The Impact of Information Technology US Commercial Bank Lending:
Implications for Small Businesses

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Abstract

Over the last three decades, advances in information technology have improved banks’ efficiency of credit scoring/rating. I infer that the technology of credit rating improves by 45% from 1990 to 2007. I evaluate the effects of this technological improvement on the US commercial banking market with a dynamic, quantitative model. In the model, banks have an economy of scale at utilizing new technology to evaluate borrowers’ hard information, but increasing marginal costs of acquiring soft information. The model shows that due to this technological improvement, large banks gain market shares, small banks exit, and risky, small businesses receive fewer loans. It also shows that to encourage lending to small businesses, we should reduce banks’ costs of acquiring soft information, but should not subsidize small banks.

Key words: Information technology, innovation, fintech, relationship banking, small business lending

JEL classification: G21

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Over the last three decades, information technology (IT) has improved with the advent of powerful personal computers, large data base programs, and networking\(^1\). These improvements increase banks’ efficiency at collecting, storing, and transmitting quantitative hard information (Petersen, 2004)\(^2\) and in turn, increase banks’ efficiency at credit rating. However, this technological improvement could produce countervailing effects on small businesses lending. Technological improvements make larger banks (Berger, 2003) that engage less in lending to small businesses than smaller banks (Berger et al., 2005, Stein, 2002). Therefore, these technological improvements could adversely impact small businesses lending. On the other hand, as technological innovations lower banks’ lending costs, banks issue more loans to risky, small borrowers (Rajan, 2006)\(^3\). If small businesses face more financial constraints, the economy grows more slowly. Chen, Hanson and Stein (2017) shows that from 2006 to 2010, counties with the greatest decline of small business lending experienced the largest rise in unemployment rates and drop in wages; and wages in these counties are persistently lower than other counties even after 2014. Therefore, it is important to know how the technological improvement of credit rating affects small business lending.

I evaluate this effect on small business lending and policies that encourage lending to small businesses with a quantitative model of relationship banking. I model small businesses as risky borrowers. Small businesses are risky, not only because they have higher exit rates than large corporations, but also because small businesses usually do not have audited financial reports about their business conditions. This lack of audited financial information makes small businesses dependent on relationship lending (Berger and Udell, 1995, 2002; Nguyen, 2014; Petersen and Rajan, 1994; Liberti and Mian, 2009).

Following Bolton et al. (2016), I distinguish two types of lending in the model: transac-
tion lending and relationship lending. I introduce transaction lending as an “arms-length” transaction based on borrowers’ delinquency rates. I introduce relationship lending as a long-term lending contract where lenders assess borrowers’ delinquency rates and acquire the information about borrowers’ financial conditions. With relationships, when the borrowers are delinquent, banks could better decide whether to terminate the loans and liquidate the projects. However, banks have increasing marginal costs of building additional borrower relationships. The relationship thus generates a surplus for the bank, a surplus that increases in the delinquency rates of borrowers and decreases in the cost of building the relationship. So, risky borrowers receive relationship lending and safe borrowers receive transaction lending. As small businesses are risky borrowers, therefore, the model implies that they receive relationship lending.

Different from Bolton et al. (2016), I introduce a technology for assessing borrowers’ hard information (the technology includes systems and software used to operate IT equipment), a technology that improves over time. A bank uses the technology and its productive assets to evaluate borrowers’ delinquency rates (assets henceforth, including premises and equipment and employees’ knowledge on how to operate banks’ machines). A bank, with more assets, assesses more borrowers. It has a broader set of relative safe borrowers. As banks have higher returns from safer borrowers, the bank chooses to build more borrower relationships with these relatively safe borrowers. The marginal cost of building an additional relationship increases. As the riskiest relationship loans previously generated zero profits and now generate negative profits, the bank stop lending to these high risk borrowers. Therefore, compared to small banks, large banks have fewer loans to high risk borrowers.

My model shows two ways technological innovations could reduce small business lending. First, the technological improvement increases banks’ advantages in transaction lending over relationship lending. When the technology of assessing borrowers increase, banks become larger and build more relationships. However, if the technology of building relationships does not improve, banks have larger costs of building additional relationships. Therefore, as explained earlier, when banks have higher costs of building relationships, risky, relationship borrowers receive fewer loans than before.

Second, the technological improvement results in the exit of small banks and when small banks leave, lending to small businesses decreases. Over time, with the same amount of assets, banks evaluate more borrowers than before. As banks lend to more borrowers, the demand for deposits and the deposit interest rate increase. The spreads between the deposit rate and the loan rates reduce and banks’ profits decrease. As large banks can accumulate
assets more efficiently than small banks, only large banks with enough additional assets can assess enough additional borrowers and issue enough additional loans to offset this reduction in profits. In contrast, small banks cannot afford the cost of staying in the market and choose to leave.

