Thesis on Technological Change in the U.S. Commercial Banking Market

by

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ABSTRACT

This thesis studies the technological change in the US commercial banking market and its influence on banks' lending practices. The second chapter provides some empirical facts.

The third chapter studies the welfare consequences of the destructive creation (bank branches replaced by internet banking) of the US commercial banking market following the Great Recession of 2009. Using a structural model, this paper finds that the cleansing effect (closure of unproductive bank branches) of the recession increases the units of internet banking by about 56% in 2016, compared to the case where the cleansing effect is absent. The share of internet banking in the retail service market is increased from 48% to 60% and the price of internet banking service is decreased by a factor of 16 by the cleansing effect of the Great Recession. The two changes lowers the price of retail banking services in 2016 by 37%: 53% of the price reduction is attributable to the replacement of branches by internet banking and 47% is attributable to the reduction of the price of internet banking. However, this cleansing effect also results in a 2.5% decrease in small business services in small cities. These findings suggest that the cleansing effect of the recession benefits retail consumers. However, small business lending may suffer.

The fourth chapter evaluates how information technology (IT) improvements contribute to the decline of small business lending in the US commercial banking market from 2002 to 2017. This paper estimates a general equilibrium dynamic model with banks that differ in size and choose the level of transaction (hard information intensive) and relationship (soft information intensive) lending. The model shows that banks costs of evaluating borrowers hard information declined over this period by 46%, and small business loans fell by 7% (12% in the data). This paper finds that banks higher reliance on IT to issue transaction loans is responsible for 37% of the

decline in the data, and the consolidation caused by IT improvements caused 22% of the decline. Contrary to previous findings, this chapter finds that when general equilibrium is considered, policy protecting small banks cannot increase small business lending.

This dissertation is dedicated to my husband, Bo. I love you to the moon and back.

ACKNOWLEDGMENTS

I am grateful for my advisors, Dan Silverman, Sreedhar Bharath and George Aragon. They help me grow and survive. I am also grateful to Alejandro Manelli and Hector Chade who served as committee members in my third-year paper. I also need to thank my husband, parents and grandparents whose love encourages me to fight for life and march on through sufferings.

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INTRODUCTION

Great technological changes happened in the US commercial banking market in the last several decades. Think about thirty year ago: we need to go to a branch to deposit a check; now, we just need to use our smartphones to scan the check and upload it to our checking account through our mobile banking app. The process of lending is also much simpler. Mortgages are standardized such that no in-person meeting is needed to issue a mortgage. Car loans, consumption loans and even lending to large corporations are now mostly based on computers and software.

In this project, I study how these technological changes have reshaped the banking market. I focus on two aspects: the welfare implications for retail consumers, large corporations and small businesses, and the welfare implications for large and small banks. I find that technological changes favor retail consumers and large corporations, but hurt small businesses. The improvement of information technology also allows large banks to gain market share and crowd out small banks.

In Chapter 2, I first provide some empirical evidence about the technological change, the change in bank lending practice and the change in banking market structures. Chapter 3 examines whether and to what degree, the cleansing effect of the Great Recession has accelerated banks' adoption of internet banking (including online banking through computers and mobile banking through smartphones) and closing of branches. Then I use a structural model to evaluate the welfare implications for retail consumers and firms. In Chapter 4, I study to what degree and through what mechanisms, the improvement of information technology has decreased lending to small businesses.

Chapter 3 finds that the cleansing effect (closure of unproductive bank branches) encourages banks to adopt 56% more units of internet banking in 2016. Compared to the case where this cleansing effect is absent, in 2016, the share of internet banking in retail service market increases to 60% from 48% and the price of internet banking service decreases by a factor of 16. The two changes lower the price of retail banking services in 2016 by 37%: 53% of the price reduction is attributable to the replacement of branches by internet banking and 47% is attributable to the reduction of the price of internet banking. However, this cleansing effect also results in a 2.5% decrease in small business services in small cities. Our findings suggest that the cleansing effect of the recession benefits retail consumers. However, small business lending may suffer.

Chapter 4 evaluates how information technology (IT) improvements contribute to the decline of small business lending in the US commercial banking market from 2002 to 2017. I estimate a general equilibrium dynamic model with banks that differ in sizes and choose the level of transaction (hard information intensive) and relationship (soft information intensive) lending. The model shows that banks costs of evaluating borrowers hard information declined over this period by 46%, and small business loans fell by 7% (12% in the data). I find that banks higher reliance on IT to issue transaction loans is responsible for 37% of the decline in the data, and the consolidation caused by IT improvements caused 22% of the decline. Contrary to previous work, I find that when general equilibrium is considered, policy protecting small banks cannot increase small business lending.

