect between transaction lending and relationship lending. Transaction lending is an "arm-length" transaction only based on hard information, which is machine readable and quantifiable (Petersen, 2004; Liberti and Petersen, 2017). In contrast, relationship lending is a long-term contract with bank-borrower relationships and acquisition of soft information. As the information technology improves, banks can collect hard information at lower costs. However, the acquisition of soft information is as expensive as before[2]. Therefore, banks' profits from transaction lending increase more than those from relationship lending. Banks thus decrease shares of relationship loans. The second effect is the crowding-out effect where larger banks with smaller shares of small business lending gain market shares. The IT improvement increases large banks' lending capacities more than those of small banks. It also intensifies the competition in the deposit market and increases the costs of deposits. Small banks that face high cost of staying in the market will find it unprofitable to stay and then exit. Overall, the shares of small business lending declines. In both situations, if banks cannot increase their lending capacities enough, lending to small businesses falls.

Quantifying the relative importance of the two effects has great policy implications. There is large debate about how to encourage lending to small businesses 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 (they are small banks).

[2]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."

The model implies that if the substitution effect dominates, then probably, we should subsidize small business lending directly; if the crowding-out effect dominates, we may need to subsidize small banks. However, it is hard to disentangle 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 build a dynamic model of relationship banking to assess the effects from IT improvements on lending to small businesses. Small business borrowers are modeled as risky borrowers who receive relationship lending. These small borrowers are risky because usually they are young and have great uncertainties about their future cash flow. Therefore, a bank needs to monitor these borrowers' cash flow and thus, to improve the returns from delinquent borrowers by restructuring the debts promptly. The lending with additional monitoring and debt restructuring is relationship lending in Bolton et al. (2016). In the model, banks receive higher returns from delinquent borrowers in relationship lending than in transaction lending and borrowers with high delinquency rates receive relationship loans. Different from Bolton et al. (2016), banks face increasing marginal costs of building an additional relationship. Therefore, larger banks have smaller shares of relationship loans. The dynamic features of the model are built on Hopenhayn (1992). In the model, banks decide to grow and exit according to the advancing rate of lending technology and the competition in the deposit market. Therefore, the bank size distribution is endogenous to the IT improvements.

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 loan applications 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 the evaluated loan applications. Therefore, per dollar transaction loan, a bank saves 0.0073 dollars, by 51% (in 2002, it is 0.0144 dollars and in 2017, it is 0.0071 dollars). This number is large if we compare this number to the average loan spread, about 3%. However, for a dollar of relationship loan, the bank needs to pay at least additionally 0.0066 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 substitution effect results in 51% of the decline in small business loans. In the model, the loan share of large banks with loans more than 1 billion dollars (large banks) increases from 76% to 85% (vs from 81% to 90% in the data). The share of small business loans decreases from 6.7% to 3.2% for all banks. For large banks, it decreases from 5.4% to 1.8% (vs 5.1% to 3% in the data). The crowding-out effect contributes to 49% of the decline in small business loans.

The model does a reasonable job of fitting the data. The share of relationship lending (small business lending) decreases from to 6.7% to 3.2% (vs from 6.7% 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). The cost of processing a dollar amount of loans has decreased by 19% from 2012 to 2017 in the model (vs 16% in the data).

With this quantitative model, I compare two policies that may combat the decrease in lending to small businesses: subsidizing small banks to encourage them to stay and subsidizing lending to risky, small borrowers. Subsidizing lending to small businesses encourages lending to risky, small businesses because this policy reduces the substitution effect. However, subsidizing small banks has no effects on lending to small businesses. This is because although this policy reduces the crowding-out effect, it encourages small banks to grow larger and thus, increases the substitution effect. This analysis 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"[3] and establish casual relationship between policy changes and the change of small business lending.

## 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 to the declining of small business lending the US. My contribution to this literature is two-fold: 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

[3]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).

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.

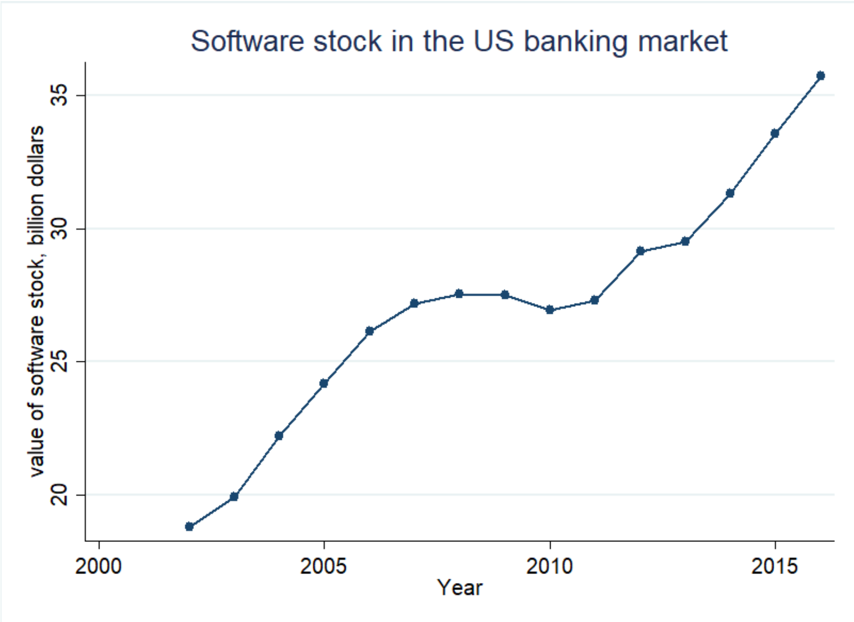
## 2 Motivation Facts

The following pictures show some key dynamic features in the US commercial banking industry and characters about the US firms. 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. Last, younger firms are smaller and have higher rates of exit.