I then calibrate the model to the U.S. individual commercial bank data from 1988 to 2007. 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 banks’ assets, total loans, and small business loans. The model shows that, with one thousand dollars of productive assets, a bank could evaluate 37 borrowers in 1990 and 53 borrowers in 2007. Therefore, due to technological improvements, banks’ efficiency of credit rating increases by 45% from 1990 to 2007.

Using the parameters identified from the calibration, I quantify the effects from the technological improvements from 1990 to 2007. I solve the dynamic maximization problems of banks. In the model, the loan share of large banks with loans more than 10 billion dollars increases from 15.1% to 66.9% (vs 31.2% to 66% in the data); the number of small banks with loans less than 100 million dollars decreases from 8896 to 5056 (vs from 10810 to 5428 in the data). Loans to borrowers with delinquency rates greater than 7% decrease by 100%. According to the US Small Business Administration, from 2000 to 2009, about 98% of small business loans have delinquency rates greater than 7%. Therefore, this paper implies that risky, small businesses receive fewer loans because of the technological improvement in credit rating.

I then compare three different policies that combat the decrease in the lending to small businesses: subsidizing small banks to encourage them to stay, subsidizing lending to risky borrowers, and decreasing the cost of building relationships. Decreasing the cost of acquiring soft information and subsidizing lending to small businesses encourage lending to risky, small businesses. However, subsidizing small banks has negative effects on lending to small businesses.

In the first policy experiment, I subsidize small banks (with total loans less than 100 million dollars) with 1% of their loan amounts to encourage them to stay. Compared to the benchmark model, this policy decreases loans to borrowers with delinquency rates greater than or equal to 5%. This policy encourages small banks to become larger. As is explained before, when banks become larger, they issue fewer loans to risky borrower. According to the literature, if we encourage small banks to stay in the market, we should increase lending to small businesses (Berger et al., 2005; Stein, 2002; Strahan and Weston, 1998). My paper
shows that within the context of information improvements, if a policy reduces the exit rate of small banks, it also encourages them to become larger. Therefore, small risky borrowers receive fewer loans under this policy.

In the second policy experiment, I subsidize banks with one percent of their loan amounts, when lending to borrowers with delinquency rates greater than or equal to 7%. Compared to the benchmark model, a borrower with delinquency rate greater than or equal to 7% receives at least 100% more loans and other borrowers receive at most 1.5% fewer loans under this policy. This policy increases banks profits from lending to risky borrowers, but discourages banks to accumulate assets. Therefore, loans to safe borrowers decrease. 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, but safe borrowers may receive fewer bank loans.

In the last policy experiment, I decrease the banks’ marginal costs of building relationships by 20%. This cost would decrease if bankers could better monitor loan officers or harden more soft information. Compared to the benchmark model, under this policy, banks accumulate more assets and issue more loans to all borrowers. Consistent with the model intuition, Berger, Frame and Miller (2005) find that small businesses receive more loans with the development of Small Business Credit Scoring (SECS) as SECS reduces banks’ cost of acquiring soft information. This paper complements their findings by indicating that this policy also encourages lending to safe borrowers.

The model indicates that when technology improves, aggregate loan delinquency rate decreases by 0.25% from 2.43% to 2.18% (in the data, it decreases from 5% to 1.87% ) from 1990 to 2007. In the model, risky relationship loans are reduced over time, so the delinquency rate of bank loans decreases. In reality, information technological improvements also increase banks’ precision of assessing borrowers and thus, further decreases the risks in banks’ loans.

1 Related Literature

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.

This paper is related with the literature on banking market concentration and small business lending (Berger et al., 1998; Strahan and Weston, 1998). This 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”

\[4\]

In contrast, with a structural model, this paper is able to address “Lucas Critique” and conduct policy evaluations.

The rest of the paper is organized as follows. Section II contains the model. Section III presents the calibration of the model. Section IV shows implications of the model. Section V concludes. Proofs and tables are in the Appendix.

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4The ‘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).
2 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.

**Borrowers:** 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 the lender’s cash flow from him when he is delinquent on his loan.

**Banks:** 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 is credit rating for firms and credit scoring for individual borrowers.

In each period, a bank accumulates assets. When the technology for assessing borrowers improves, compared to small banks, large banks have larger returns from accumulating assets and invest more in assets accumulation. Therefore, large banks grows faster than small banks. When the demand for deposits increases and drives up the deposit interest rate, only large banks can afford the cost of deposits and the cost of staying in the market. Small banks, on the other hand, will leave.

Before lending to a borrower, the lender evaluates the borrower’s delinquency rate. 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 stop financing the least profitable relationship loans. These borrowers are the riskiest relationship borrowers. Hence, risky borrowers receive fewer loans over time.

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.