Chapter 2

MOTIVATION FACTS

In this chapter, I provide facts about banks' increasing adoption of information technology, the increasing market concentration in the US commercial banking market and the decreasing lending to small businesses. I also provide evidence about why small businesses are important in the economy.

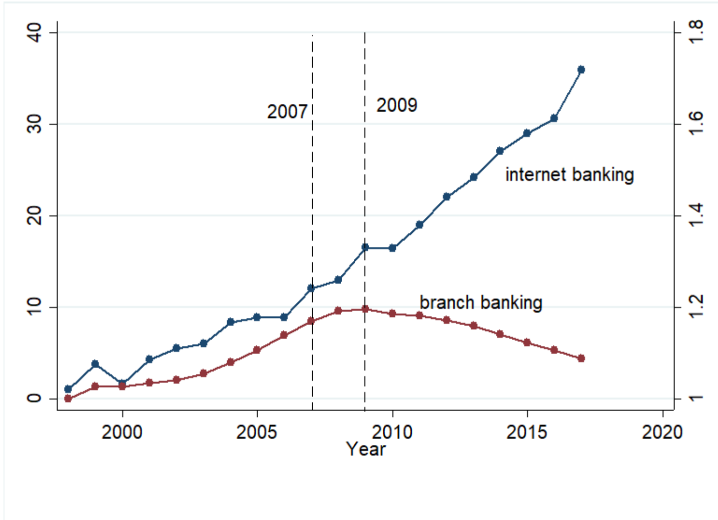
2.1 Facts about Banks Technology Adoption: Branches vs Internet Banking

A dynamic trend continues in the US commercial banking market in recent ten years. Banks started to close their physical branches after the Great Recession and continue to do so. The total number of branches of all US commercial banks declined by 9% (from about 99,000 to about 89,000) from 2009 to 2017 (Fig.2.1). Meanwhile, more and more bank customers are using online banking and mobile banking–together as internet banking. In 2001 there are about 50 million internet banking users, and in 2017 there were about 300 million users (The data about online banking and mobile banking is from the following sources: Survey of Consumers' Use of Mobile Financial Services (2012-2016) conducted by the Federal Reserve Board; Digital Banking Consumer Survey done by PwC, Emarketer, and Bank of America). Most strikingly, after the recession, internet banking users increased faster than before: from 1998 to 2009, the number of internet banking users increased by 14 million annually; however, from 2010 to 2017, the number of internet banking users increased by 28 million annually (Fig.2.3). Since banks adopted mobile banking in 2008, the number of users has increased by more than 200% (Fig.2.2). The Survey of Consumers' Use of Mobile

Financial Services (2012-2016) shows that from 2012 to 2015 the market share of internet banking (online banking and mobile banking) increased from 52% to 57%.

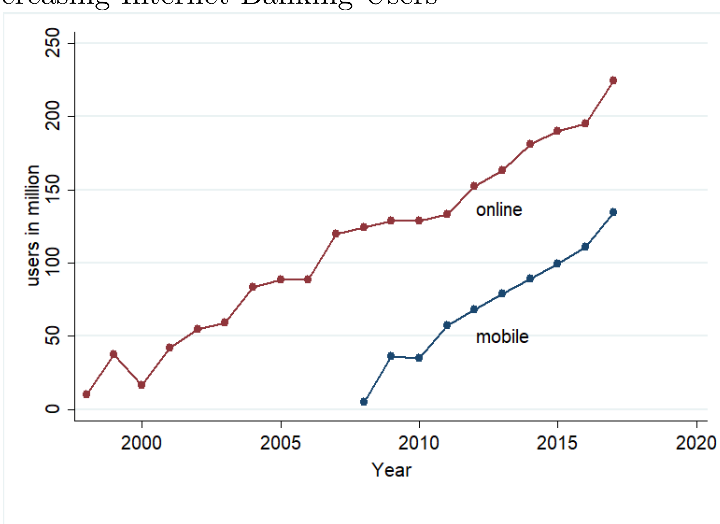
The recession was a turning point for banks. Before the recession, banks built up branches, but after the recession, banks began to close their branches in both large and small cities. Most interestingly, large banks built up more branches in large cities (compared to in small cities) before the recession and closed more branches in small cities (compared to in large cities) after the recession; however, small banks built up more branches in small cities (compared to in large cities) before the recession and closed more branches in large cities (compared to in large cities) after the recession. Table 2.1 shows this fact. (I define large banks as the banking holding company with total deposits in the upper 20% and small banks as other banks. I define large cities as metro areas containing a core urban area containing population of 50,000 or more and small cities as other cities). From 1998 to 2009, the number of large banks' branches in large cities increased by 25%, from 54,016 to 67,527; the number of large banks' branches in small cities increased by 9%, from 10,909 to 11,846; the number of small banks' branches in large cities increased by 16%, from 9,373 to 10,900; the number of large banks' branches in small cities increased by 6%, from 8,424 to 8,922. From 2010 to 2017, the number of large banks' branches in large cities decreased by 7%, from 66,730 to 62,268; the number of large banks' branches in small cities decreased by 10%, from 11,829 to 10,627; the number of small banks' branches in large cities decreased by 17%, from 10,588 to 8,772; the number of large banks' branches in small cities decreased by 7%, from 8,807 to 8,190.