### 2.1 The Trend of Technology Usage

Figure.1 shows the increasing use 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 in 2002 to about 36 billion dollars in 2016, by 100% (in the constant 2017 US dollar). 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**

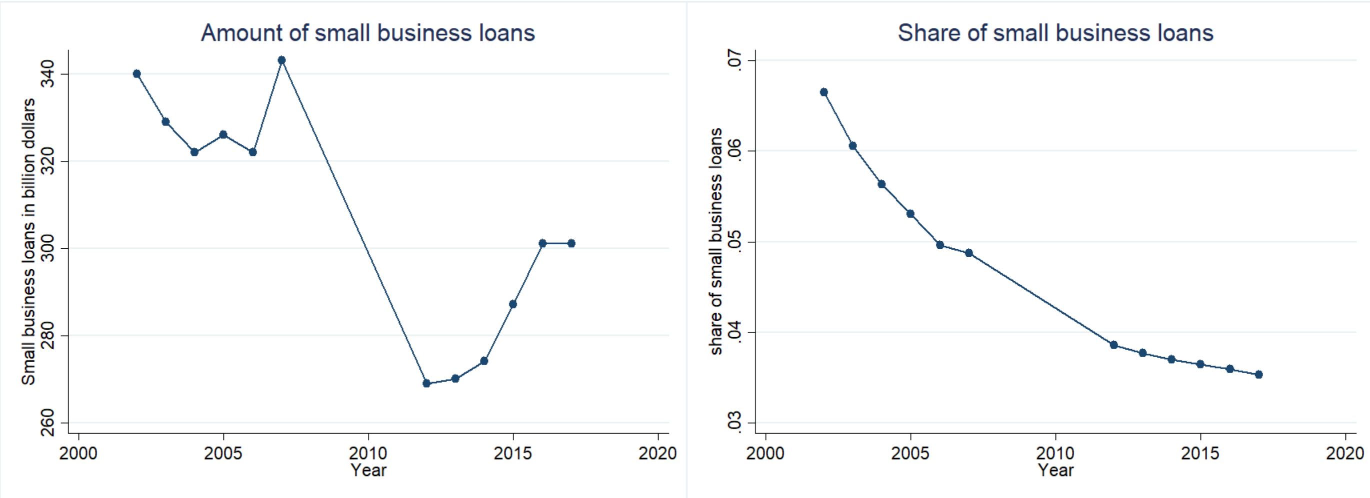



*Note: This figure shows banks' software stock from 2002 to 2016 in billion dollars of 2017. Banks' software stock includes prepared software (ENS1), custom software (ENS2) and own account software (ENS3).*

## 2.2 The Trend of Lending Practice

I use the data from FDIC reports on US depository institutions, 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 decline of small business lending, in dollar amount and in relative 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 of large banks with loans more than 1 billion dollars increased from 82% to 90%;

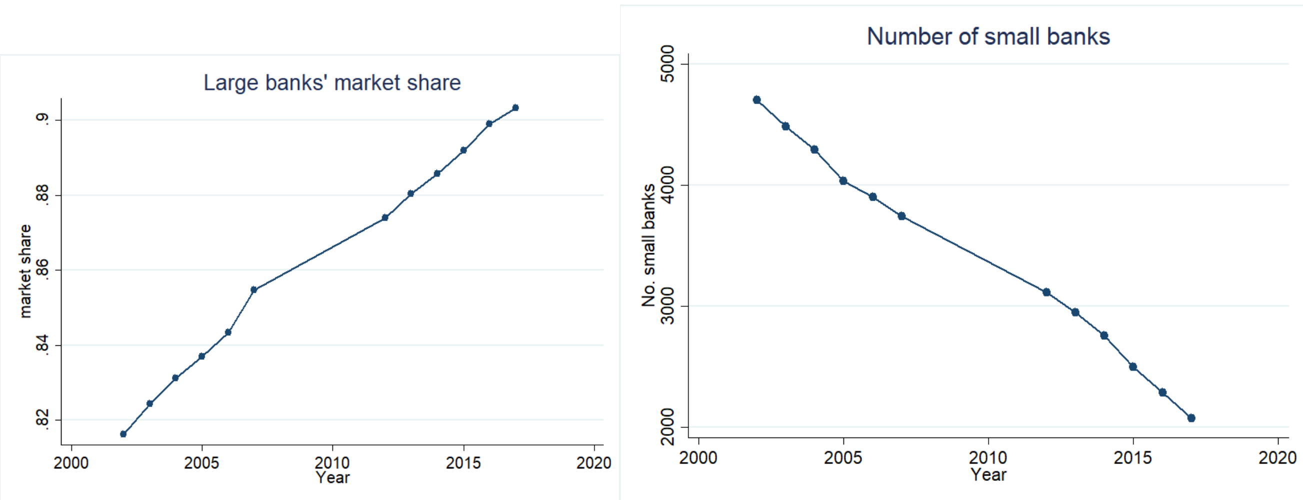
**Figure 2: Declining of Small Business Lending**




*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%.*

the number of small banks with loans fewer than 100 million dollars decreased from 4707 to 2072.

**Figure 3: Increasing concentration**

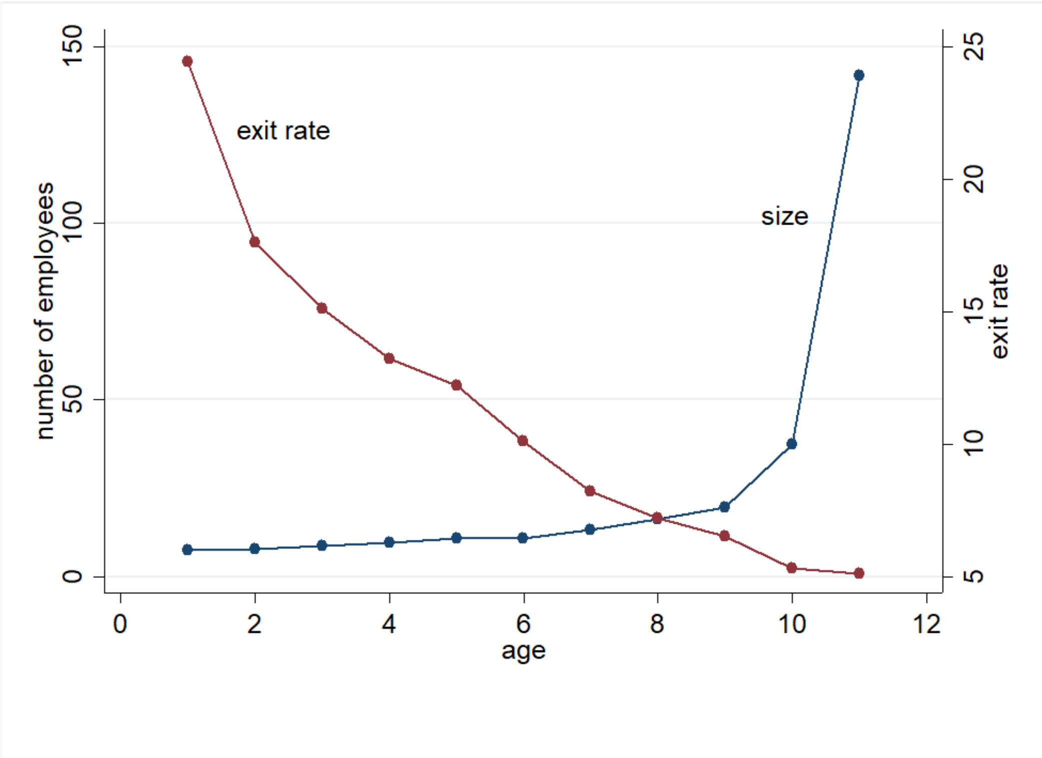



*Note: The picture on the left shows that the market share of large banks with loans more than 1 billion dollars increased from 82% to 90%. The picture on the right shows that the number of small banks with loans fewer than 100 million dollars decreased from 4707 to 2072.*