2.1 Model Details

**Time Line:** There are infinite periods \( t = 0, 1, 2, \ldots \). 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 \( \theta \), \( \theta \in [0, 1] \). 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, his project generates high cash flow with a probability of \( \xi \) 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, \( D = e^{nr} - r \), where \( r \) is the deposit interest rate, \( D \) is the supply of deposits, and \( n_r \) is a parameter that 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 assume that banks price loans according to borrowers’ risks, the results will not change. However, if I did so, the computation will be too complicated because the dimension of borrowers’ risks is infinite. 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 1: Banks’ returns from a project**

\[
\text{Nature} \quad 1 - \theta \quad R_H \\
\text{Nature} \quad \theta \\
\text{High, } \xi \\
\text{Low, } 1 - \xi \\
\text{Bank} \\
\text{continue} \quad R_H \\
\text{liquidate} \quad R_L \\
\text{Bank} \\
\text{continue} \quad 0
\]

*Note: This figure shows banks’ returns from a project with a delinquency rate of \( \theta \), 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 \( \ln N(\mu_z, \sigma_z) \). 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 evaluate 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 the 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 \( \alpha \in (0, +\infty) \) 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 the parameter \( \lambda \) 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 \( c(L^S) \) 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

\[
c(L^S) = \frac{1}{F(\omega + 1)} (L^S)^\omega, \quad L^S
\]

is the number of relationships that the bank has built, \( \omega \) is a parameter that captures the elasticity between marginal costs of building relationships and the number of relationships, and \( F \) is a parameter that 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,

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

where $e_t$ is from a log-normal distribution $lnN(\mu, \sigma)$, $g_t$ is the money used for assets accumulation, $\delta_z$ 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 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:**

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

where $c$ is the cost of building a relationship.

**Return from a transaction loan:**

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

**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 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.

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

s.t.

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

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 $\{z_{t+1}, I^R(\theta, z_t), I^T(\theta, z_t)\}$, 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 2: 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, \( \theta \). 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.

3. 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. Banks with more assets have more total loans and relationship loans, but smaller shares of relationship loans. These three variations allow me to identify the parameters in the technology of assessing borrowers and building relationships. Banks differ in assets and produce different new assets. This variation allows me to identify parameters in the technology accumulating assets.

In the calibration, I find that in 1990, if a bank has assets of one thousand dollars, it could assess 37 borrowers; in 2007, it assesses 53 borrowers. Consequently, banks’ efficiency of evaluating borrowers has improved by 45% from 1990 to 2007. I may over estimate the effects from technological improvements on banks’ productivity because during this period, two deregulation may also increase banks’ productivity. Some may argue that deregulation
in 1999 allows banks to expand their business scopes and to collect a borrower’s information from different aspects. Thus, this deregulation enhances banks’ ability of collecting borrowers’ information. However, before the two deregulation, commercial banks have already find ways to circumvent the regulations on geographic expansion and taking businesses of investment banks. They organize bank holding companies and use ATM machines. Many states also relaxed the restrictions on geographic expansion during 1980s. Since the late of 1990s, commercial banks and investment banks have been sharing borrowers’ information through information center provided by third parties. Therefore, the two deregulation may not have much impact on banks’ productivity growth of assessing borrowers.

3.1 Data

The data are provided by the Federal Reserve Bank of Chicago (Consolidated Report of Condition and Income–Call Reports). The measurements of key variables are as follows.

Productive assets in the model are measured by a bank’s tangible assets and the human capital of employees. A bank’s tangible assets is measured by its equipment and premises. The human capital is measured by its total payment of salaries and employee benefits. I also consider that in each year, the growth rate of wages and interest rates should be

\[ \frac{\Delta l}{l} = \frac{\Delta k}{k} = \lambda \]

Banks use labor and capital to produce asset using technology:

\[ Z = (l^\phi + k^\phi)^{\phi} \]

subject to the budget constraint:

\[ wl + rk = H \]

A bank maximizes the total amount of assets:

\[ L = (l^\phi + k^\phi)^{\phi} + \lambda(H - wl - rk) \]

Focs:

\[ (l^\phi + k^\phi)^{\phi - 1} l^{\phi - 1} = \lambda w \]

\[ (l^\phi + k^\phi)^{\phi - 1} k^{\phi - 1} = \lambda r \]

From (1) and (2):

\[ \frac{1}{k} = \left( \frac{w}{r} \right)^{\phi-1} \]

Then

\[ Z = (l^\phi + k^\phi)^{\phi} = k\left( \frac{w}{r} \right)^{\phi-1} + 1)^{\phi} \]

\[ H = wl + rk = r\left( \frac{w}{r} \right)^{\phi-1} + 1)k \]
consistent with the growth rate of GDP (averagely, 2%). Therefore, in each year, I deflate total assets by 2%. By doing so, I assume that in each year, a constant proportion of banks’ resources are used to evaluate borrowers’ delinquency rates. However, under this assumption, I may over-estimate the productivity growth in the banking sector, because with the development of information technology, more and more tasks in the banks are IT related and a larger and larger proportion of salaries are paid to workers who are doing IT related tasks.