Figure 2.1: Internet Banking and Branches



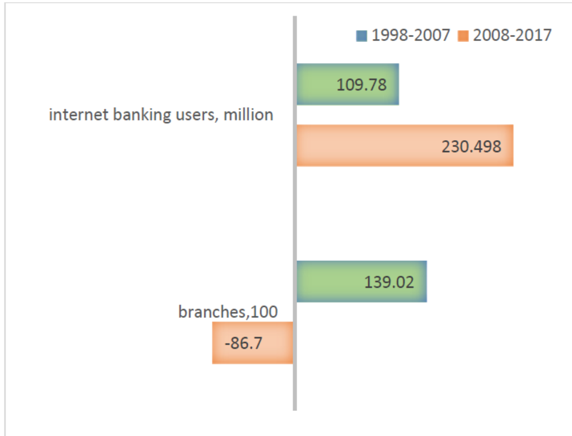
This picture compares the percent change in branches, online banking users and mobile banking users. Data source: Deposit Market Share Reports - Summary of Deposits Data from Federal Deposit Insurance Corporation and Pew Research Center.

Figure 2.2: Increasing Internet Banking Users



This picture shows that the number of internet banking users has increased. Internet banking includes online banking and mobile banking. Data source: Pew Research Center.

Figure 2.3: Change in Internet Banking and Branches



This figure compares the change in branches (in hundreds), online banking users and mobile banking users (in millions). Internet banking includes mobile banking and online banking. Data source: Deposit Market Share Reports - Summary of Deposits Data from Federal Deposit Insurance Corporation and Pew Research Center.

2.2 Motivation Facts about Lending to Small Businesses and the Importance of Small Businesses

The following figures and table show some key dynamic features of the U.S. commercial banking industry and the characteristics of US firms. First, US banks have increased their use of software. Second, US banks have reduced lending to small businesses. Third, the US banking market is increasingly concentrated. Fourth, younger firms are smaller and have higher rates of exit, but have the largest employment growth with 1 million dollars of bank loans.

Table 2.1: Branches in Large and Small Cities

This table shows the difference growth rates of bank branches in large and small cities for large and small banks. I define large banks as the banking holding company with total deposits in the upper 20% and small banks as other banks. I define large cities as metro areas contains a core urban area containing population of 50,000 or more and small cities as other cities

From 1998 to 2009		
	large cities	small cities
large bank	+25%	+9%
small bank	+16%	+6%

From 2010 to 2017		
	large cities	small cities
large bank	-7%	-10%
small bank	-17%	-7%