## 2.3 Firm Sizes, Ages and Exit Rates

I use the data from the Business Dynamics Statistics (BDS) from 1977 to 2015. Firms in the first age group are one year old. Firms in the second age group are two years old. Firms in the third age group are three years old. Firms in the fourth age group are four years old. Firms in the fifth age group are five years old. Firms in the sixth age group are six to ten years old. Firms in the seventh age group are eleven to fifteen years old. Firms in the eighth age group are sixteen to twenty years old. Firms in the ninth age group are twenty-one to twenty-five years old. Firms in the tenth age group are over twenty-six years old. Figure.4 shows that younger firms are smaller and have higher exit rates.

**Figure 4: Firm ages, sizes and exit rates**




*Note: This figure shows that small and young firms have higher exit rates than large and old firms.*

## 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). Borrowers have no preference or behaviors in the model. A borrower lives for one period. A borrower has a project that needs financing from a bank. His delinquency rate is unknown to banks. Banks take deposits and issue loans to maximize expected discounted profits. Banks have productive assets for assessing borrowers' delinquency rates. The evaluation of a borrower's delinquency rate is a statistical analysis, which is based on borrowers' hard information. Banks can also choose to invest in long-term relationships with borrowers 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; Bolton et al., 2016). In their models, the bank-borrower relationship gives the bank an option to restructure the debt when the borrower is delinquent and therefore, increases the bank's returns.

I model relationship banking by simplifying Bolton et al. (2016): banks have higher returns from a delinquent borrower in relationship lending than in transaction lending. Hence, risky borrowers receive relationship lending and safe borrowers receive transaction lending. I add two features to Bolton et al. (2016): first, a bank's marginal cost of building an additional relationship is increasing in the amount of relationships built; second, a bank can accumulates assets to grow and choose to exit. Over time, the technology of assessing hard information improves relative to the technology of building relationships. As banks have increasing marginal costs of building additional relationships, banks find it more profitable to switch to transaction lending from relationship lending. As banks have economy of scale in accumulating assets, larger banks grow faster and gain market shares with IT improvements. Because the IT improvements also intensify the competition in the deposit market and increase the costs of deposits, smaller banks cannot afford to stay and choose to exit .

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 four dates, $d = 0, 1, 2, 3$. On date zero, a bank assesses 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 either restructures the debt or liquidates the project. On date 3, the bank receives the returns from its projects and after the bank sees its cost of staying for the next period, the bank decides whether to stay in the market and on 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 $\theta$, $\theta \in [0, 1]$. 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, the bank receives different returns from transaction and relationship lending. In transaction lending, the bank liquidates the project and receives the liquidation value of the project, $R_L$. In relationship lending, the bank can restructure the debt and receives a higher return, $R_R$, $R_R > R_L$. I abstract the process of debt restructuring in Bolton et al. (2016), as this part is not relevant to my results. In the model, loan rates are exogenously given. If banks price loans according to borrowers' risks, the results of the model will not change. As information technology improves, banks will increase its loan rates to risky borrowers and borrowers cannot afford bank loans. Similarly, we will still have risky borrowers who receive relationship loans are hurt by the technology improvements. 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.

***Return from a relationship loan***:

$$q^R(\theta) = (1 - \theta)R_H + \theta R_R - r$$

***Return from a transaction loan***:

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

On date 0, measure of $B$ newborn banks enter the market. A newborn bank has assets $z^0$, which is drawn from a log-gamma 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 of this period. 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 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 in banks' technology of assessing borrowers' hard information and $M_t = e^{\lambda t} M_0$. The parameter $M_0$ measures banks' technology at period 0 and $\lambda$ measures the advancement of bank's technology of each period.

According to the delinquency rates of borrowers, a bank chooses to whom to lend and by relationship or 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, $\omega$ 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. With these information collected, the loan officer can better monitor the cash flow from this project. 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 2, 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 restructuring his debt. In transaction lending, the bank liquidates the project and receives the liquidation value of the project, $R_L$. In relationship lending, the bank has the option to restructure the debt and receives $R_R$, a higher return than the liquidation value. 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, 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.

This process is debt restructuring, which increases banks' returns.

On date 3, 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-gamma distribution $log - gamma(\mu, \sigma)$, $g_t$ is the money used for assets accumulation, $\delta_z$ is the depreciation rate of assets, $A$ and $\gamma$ 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 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 and benefit more from the adoption (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.

#### Bank's Decisions

The bank with assets $z_t$ solves the following problem: first, based on a borrower's delinquency rate, $\theta$, 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 the 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.

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

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, $\delta_z$ is the depreciation rate of assets, $\beta$ 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 $\Omega_t$, a set of bank's decisions $\{z_{t+1}, I^R(\theta, z_t), I^T(\theta, z_t), g_t\}$, 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 $r_t^*$,

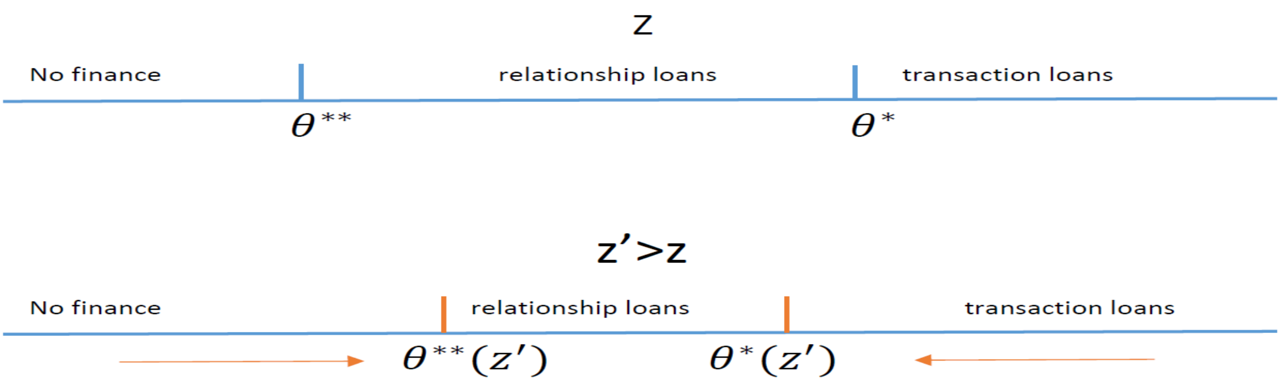
The deposit market is cleared at the market rate $r_t^*$,