A bank’s total loans in the model are measured by total loans and leases net of unearned income\(^6\). 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 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 and small farms\(^7\). This measure is widely used in the literature. People find that banks build relationships when they lend small firms because small firms are usually informationally opaque. Transaction loans are defined as a bank’s total loans minus its relationship loans. They are car loans, consumption loans, mortgages and loans to large firms. Because of the development of securitization market, car loans, mortgages and personal consumption loans can be easily securitized and sold. These loans are transaction loans. Because of the development of

\[
Z_t = H_t\left(\frac{w_t}{r_t}\right)^{\frac{\phi}{r_t}} + 1)^{\phi-1}/r_t
\]

From (3) and (4):

\[
Z_t = H_t\left(\frac{w_t}{r_t}\right)^{\frac{\phi}{r_t}} + 1)^{\phi-1}/(1 + g)^t
\]

Therefore, a bank’s total assets is linear function of the bank’s total expenses on capital and labor. Normalize the price of capital at period 0 to one, then we have,

\[
Z_t = H_t\left(\frac{w_t}{r_t}\right)^{\frac{\phi}{r_t}} + 1)^{\phi-1}/(1 + g)^t
\]

where \(g\) is the growth rate of interest rate.

The implicit assumption I make when calibrating the model is that \(\frac{w_t}{r_t}\) is constant over time.

\(^6\)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

\(^7\)Refer to https://www.fdic.gov/regulations/resources/call/crinst/605rc-c2.pdf for the definition of loans to small businesses and small farms.
syndicated loan market, banks work together to provide funds to large firms and only the leading banks carry out some administrative tasks. Therefore, loans to large firms are transaction loans.

Interest income from loans are measured by total interest and fee income on loans. Loan delinquency rate is the ratio of the sum of loans past due 30 to 89 days and more than 90 days, loans unaccrual and total charge-offs to total loans.

I use data from 1988 to 2007. I exclude the data after 2007 because, after the subprime crisis, the bank size distribution is strongly affected by the government bailout policy. The fluctuation in the banking market does not change how technology innovations affect bank size distribution, even if it may accelerate the concentration in the banking market. Since 1993, data on bank’s small businesses and small farms lending are available from Schedule RC-C Part II - Loans to Small Businesses and Small Farms. Other variables, including bank’s total loans and leases, net of unearned income (RCFD2122), bank’s premises and equipment (RCFD2145), bank’s salaries and employee benefits (RIAD4135), loans past due more than 90 days, loans unaccrual (these three terms are from Schedule RC-N), interest income from loans (RIAD4010) and leases and total charge-offs (RIAD4635) are available since 1976. Loans past due 30 to 89 days (RCFD1406) is available since 2001. Table 1 shows the definition of each variable. Table 2 shows the summary of statistics.

Table 1 inserted here.

Table 2 inserted here.

3.2 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. The simulation is as follows. From the data, I calculate each bank’s assets. Then, I compute the optimal choices of each banks and the deposit interest rate in the equilibrium. The solution to the banks’ problems is provided in the Appendix 2.

The calibration contains two parts. In the first part, I use data from 1993 to 2007 to estimate the parameters that characterize bank’s technology of evaluating borrowers’ delinquency rates, $\theta$, $\lambda$, $\alpha$, the parameters that characterize bank’s technology of building
relationships, $F, \omega$, the parameters that characterize deposit supply function, $n_r$ and the parameters that characterize the returns from the projects, $R_H, R_L, \xi$. In this part, I solve the static problem faced by each bank: given its assets, how many relationship loans and transaction loans to issue. The parameter $R_H$ is calculated as the ratio of incomes from loans to total loans and leases net of unaccrual loans and total charge-offs. The parameters $\xi, R_L$ are positively related with loan delinquency rates. When banks have better returns from financial distressed projects than before, loans are extended to borrowers with higher delinquency rates. The parameter $\xi$ positively determines banks’ returns from relationships and thus, is positively related with banks’ levels and shares of relationship loans; in contrast, the parameter $R_L$ negatively determines shares of relationship loans. The technology for evaluating borrowers is given by $(M_0e^{\lambda t})z^\alpha\omega^\omega$, where $M_0, \lambda, \alpha, \omega$ are parameters to be estimated. The parameter $\alpha$ increases, banks have larger economy of scale and the loan shares of large banks increase. The parameter $\lambda$ is estimated from the annual growth rate of the mean of banks’ total loans from 1993 to 2007. Other parameters are identified jointly. I find $M_0 = 37, \lambda = 0.022$, which means that banks’ efficiency of assessing borrowers increases by about 2.5% annually.