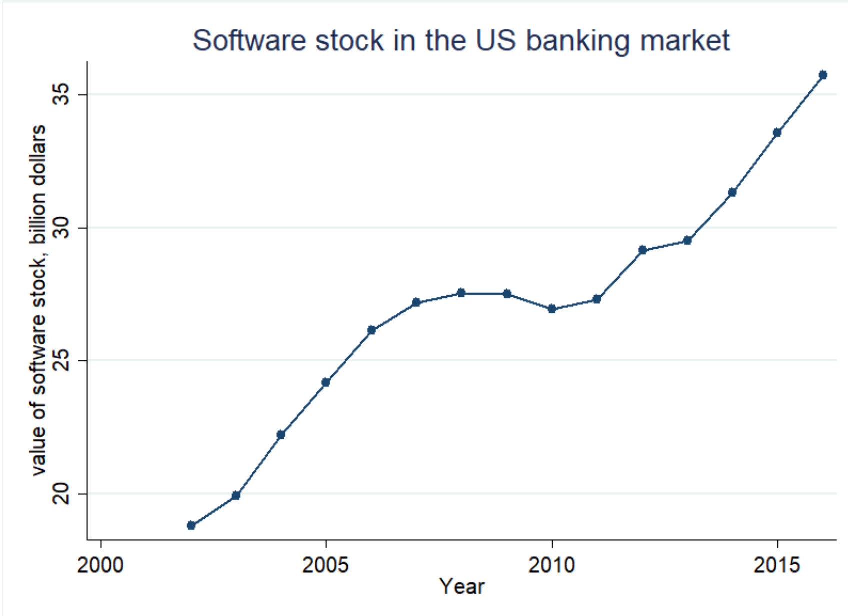
2.2.1 An Upward Trend in Technology Usage

Fig.2.4 shows the increasing use of software in the U.S. commercial banking sector. Banks' software stock, including prepared software (ENS1), custom software (ENS2), and own-account software (ENS3) increased from about $18 billion in 2002 to about $36 billion in 2016, by 100% (in constant 2017 U.S. dollars). The data are from the Bureau of Economic Analysis (BEA), Current-Cost Net Capital Stock of Private Nonresidential Fixed Assets. Fig.2.5 shows that the cost of processing information per dollar of loans decreased over time, from .078% to .067% from 2012 to 2017.

2.2.2 Trends in Lending Practice

I use data from the FDIC reports on US depository institutions for 2002 to 2017. All the dollar amounts are in constant 2017 US dollars. Fig.2.6 shows the decline in

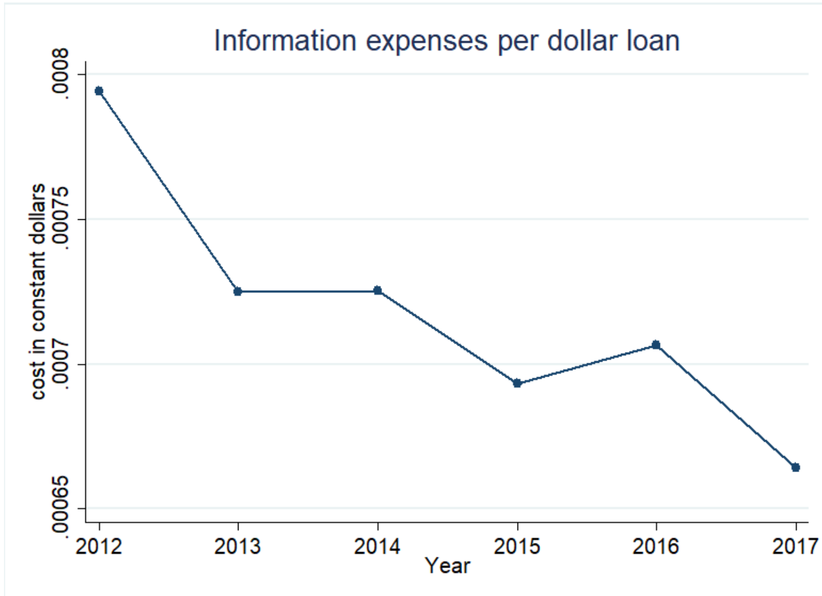
Figure 2.4: Increasing Usage of Information Technology



The figure shows banks' software stock increased from $18 billion to $36 billion during 2002 to 2016 in constant 2017 dollars. Banks' software stock includes prepared software (ENS1), custom software (ENS2), and own-account software (ENS3). The data are from the Bureau of Economic Analysis (BEA), Current-Cost Net Capital Stock of Private Nonresidential Fixed Assets Table.

small business lending relative to total bank loans. Small business loans as a share of total bank loans decreased monotonically from about 6.7% to about 3.5%. Fig.2.7 and Fig.2.8 show the increasing concentration in the US commercial banking market: the market share of large banks with loans of more than $1 billion increased from 82% to 90%; the number of small banks with loans of less than $100 million dollars decreased from 4,707 to 2,072.