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

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

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

**Figure 5: 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, $\theta(R_R - R_L) - c$ , is increasing in the delinquency rate of the project, $\theta$. Therefore, if a project is too safe, the additional return from a relationship exceeds the cost of building a relationship. So, there is a $\theta^*$ 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 $\theta^{**}$ 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 $\theta^*$ 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 $\theta^{**}$ 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 the model to the U.S. individual commercial bank data to quantify the IT improvement and its effects on lending to small businesses. 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. In the data, the bank size distribution changes over time: banks make more loans and the market concentration increases. The model does a very good job in explaining the increase in the aggregate bank loans, but underestimate the increasing concentration. Therefore, the model may ignore some factors that increase the market concentration, but does not increase bank loans. For example, since 2010, the Dodd-Frank act may disproportionately increase the regulatory burdens of small banks and increase the market concentration. I may overestimate the technology improvements, because in the model, the costs of data processing using IT technologies decreased by 19% from 2012 to 2017; however, in the data, it decreased only by 16%. Cross-sectionally, larger banks have smaller shares of small business lending and over time, the share of small business lending declines. These two data features identify the parameters in the technology of building relationships. The model does a very good job in explaining the decline of small business lending in dollar amounts and in relative shares to total loans. However, as I may overestimate the IT improvements, potentially, I may over explain the decline of small business lending by IT improvements. To overcome this problem, I re-estimate the model by assuming that the costs of data processing using IT technologies decrease by 16% as is the same in the data. I find that, under this condition, lending to small business declines by 6% instead of

12%. Therefore, my model can explain 50% to 100% of the decline in small business loans.

### 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 it 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 mortgage lending. The collapse of loan securitization market may not have effects on lending to small businesses. Third, the decline 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 (Venture 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 or agricultural loans.

A bank's total loans in the model are measured by total loans and leases net of unearned income[4]. 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. Table. 1 shows the definition of each variable. Table. 2 shows the summary of statistics.

The cost of data processing is from Compustat, Bank Fundamental Annual. This data set has 3200 banks from 2012 to 2017. The average total loans of these banks is 28025 million dollars.

[4]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

However, in the FDIC data set, the average loans for a bank is 7880 million dollars. So these banks are much larger than the average bank in the US. The data processing costs represent total costs and fees incurred in processing bank's data, including the costs of computer services, technology expense and software expense. The data shows that from 2012 to 2017, the data processing costs per dollar of loans has decreased by 16%.

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 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 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 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 increases over time. Third, 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 specifications are consistent with the data observations.

The calibration is to identify the parameters in bank's technology of evaluating borrowers' delinquency rates, $M_0, \lambda, \alpha$, the parameters in bank's technology of building relationships, $F, \omega$, 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, $\mu, \sigma$ , the parameter in the deposit supply function, $n_r$ and the parameters that characterize the returns from the projects, $R_H, R_L, R_R$. 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 $\delta_z$ is set to 0.004. The discounting factor $\beta$ 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.6-14 show 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, total loans increase from 5.16 to 9.1 trillion dollars (vs 5.11 to 8.54 trillion dollars). The standard variations of bank loans increase from 8.69 to 17.5 billion dollars (vs 8.78 to 24.6 billion dollars). The loan delinquency rates decrease from 2.33% to 2.3% (vs 2.37% to 2.14%). The average bank loans of banks at the top 25% increase from 2.36 to 5.17 billion dollars (vs 2.43 to 6.58 billion dollars in the data). The average bank loans of banks at the bottom 25% increase from 14.7 to 29.4 million dollars (vs 20.7 to 31.5 million dollars in the data). 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 number of banks with loans fewer than 100 million dollars decreases from 3609 to 2034 (vs 4707 to 2072 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). 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).

The most important untargeted moment is the cost of data processing per dollar loans issued. In the model, it reduces by 19% (the cost of processing hard information in the model equals to the aggregate bank productive assets divided by bank total loans). In the data, it reduces by 16%.

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 .0073 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 0.0066 (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%. As the technological improvement has different effects on transaction lending and relationship lending, banks 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, $F, -\omega, R_R, -n_r$. 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 $\alpha$ from .89 to .9, decreases from 1.09 to .88, increase $\mu_0$ from 21 to 21.2, and increase $\sigma_0$ from .4 to .42 (Table.4). Only the increase of $\mu_0$ can increase $\frac{r_{2,12}}{r_{2,1}}$ and only the increase of $\sigma_0$ 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 $\omega$ from .0279 to .0259, increase $R_R$ from .55 to .56, and decrease $n_r$ from .152 to .15 (Table.5). Only the increase of $-n_r$ can increase the loan delinquency rate in 2017; only the increase of $F$ can decrease the loan share of large banks with loans more than 1 billion dollars in 2017; the increase of $R_R$ decreases the number of banks with loans fewer than 100 million dollars in 2017.

To identify the parameters in the third group, I need to use $r_{1t}$ and $r_{2t}$ again. I increase $\lambda$ from .042 to .043, decrease $\gamma$ from .31 to .29, and increase $A$ from .36 to .38 (Table.6). Only the decrease of $\gamma$ 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 substitution mechanisms and the crowding-out mechanisms. I find that the first mechanism contributes to 51% 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 Two Mechanisms

In this experiment, I keep the substitution effect and shut down the crowding-out effects between large and small banks. I 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 substitution effect accounts for at least 51% of the declining. This result implies that as the substitution 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%. This policy reduces the substitution effects. My model 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% 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. Therefore, I only subsidize lending to risky borrowers. 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. This policy targets at crowding-out effects. Compared to the benchmark model, this policy does not increases relationship loans.

This is because, under this policy small banks have incentive to grow larger. When these small banks grow larger, they reduce their shares of relationship loans to small businesses. 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 technological improvements, this policy may not have the positive effects as expected.

## 6 Conclusions and Implications

I study the effects from IT improvements on small business lending in a quantitative, structural framework. The framework includes a dynamic model of relationship banking, a calibration that quantifies the advancement of IT improvements in the banking market and an evaluation of policies that may encourage lending to small businesses. The model does a reasonable job in explaining the key features in the US commercial banking market: the increasing market concentration, the exiting of small banks and the declining of small business loans. The model shows that when the data processing costs of one dollar loan declines by 2.7% to 3.2% annually, lending to small businesses declines 0.5% to 1% annually. This decline may lead to an annual loss of 25 thousand to 50 thousand jobs according to Chen, Hanson and Stein (2017). The paper provides insights on the debate about how to encourage lending to small businesses. It shows that we should subsidize small risky borrowers, not small banks, even though small banks may have comparative advantage in relationship lending.