In the model, a bank’s size is negatively related with its share of small business loans, so variations of bank’s small business loans and variations of shares of small business loans are key moments to match. The technology of building relationships is summarized by the cost of building a relationship, $c(L^S) = \frac{1}{F(\omega+1)}(L^S)^\omega$, where $F, \omega$ are parameters to be estimated. The parameter $\omega$ determines the difference of the shares of small business loans among banks of different sizes. If the cost function of building relationships becomes more convex ($\omega$ increases), the marginal cost of building additional relationships of large banks increase more than that of small banks. Large banks’ relationship loans decrease more than these of small banks. The share of relationship loans of large banks decreases more than that of small banks. The standard deviation of shares of relationship loans will increase. I find $\omega = 0.088, F = 573$, which means that by issuing additional relationship loans of one thousand dollars, bank’s marginal cost of building relationships increase by about 0.17%. Other parameters are estimated jointly. Table.3 shows the values for each parameter and the targeting moments that identify them and Table.4 shows that the targeting moments in the data matched well with the moments in the model.

Table.3 inserted here.

Table.4 inserted here.
In the second part, I use the data from 1988 to 1990 to estimate the parameters in the technology that is used by a bank to accumulate assets and the parameters that characterize bank’s entry and exit. In this part, I solve the dynamic programming of each bank. From 1988 to 1990, the bank size distribution changed minimally. I calibrate my model to this steady state. By doing so, I simplify my calibration. The measure of banks entering in each period, \( B \), is calculated as the number of banks entering divided by total number of banks and equals to 0.033. The mean of the natural logarithm of assets of newly entered banks is \( \mu_z = 6.53 \), and the standard deviation is \( \sigma_z = 1.38 \), which are calculated directly from the data.

The technology used by banks to accumulate assets is given by 
\[
z_{t+1} = (1-\delta_z)z_t + Az_t^{1-\gamma}g_t. 
\]
The distribution of the staying costs is given by \( \ln N(\mu, \sigma) \). Assets depreciating rate \( \delta_z \) is set to 0.034 to accommodate findings in Nadiri and Prucha (1996). The discounting factor \( \beta \) is set to 0.996. The increase of \( \gamma \) reduces large bank’s advantage of accumulating assets compared to small banks and hence, decreases the market shares of large banks. When \( A \) increases, large banks become more productive at producing new assets than small banks; therefore, the increase of \( A \) increases the market shares of large banks. When the variation of the cost of staying, \( \sigma \), increases, large banks face higher probability of being hit by a large staying cost and exiting the market. Therefore, the ratio of mean natural log of assets of staying banks to the mean of those of exiting banks decreases. When all banks are exposed to larger staying cost (\( \mu \) increases), the ratio of the mean of log assets of staying to the standard deviation of those increases. Table 5 shows the values for each parameter and the targeting moments that identify them and Table 6 shows that the targeting moments in the data matched well with the moments in the model.

Table 5 inserted here.

Table 6 inserted here.

4 Test of Theory and Model Implications

Using the parameters identified from the calibration, I solve the dynamic maximization problems of banks. The simulated model quantifies the effects from the technological improvements. In the model, the loan share of large banks with loans more than 10 billion
dollars increases from 15.1% to 66.9% (vs 31.2% to 66% in the data); the number of small banks with loans less than 100 million dollars decreases from 8896 to 5056 (vs from 10810 to 5428 in the data). The model implies that with the technological improvements in credit rating, small businesses receive fewer loans. I model small businesses as risky borrowers and I find that loans to borrowers with delinquency rates greater than 7% decrease by 100%. I then compare three different policies that combat the decrease in the lending to small businesses: subsidize small banks to encourage them to stay, subsidize lending to risky borrowers, and decrease the cost of building relationships. 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 small businesses.

4.1 Simulation Method

Taking parameters identified in the calibration, I simulate the model to solve the maximization problems of the banks. The starting point of the simulation is the steady state, which was calibrated to the data from 1988 to 1990. In the simulation, banks are expecting the future changes of the technology and the responses from other banks. Banks accumulate assets to accommodate their knowledge about the changes of future technology and the equilibrium results of these changes. In the simulation, I assume that banks expect that the technological improvements continues for 60 periods. This assumption actually has no effect on the calibration result, but simplifies the computation. The results from simulation does not change if technological improvement continues for 30 periods, 40 periods, or 50 periods.