Figure 2.5: Decreasing Costs of Using Information Technology

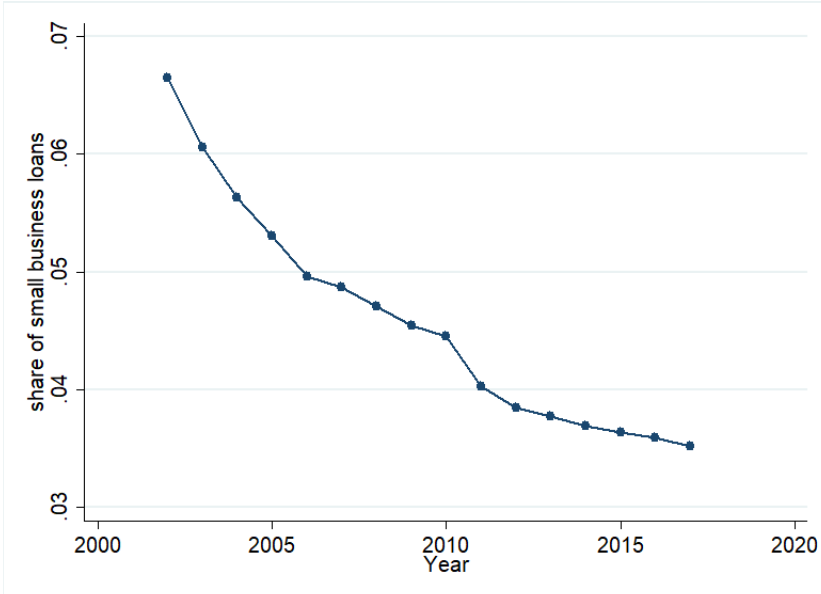


The figure shows that the cost of processing information per dollar of loan decreased over time, from .078% to .067% from 2012 to 2017. This item represents total costs and fees incurred in processing banks' data, including computer services, technology expense and software expenses. The information costs of per dollar loans equal banks' information expenses divided by total loans. Data are from Compustat Bank Fundamentals Annual.

2.2.3 Firm Sizes, Ages, Exit Rates, Loan Denial Rates and Job Creation Rates

I use data from the Business Dynamics Statistics (BDS) from 1977 to 2015, the 2014 Annual Survey of Entrepreneurs, US Census Bureau and Brown *et al.* (2015). Table 2.2 shows that younger firms have lower loan approval rates conditional on application, but can create more jobs with $1 million dollars of financing. Fig.2.9 shows that younger firms are smaller and have higher exit rates.

Figure 2.6: Share of Small Business Loans



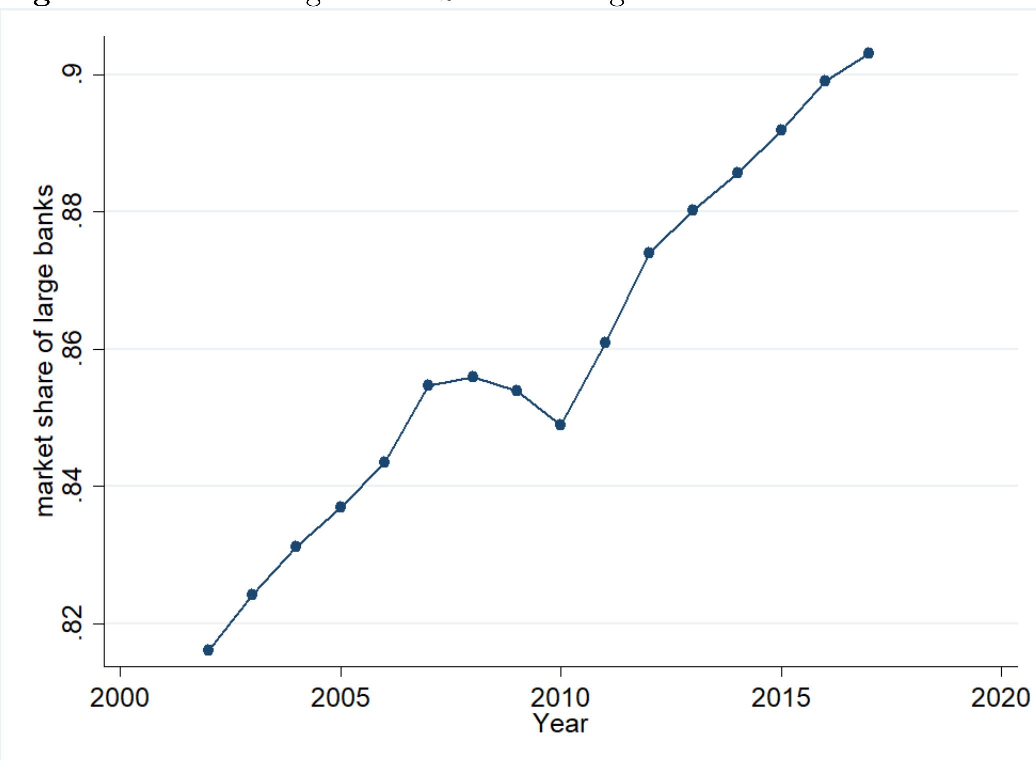
The figure shows that small business loans as a share of total bank loans decreased monotonically from about 6.7% to about 3.5% from 2002 to 2017. The data is from the FDIC reports on US depository institutions.