One limitation of the paper is that I assume except small business loans, all other loans are transaction lending. This assumption is another way of saying that bank-borrower relationships play more important role in lending to small businesses than in lending to other borrowers. Therefore, even if I relax this assumption, my results will still hold. The second limitation is that I ignore other factors that may also contribute to the decline of small business loans, for example, Dodd-Frank Act. My future work will focus on enrich the model to study to what degree the Dodd-Frank Act contributes to the decline of small business loans.

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# A Mathematical Appendix

## A.1 Proof of Theorem 1

The the bank with assets $z$ solves:

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

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

Take the first order conditions of $\theta^{**}, \theta^*$ :

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

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

Solve $\theta^{**}$ from equation (6),

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

From (5) and (6):

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

Take (7) into (8),

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

from (9) we see that when $z$ increases, $\theta^*$ is larger. Similarly, I solve $\theta^{**}$ and I find that when $z$ increases, $\theta^{**}$ 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.[5] 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.

[5] 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 | 1339 | total loans: mean |
| $\alpha$ | of evaluating borrowers' credit | .89 | market concentration |
| $F$ | parameters in the technology | 148 | log(small business loans): mean, std |
| $\omega$ | of building relationships | .0279 | share of small business loans: mean, std |
| $R_L$ | liquidation value | .34 | share of small business loans: mean, std |
| $R_R$ | return from restructured debt | .55 | delinquency rate: mean |
| $R_H$ | sum of principal and interest rate | 1.0375 | interest incomes from loan/accrual loans |
| $\lambda$ | measure of technological improvement | .043 | annual loan growth rate |
| $\gamma$ | parameter in assets accumulation technology | .31 | market concentration |
| $A$ | | .36 | |
| $\mu$ | mean of the log of the staying costs | 5 | number of small banks |
| $\sigma$ | std of of the log of the staying costs | 7.8 | |
| $B$ | measure of new born banks | 89 | number of newly entered banks |
| $\mu_z$ | log of assets of new born banks | 11.62 | mean of loans of new born banks |
| $\sigma_z$ | | .6 | std of of loans of new born banks |
| $\mu_0$ | log of assets of incumbent banks | 21 | |
| $\sigma_0$ | | .4 | |
| $n_r$ | 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% |
| $R_R = .56$ | .0226 | 2771 | 84.3% |
| $n_r = .15$ | .0233 | 2514 | 80.9% |
| baseline | .023 | 2790 | 80.8% |

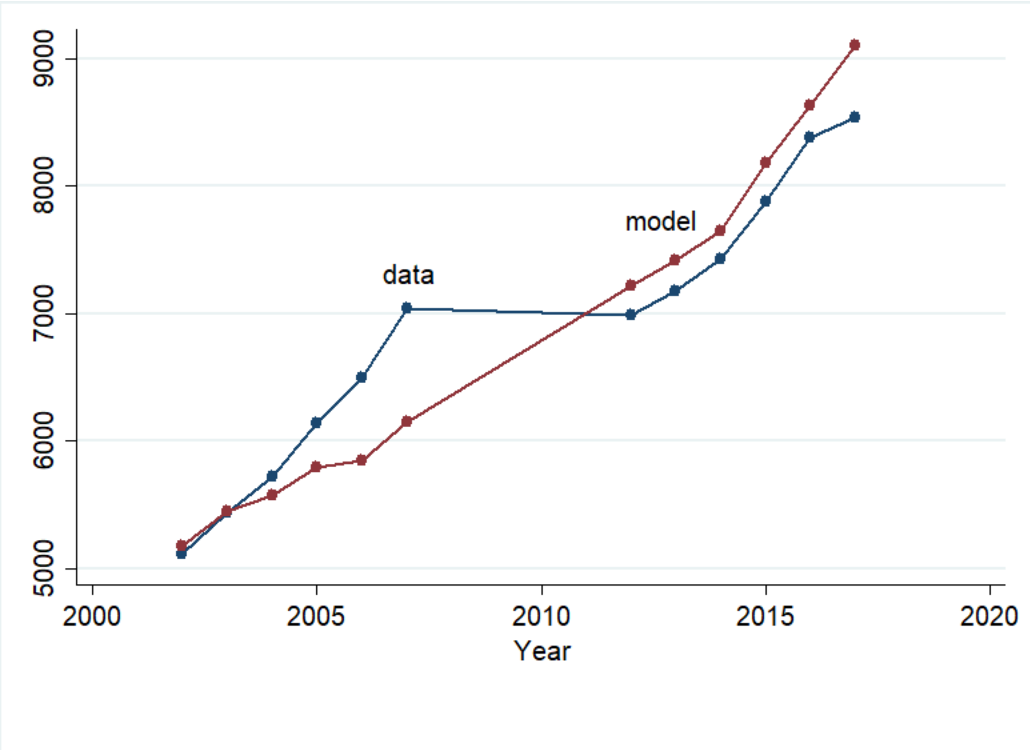
*Note:In the table, the delinquency rate, the number of small banks and the loan share of large banks are the average of these moments of each year. Small banks are banks with loans fewer than 100 million dollars and large banks are banks with loans more than 1 billion dollars.*

### 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 |

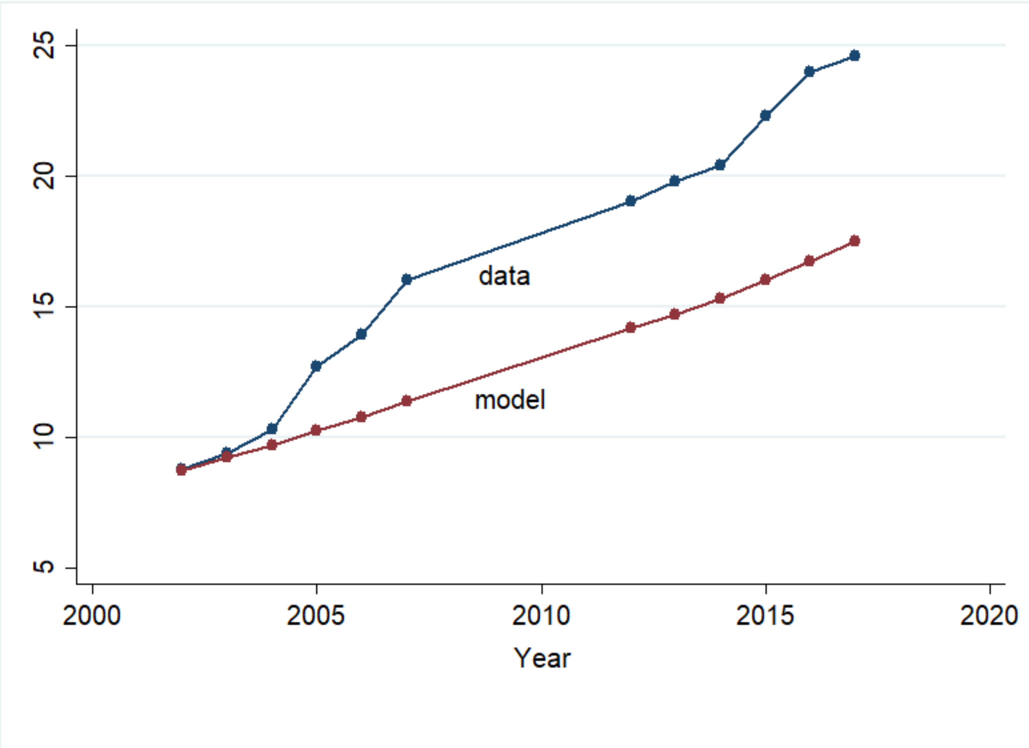
*Note:In the table, the ratio of loan standard variation to total loans, is defined as $r_{1t}$ and the ratio of average loans of large banks (banks at the top 25%) and the average loans of small banks (banks at the bottom 25%), is defined as $r_{2t}$, where $t = 1, ..., 12$.*