4.2 Simulation Results

The simulation shows that in the model, from 1990 to 2007, the technological improvements result in an increasing concentration in the US banking market: the loan share of large banks with loans more than 10 billion dollars increases from 15.1% to 66.9% (vs 31.2% to 66% in the data); the number of small banks with loans less than 100 million dollars decreases from 8896 to 5056 (vs from 10810 to 5428 in the data). The increasing concentration is a result of increasing competition among banks. When the technology improves, a bank could evaluate more borrowers with the same assets. Thus, banks fund additional loans with additional deposits. The increasing demand for deposits increases the deposit
interest rate. The spread between deposit rate and loan rates reduces, as in the model loan rates are exogenously fixed. When this reduction of spread decreases banks’ profits, large banks crowd out small banks because only large banks can accumulate enough assets and issue enough additional loans to offset this reduction in profits. Small banks will choose to leave instead of paying the staying cost. There are two potential reasons why this model cannot replicate the data perfectly with such a high concentration: in the model, banks compete perfectly, but in reality, large banks possibly have market powers; second, in the model, banks have no search costs of collecting deposits, but in reality, banks may have these search costs and large banks may have lower search costs than small banks.

In the model, with these technological improvements, risky small businesses receive fewer loans. In the model, loans to borrowers with delinquency rates greater than 7% decrease by 100%. This result implies that due to information technological improvements, lending to small businesses may decrease. I, therefore, compare three different policies that combats the decrease in the lending to small businesses: prevent small banks from exiting, decrease the cost of building relationships, and subsidize lending to risky borrowers. I compare the results from these policies in Table 7.

Table.7 inserted here.

In the first policy experiment, I subsidize small banks (with total loans less than 100 million dollars) with 1% of their loan amounts to encourage them to stay. This subsidy is unexpected by banks in the model. In the literature, the exit of small banks results in the reduction of loans to risky small businesses (Strahan and Weston, 1998, Berger et al., 2005, Stein, 2002). However, compared to the benchmark model, this policy decreases loans to borrowers with delinquency rates greater than or equal to 5%. This policy encourages small banks to become larger and thus, to accumulate more assets. When banks have more assets than before, banks assess more borrowers and build more borrower relationships, and the marginal cost of building an additional relationship increases. The surplus to the bank from relationship lending decreases. Among relationship lending, the riskiest borrowers contribute zero profits before and negative profits now. Therefore, the bank stops financing these high risk borrowers.

In the second policy experiment, I subsidize banks with one percent of their loan amounts, when lending to borrowers with delinquency rates greater or equal to 7%. Under this policy, compared to the benchmark model, a borrower with delinquency rates greater than or equal to 5% receives at least 100% more loans; however, other borrowers receive at
most 1.5% fewer loans. This policy increases banks profits from lending to risky borrowers, but discourages banks to accumulate assets (on average banks accumulate 25% less assets compared to the benchmark model). Therefore, loans to safe borrowers decrease. Thus, in the context of the model, it is a good policy that the U.S. Small Business Administration provides subsidized loans and loan guarantees to small businesses for start-up and expansion seems.

In the last policy experiment, I improve the technology of building relationships to decrease the banks’ marginal costs of building relationships by 20% ($F$ is increased from 573 to 716). This cost reduction would happen if bankers could monitor loan officers better or harden more soft information. Compared to the benchmark model, this policy increases banks’ assets and loans to all borrowers because it not only encourages banks to acquire more soft information, but also encourages banks to accumulate more assets to acquire more hard information (on average banks accumulate 8% more assets compared to the benchmark model). Consistent with the model intuition, Berger, Frame and Miller (2005) find that small businesses receive more loans with the development of Small Business Credit Scoring (SECS) as SECS reduces banks’ cost of acquiring soft information. This paper complements their findings by indicating that this policy also encourages lending to safe borrowers.

The model indicates that when technology improves, aggregate loan delinquency rate decreases by 0.25% from 2.43% to 2.18% (in the data, it decreases from 5% to 1.87% ) from 1990 to 2007. In the model, risky relationship loans are reduced over time. Therefore, the delinquency rate of bank loans decreases. In reality, information technological improvements also increase banks’ precision of assessing borrowers and thus, decreases the risks in banks’ loans. In my model, I can basically predict the delinquency rates in 2007, however, I fail to predict the delinquency rates in 1990. The delinquency rate in 1990 in the data is much higher than that predicted by my model. In the model, I assume that banks could perfect evaluate borrowers’ delinquency rates without any error. This assumption may be true if banks use the most advanced information technology of today. However, this assumption is probably not true when banks had not developed good enough technology of assessing borrowers in 1990.
5 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 hurt.

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.

The caveat of this paper is that I cannot explain the decrease of the delinquency rates of banks’ loans. In the model, information technological improvements only increase banks’ capacity of assessing borrowers, but not increase banks’ precision of assessing borrowers. However, in reality, both may have happened. Even though the former may increase the risks in banks’ loans, the later may decrease the risks in banks’ loans because banks can screen out more risky borrowers with better information technology. The study of how information technology advances help banks better screen out risky borrowers and reduce the risks in banks’ balance sheet can be my future work.
Reference


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.”