Table 2.2: Firm Age, Loan Approval Rates and Net Jobs Created

This table shows the relationship between firm ages, firms' loan approval rates and the net jobs created with one million dollars of bank loans. In the table, firms younger than 2 years in age created the most net new jobs with $1 million of bank loans; however, they had the least loan approval rates. Data Source: 2014 Annual Survey of Entrepreneurs, U.S. Census Bureau and Brown *et al.* (2015).

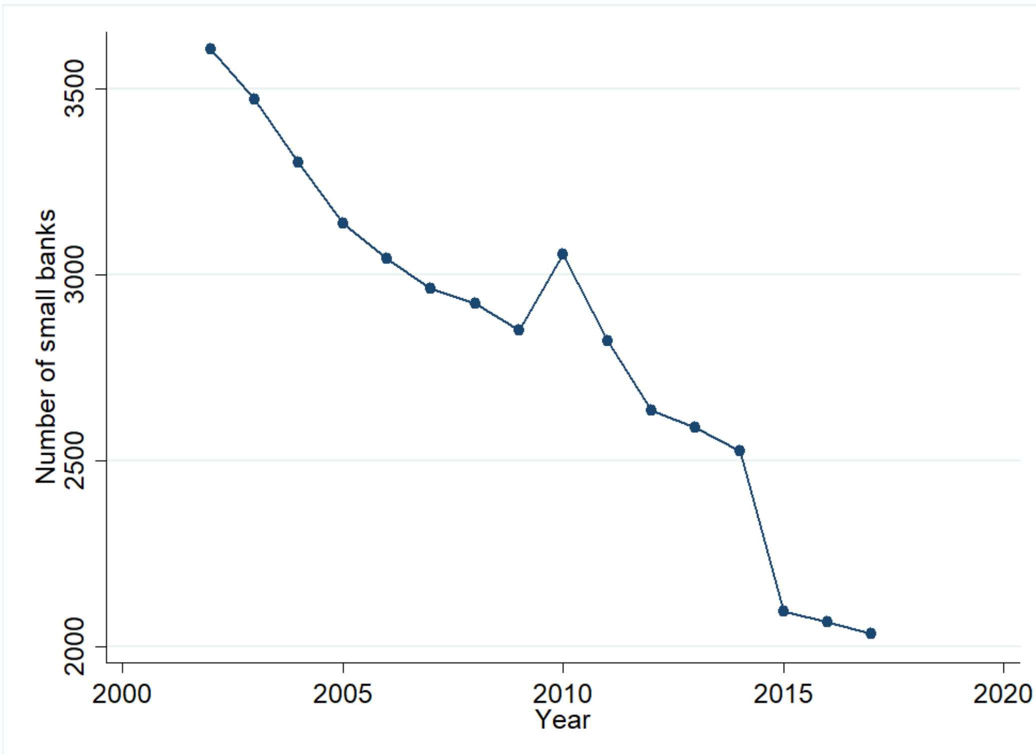
Age	**Approval Rates (%)**	**Net Jobs Created with $1 Million of Loans**
<2	61.5	3.13–5.34
2-3	65.7	3.13
4-5	69.3	2.96
6-10	72	2.96
11-15	79.3	3.02
>16	84.9	3.02