**Figure 6: Total loans in billion dollars**



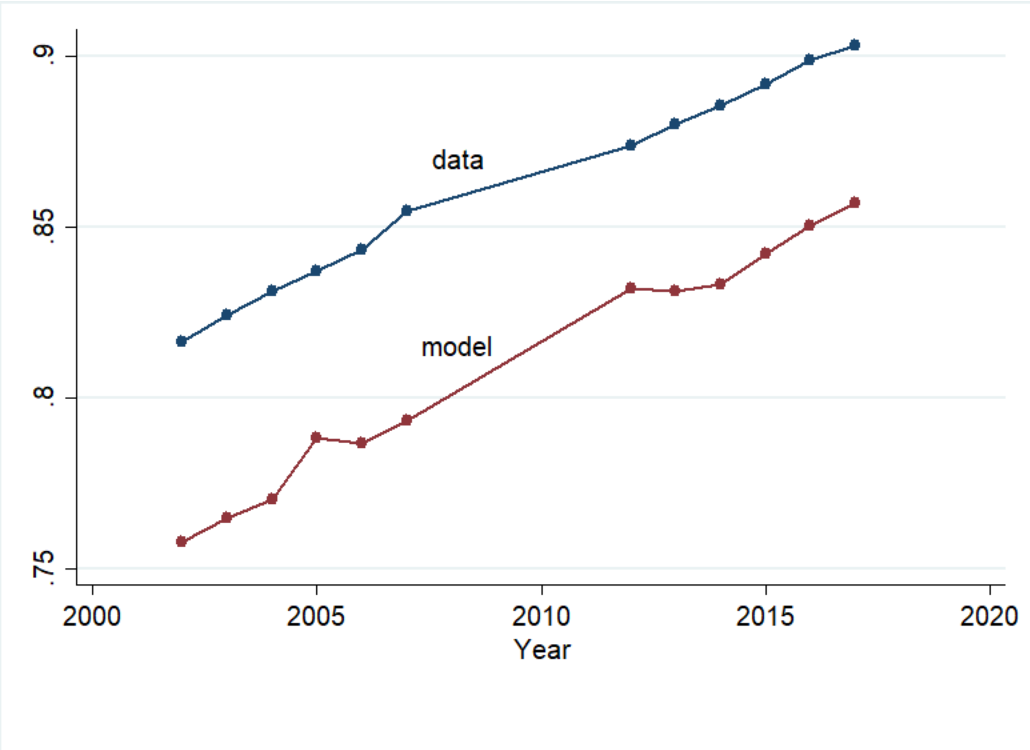

*Note: This figure shows that the model does a reasonable work in explaining the increasing loan amounts in the US commercial banking market from 2002 to 2017.*

**Figure 7: Standard variations of total loans**



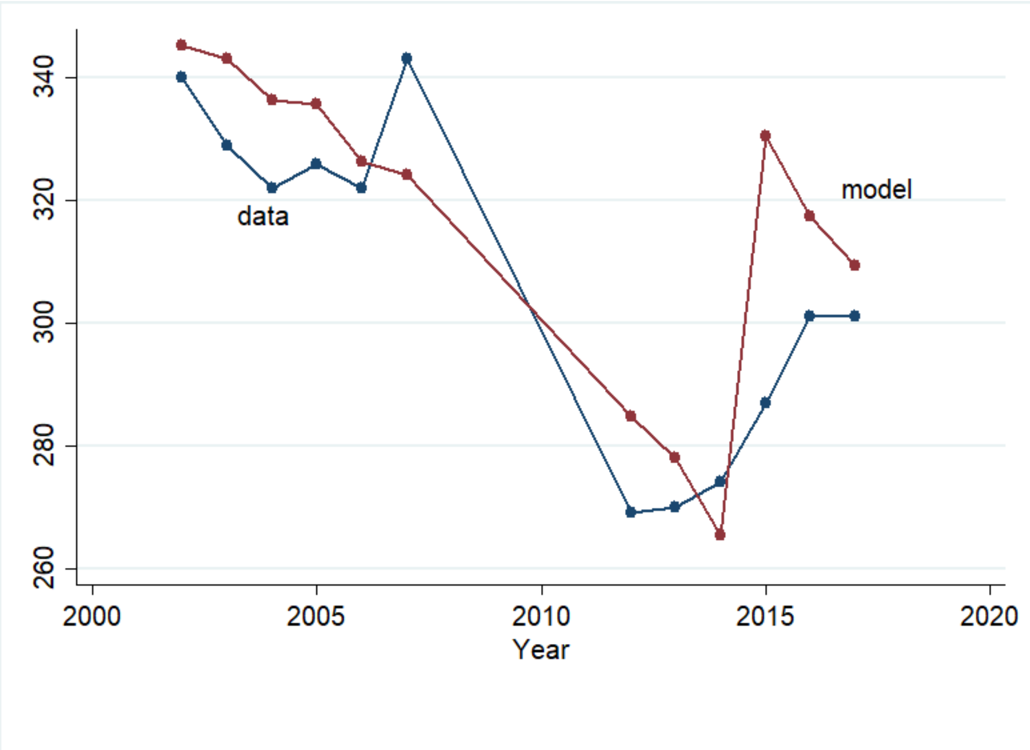

*Note: This figure shows that the model does a reasonable work in explaining the increasing variations of loan amounts in the US commercial banking market from 2002 to 2017.*