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


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

A  Mathematical Appendix

A.1  Proof of Theorem 1

The bank with assets $z$ solves:

$$
\max_{I, T} \{m(z) \int_{0}^{\theta^*} ((1 - \theta) R_H + \theta (\xi R_H + (1 - \xi) R_L) - r) d\theta + \int_{0}^{\theta^*} ((1 - \theta) R_H + \theta R_L - r) d\theta - L^* c(L^*) \}
$$

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

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

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

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

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

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

From (5) and (6):

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

Take (7) into (8),

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

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.\textsuperscript{8}

\textsuperscript{8} The computation of value function is referred to http://home.uchicago.edu/hickmanbr/uploads/chapter5_2.pdf
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.
### Table 1: Definitions of variables

<table>
<thead>
<tr>
<th><strong>definitions</strong></th>
<th><strong>variables</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>total loans and leases</td>
<td>total loans</td>
</tr>
<tr>
<td>premises &amp; equipment and salaries</td>
<td>bank assets, $z$</td>
</tr>
<tr>
<td>loans to small businesses and small farms</td>
<td>relationship loans, $L^S$</td>
</tr>
<tr>
<td>interests expense/total assets</td>
<td>deposit interest rate, $r$</td>
</tr>
<tr>
<td>sum of loans past due, unacrual and charged</td>
<td>delinquency rate</td>
</tr>
<tr>
<td>off/ total loans</td>
<td></td>
</tr>
</tbody>
</table>
Table 2: Summary of statistics


<table>
<thead>
<tr>
<th>variables</th>
<th>mean</th>
<th>std</th>
<th>min</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(total loans)</td>
<td>10.36</td>
<td>1.43</td>
<td>0.16</td>
<td>18.63</td>
</tr>
<tr>
<td>log(premises &amp; equipment plus salaries)</td>
<td>7.20</td>
<td>1.37</td>
<td>.11</td>
<td>15.29</td>
</tr>
</tbody>
</table>

Panel B: 1993-2007, No.banks= 130,723

<table>
<thead>
<tr>
<th>variables</th>
<th>mean</th>
<th>std</th>
<th>min</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(total loans)</td>
<td>10.77</td>
<td>1.44</td>
<td>0.67</td>
<td>19.96</td>
</tr>
<tr>
<td>log(small businesses loans)</td>
<td>9.69</td>
<td>1.34</td>
<td>0</td>
<td>16.83</td>
</tr>
<tr>
<td>log(premises &amp; equipment plus salary)</td>
<td>7.53</td>
<td>1.4</td>
<td>0</td>
<td>16.26</td>
</tr>
<tr>
<td>delinquency rate</td>
<td>0.025</td>
<td>0.028</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>total interest and fee income on loans</td>
<td>13779.21</td>
<td>177616</td>
<td>0</td>
<td>177616</td>
</tr>
</tbody>
</table>

Note: This table shows statistics of some key variables. Total loans are bank’s total loans and leases. Small business loans are bank’s loans to small business and small farms. Banks’ total loans, small business loans, premises and equipment and salaries are all in constant thousand dollar of 1993. The data is from Call Report, 1988-2007.
Table 3: Values of parameters and targeted moments

<table>
<thead>
<tr>
<th>parameter</th>
<th>description</th>
<th>value</th>
<th>moments</th>
</tr>
</thead>
<tbody>
<tr>
<td>$M_0$</td>
<td>parameters in the technology</td>
<td>37</td>
<td>log(total loans): mean</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>of evaluating borrowers’ credit</td>
<td>1.28</td>
<td>log(total loans): std</td>
</tr>
<tr>
<td>$F$</td>
<td>parameters in the technology</td>
<td>573</td>
<td>log(small business loans): mean, std</td>
</tr>
<tr>
<td>$\omega$</td>
<td>of building relationships</td>
<td>0.088</td>
<td>share of small business loans: mean, std</td>
</tr>
<tr>
<td>$R_L$</td>
<td>liquidation value</td>
<td>0.7</td>
<td>share of small business loans: mean, std</td>
</tr>
<tr>
<td>$\xi$</td>
<td>possibility of high cash flow</td>
<td>0.35</td>
<td>delinquency rate: mean</td>
</tr>
<tr>
<td>$R_H$</td>
<td>sum of principal and interest rate</td>
<td>1.042</td>
<td>interest incomes from loan/accrual loans</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>measure of technological improvement</td>
<td>0.022</td>
<td>annual loan growth rate</td>
</tr>
<tr>
<td>$n_r$</td>
<td>parameter in deposit supply function</td>
<td>0.35</td>
<td>deposit interest rate</td>
</tr>
</tbody>
</table>

Note: This table shows the values for each parameter.