Figure 2.7: Increasing Market Share of Large Banks



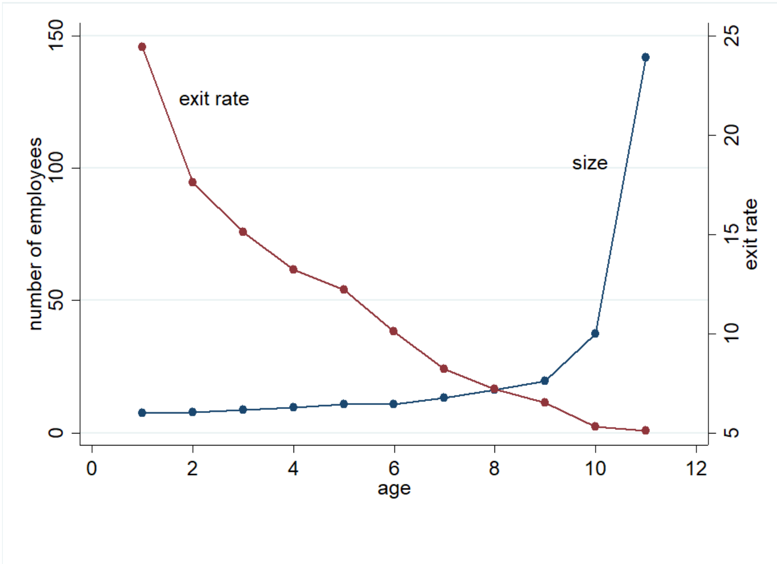
The figure shows that the market share of large banks with loans of more than \$1 billion increased from 82% to 90%. The data is from the FDIC reports on U.S. depository institutions. Dollars are in 2017 constant US dollars.

Figure 2.8: Exit of Small Banks



The figure shows that the number of small banks with loans of less than $100 million decreased from 4,707 to 2,072. The data is from the FDIC reports on US depository institutions. Dollars are in 2017 constant US dollars.

Figure 2.9: The Exit Rates of Small Firms



This figure shows that small and young firms have higher exit rates than large and old firms. Firms in the first age group are younger than two years 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-five years old. The data are from the Business Dynamics Statistics (BDS) for 1977 to 2015.

Chapter 3

DESTRUCTIVE CREATION IN THE US COMMERCIAL BANKING MARKET

We study the cleansing effect of the Great Recession on the US commercial banking market. The cleansing effect of recessions is "the essential fact about capitalism" and involves a large reallocation of labor and capital from inefficient to efficient production units of the economy (Schumpeter, 2010). Although the existence and the welfare implications of the cleansing effect are well established in theoretical framework (Aghion *et al.*, 2015; Caballero and Hammour, 1996), it is not clear empirically (Argente *et al.*, 2018; Barlevy, 2003; Aghion *et al.*, 2015; Foster *et al.*, 2016). Without a better understanding of the cleansing effect, we cannot better understand firms' technology adoption along business cycles and the barriers that prevent firms from adopting more advanced technology. If, during recessions, firms are encouraged to adopt new technology and abandon old, unproductive ones, then policy during recessions may be redesigned based on the mechanisms of the cleansing effect. This paper first uses a difference in differences empirical design to establish the causal relationship between the Great Recession and the accelerated adoption of internet banking (online banking and mobile banking) by commercial banks. Then we build a quantitative model to evaluate to what extent the cleansing effect during the Great Recession contributes to banks' adoption of internet banking and the welfare implications of the cleansing effect for retail consumers and firms in large and small cities.

In order to establish a causal relationship between the recession and banks' adoption of internet banking, we use a difference in differences empirical method. We use data from the Consumer Payment Survey to identify whether a consumer uses internet banking. We use the data from US Bureau of Labor Statistics to identify the states that were hit harder than average by the Great Recession. In the regression, states hit harder than average are the states with an increase in unemployment rates that is greater than the median level from January 2008 to January 2010. We compare the increase in consumer adoption of internet banking before and after the Great Recession in states that were hit harder and in the states hit less by the recession. We find that consumers in the first group of states are more likely to increase their adoption of internet banking after the recession. In the regression, we also find that consumers with higher income and consumers who are employed are more likely to adopt internet banking. Therefore, we exclude the concern that the recession lowers consumers' income and they then choose a cheaper method of banking.

To quantify to what extent the recession has increased banks' adoption of internet banking and to evaluate welfare implications of this change on retail consumers and firms, we build a quantitative framework with a model of general equilibrium. In the model, banks trade off branches and internet banking along business cycles in large and small cities and retail consumers decide whether to use internet banking and branch banking given the price ratio between internet banking and branch banking and their access to internet and smartphones. In the model, a large bank and a small, comparatively less productive bank, compete in three markets: that of retail service and the markets of business service in both large and small cities. Banks have two technologies: bank branches and internet banking. Branches can be used to provide business service and retail service. Internet banking can be used to provide retail service, but at a much lower cost. Therefore it is more productive to provide retail service by internet banking. However, banks have to pay costs to adjust their units of branches and internet banking. In the model, a bank has an option to restructure its production line of internet banking at a cost proportionate to its current profits. By doing so, the bank will have no cost to increase their units of internet banking, In normal times, when banks' profits are high, it is very costly to restructure; however, during a recession time period, banks have lower profits and thus lower costs to restructure. This is the benefit of waiting for a recession to restructure. However, as consumers have more and more access to the internet through computers and smartphones, they demand more and more internet banking. If a bank restructures earlier, it can better satisfy the increasing demand from consumers and can thereby gain profits. This is the cost of waiting for the recession to restructure. In the model, banks trade off the benefits and costs and decide when to restructure.