**Figure 8: Market shares of banks at the top 25%**



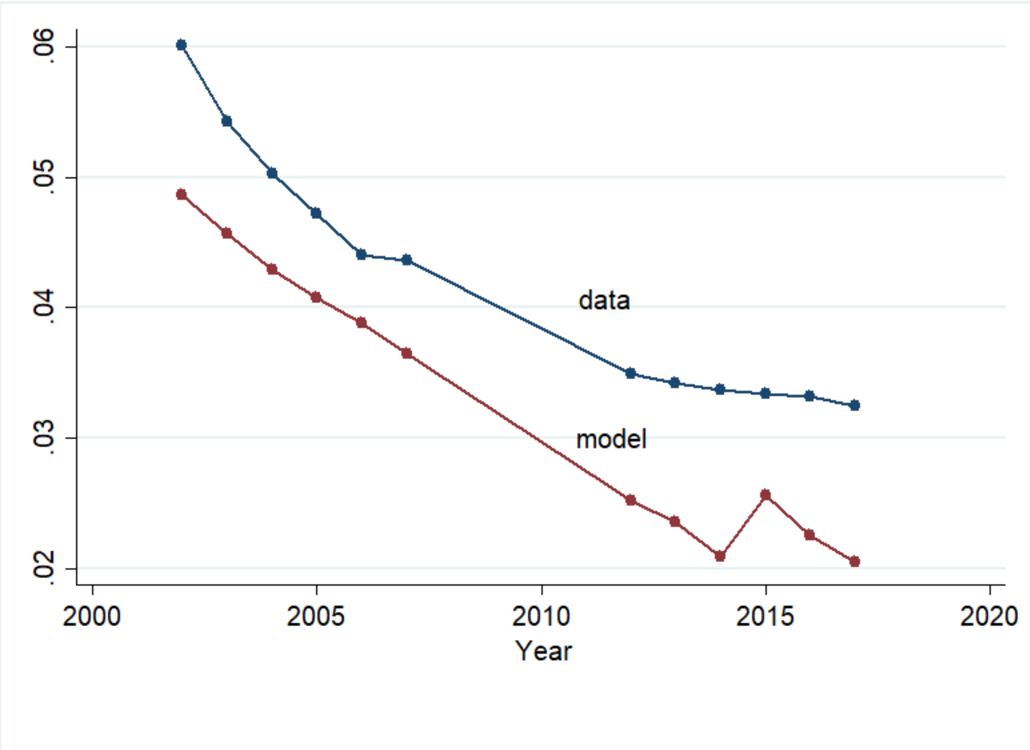

*Note: This figure shows that the model does a reasonable work in explaining the increasing concentration in the US commercial banking market from 2002 to 2017.*

**Figure 9: Decreasing small business loans**



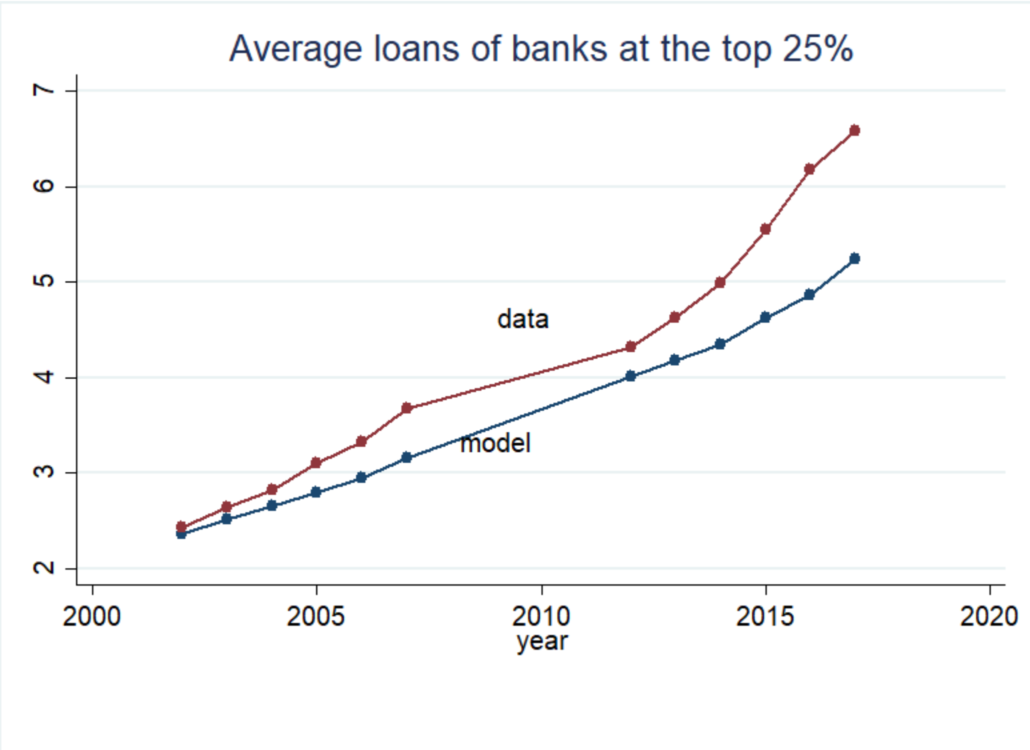

*Note: This figure shows that the model does a reasonable work in explaining the decreasing small business loan in the US commercial banking market from 2002 to 2017.*