Table 4: Model moments vs data moments

<table>
<thead>
<tr>
<th>moments</th>
<th>model moments (mean)</th>
<th>data moments (mean)</th>
<th>model moments (std)</th>
<th>data moments (std)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(total loans)</td>
<td>11.16</td>
<td>11.12</td>
<td>1.72</td>
<td>1.38</td>
</tr>
<tr>
<td>share of small business loans</td>
<td>0.32</td>
<td>0.30</td>
<td>0.18</td>
<td>0.17</td>
</tr>
<tr>
<td>log(small business loans)</td>
<td>9.86</td>
<td>9.68</td>
<td>1.46</td>
<td>1.35</td>
</tr>
<tr>
<td>annual loan growth rate</td>
<td>6.16%</td>
<td>6.12%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>deposit interest rate</td>
<td>0.028</td>
<td>0.026</td>
<td></td>
<td></td>
</tr>
<tr>
<td>loan share of the top 10% banks (%)</td>
<td>95.24</td>
<td>85.72</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: This table shows that my model can replicate the targeting moments in the data.
### Table 5: Values of parameters and targeted moments

<table>
<thead>
<tr>
<th>parameter</th>
<th>description</th>
<th>value</th>
<th>moments</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma$</td>
<td>parameter in assets accumulation technology</td>
<td>0.2</td>
<td>assets of exiting and staying banks:</td>
</tr>
<tr>
<td>$A$</td>
<td>mean of the log of the staying costs</td>
<td>7.9</td>
<td>mean, std</td>
</tr>
<tr>
<td>$\mu$</td>
<td>std of of the log of the staying costs</td>
<td>6.2</td>
<td></td>
</tr>
<tr>
<td>$\sigma_2$</td>
<td>measure of new born banks</td>
<td>0.033</td>
<td>bank’s entry rate</td>
</tr>
<tr>
<td>$\mu_z$</td>
<td>mean of the log of assets of new born banks</td>
<td>6.53</td>
<td>assets of new entered banks:</td>
</tr>
<tr>
<td>$\sigma_z$</td>
<td>std of of the log of assets of new born banks</td>
<td>1.38</td>
<td>mean, std</td>
</tr>
</tbody>
</table>

*Note: This table shows the values for each parameter.*

### Table 6: Model moments vs data moments

<table>
<thead>
<tr>
<th>moments</th>
<th>model moments</th>
<th>data moments</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean($z^e_i$)/mean($z^s_i$)</td>
<td>1</td>
<td>0.97</td>
</tr>
<tr>
<td>mean($z^e_i$)/std($z^s_i$)</td>
<td>4.97</td>
<td>5.26</td>
</tr>
<tr>
<td>loan share of the top 10% banks (%)</td>
<td>87.15</td>
<td>82.97</td>
</tr>
<tr>
<td>loan share of the top 5% banks (%)</td>
<td>78.49</td>
<td>76</td>
</tr>
<tr>
<td>loan share of the top 1% banks (%)</td>
<td>55.65</td>
<td>53.15</td>
</tr>
</tbody>
</table>

*Note: This table shows that my model can replicate the targeting moments in the data. $z^e_i$: assets of exiting banks, $z^s_i$: assets of staying banks.*
Table 7: Loans to borrowers of different risks

<table>
<thead>
<tr>
<th>Year</th>
<th>delinquency rates</th>
<th>Benchmark</th>
<th>Subsidizing small banks</th>
<th>Subsidize risky loans</th>
<th>Decrease the costs by 20%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990</td>
<td>0.07</td>
<td>$1.5 \times 10^3$</td>
<td>$1.6 \times 10^3$</td>
<td>$82 \times 10^3$</td>
<td>$14.2 \times 10^3$</td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>$5.6 \times 10^5$</td>
<td>$5.67 \times 10^5$</td>
<td>$5.7 \times 10^5$</td>
<td>$5.5 \times 10^5$</td>
</tr>
<tr>
<td>2007</td>
<td>0.07</td>
<td>40.2</td>
<td>3.2</td>
<td>$2.5 \times 10^5$</td>
<td>$1.6 \times 10^4$</td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>$33.9 \times 10^5$</td>
<td>$58.6 \times 10^5$</td>
<td>$33.2 \times 10^5$</td>
<td>$39.1 \times 10^5$</td>
</tr>
<tr>
<td>Loan delinquency rate in 2007</td>
<td>2.18%</td>
<td>2.17%</td>
<td>2.46%</td>
<td>2.17%</td>
<td></td>
</tr>
<tr>
<td>Average assets in 2007</td>
<td>25.2</td>
<td>29.4</td>
<td>20.5</td>
<td>27.1</td>
<td></td>
</tr>
</tbody>
</table>

Note: This table compares the results from different policy experiments. In the first policy, I subsidize small banks with loans fewer than 100 million dollars. In the second one, I subsidize banks with one percent of loans to borrowers with delinquency rates greater than or equal to 7%. In the last policy, I decrease the marginal cost of building relationships by 20%. In the table, the amount of loans are in constant million dollars of 1993.