**Figure 10: Share of small business loans of large banks**



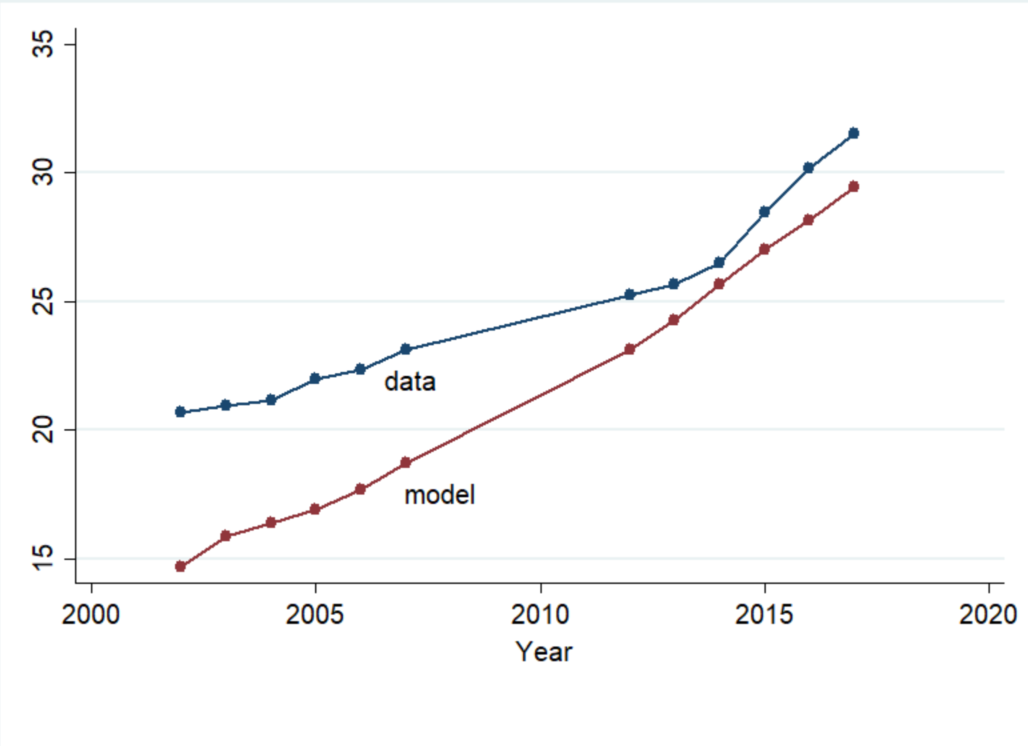

*Note: This figure shows that the model does a reasonable work in explaining the decreasing share of small business loans of the banks at the top 25% in terms of total loans in the US commercial banking market from 2002 to 2017.*

**Figure 11: Decreasing small business loans**



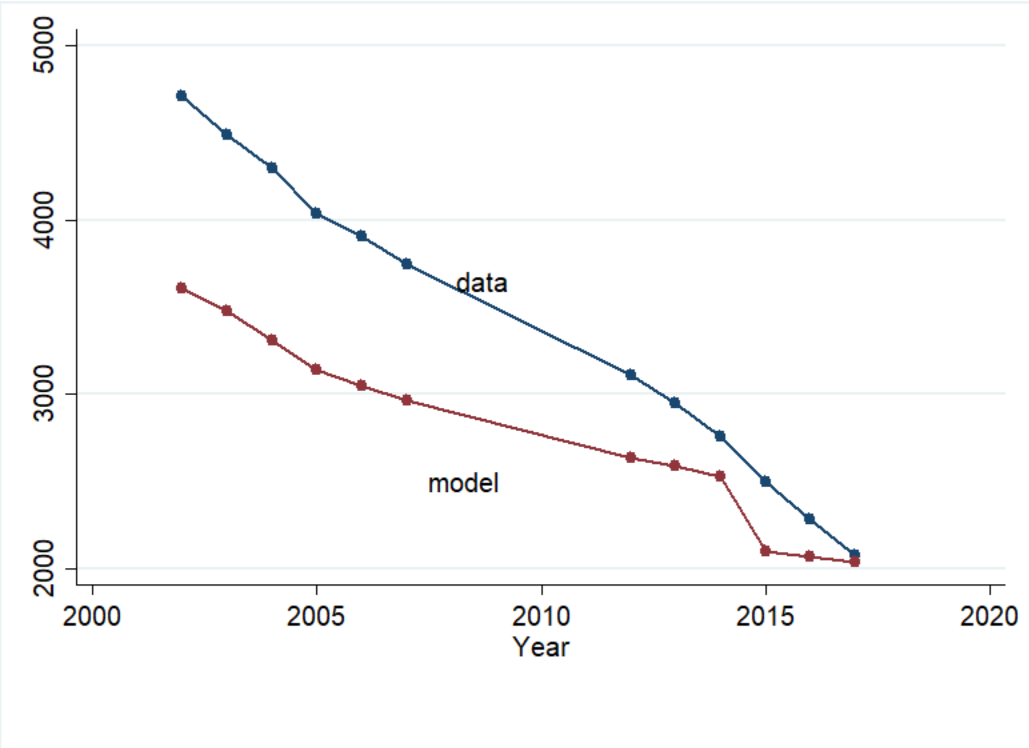

*Note: This figure shows that the model does a reasonable work in explaining the decreasing small business loan in the US commercial banking market from 2002 to 2017.*

**Figure 12: Average loans of small banks**



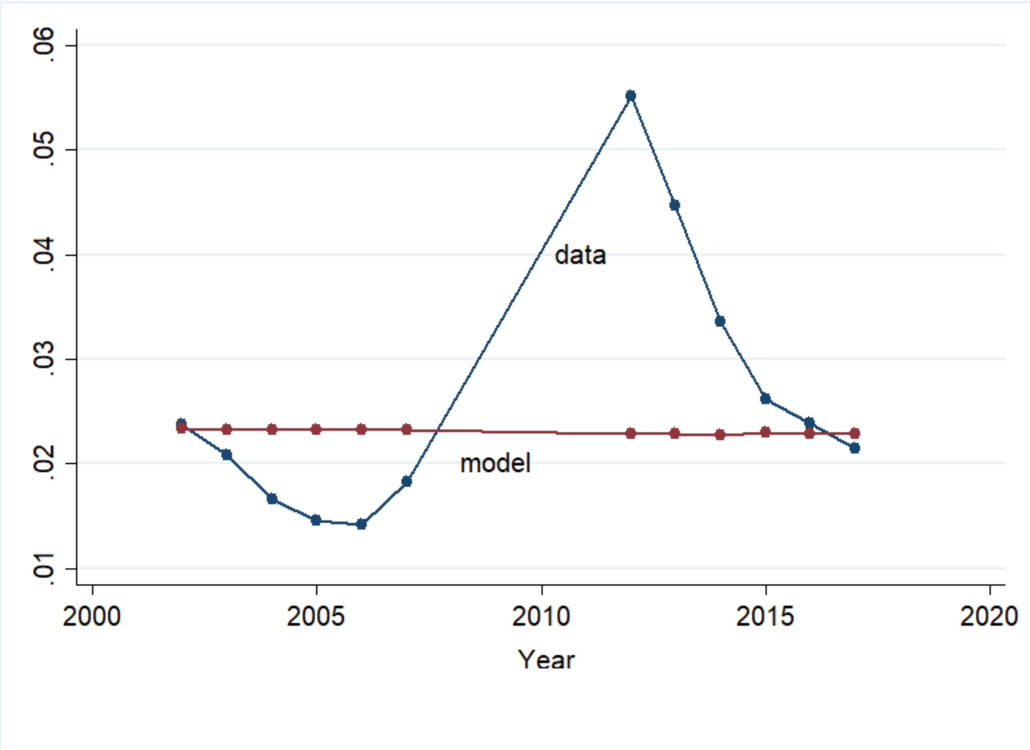

*Note: This figure shows that the model does a reasonable work in explaining the average loans of banks at the bottom 25% in the US commercial banking market from 2002 to 2017.*

**Figure 13: 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 14: 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.*