The popularity of smartphones coincides with the Great Recession. Therefore, there is a concern that banks may have restructured their production line of internet banking around the year 2009, not because of the cheaper costs to do so but because there was a jump in consumer demand for internet banking. To alleviate this concern, we model consumers' choices over internet banking and branches considering their access to internet and smartphones. By doing so, we can evaluate to what extent the cleansing effect of banks restructuring their line of production and reallocating their resources from less productive units (branches) to more productive units (internet banking) has increased banks' adoption of internet banking after the recession.

We use the simulated method of moments to identify the values of parameters in the model. The parameter in the adjustment costs of bank branches is identified from how fast banks closed branches from 2010 through 2016. The parameter in the adjustment costs of internet banking is identified from the percentage change in internet banking users from 1998 to 2009. The parameter that captures competition of large and small banks is identified from the difference in changes of bank branches in metropolitan areas and nonmetropolitan areas from 1998 through 2009. The parameter that measures banks' marginal costs of maintaining branches is identified from the difference in the number of branches opened by large banks between large and small cities from 1998 through 2009.The cost of internet banking is identified from the increase of internet banking after 2010. The parameters of consumers' preferences are identified from the share of internet banking from 2012 through 2015. In the data, we see that the number of internet banking users increased faster after the recession; therefore, banks chose to restructure during the recession. The parameter that measures the costs of restructuring is identified from this fact.

The model does a reasonable job in explaining the data. We set the first period of the model to the year 1998 in the data. That is, we take the average number of branches of a large bank, of a small bank in a large city, and of a small bank in a small city in 1998 as the starting values of the model. The number of branches increases/decreases gradually at a linear trend; therefore, we do not need to match all the points in each year period. We just need to match the critical points that include the number of branches in 2009 (when the number of branches peaked), the number of branches in 2010 (when the recession decreased banks' productivity), the number of branches in 2016 (the last period in the data), the increased percentage of internet banking from 1998 through 2009 (the time periods before the restructure) and the increased percentage of internet banking from 2010 through 2016 (the time periods after the restructure). The first group of moments is the number of branches for a large bank in a large city, a large bank in a small city, and a small bank in a small city in 2009. In the model, in 2009, the number of branches for a large bank in a large city is 8.4 (vs 8.24 in the data); the number of branches for a large bank in a small city is 2.41 (vs 2.56 in the data); the number of branches for a small bank in a large city is 2.17 (vs 2.27 in the data); the number of branches for a small bank in a small city is 1.83 (vs 1.71 in the data). The second group of moments is the number of branches for a large bank in a large city, a large bank in a small city, and a small bank in a small city in 2010. In the model, in 2010, the number of branches for a large bank in a large city is 7.87 (vs 8.91 in the data); the number of branches for a large bank in a small city is 1.9 (vs 2.25 in the data); the number of branches for a small bank in a large city is 2.22 (vs 2.59 in the data); the number of branches for a small bank in a small city is 1.73 (vs 1.7 in the data).The third group of moments is the number of branches for a large bank in a large city, a large bank in a small city, and a small bank in a small city in 2016. In the model, in 2016, the number of branches for a large bank in a large city is 8.31 (vs 8.57 in the data); the number of branches for a large bank in a small city is 2.22 (vs 2.49 in the data); the number of branches for a small bank in a large city is 2.1 (vs 1.98 in the data); the number of branches for a small bank in a small city is 1.78 (vs 1.62 in the data).The fourth group of moments includes the percentage of increase of internet banking from 1998 through 2009 and from 2010 through 2016. From 1998 through 2009, the unit of internet banking increased by 13 times (vs 14 times in the data) and from 2010 through 2016, the unit of internet banking increased by 0.97 times (vs 0.9 times in the data).

The estimation of the model shows that the cost of building up branches is one-eighth the cost of building up internet banking before the Great Recession. That is why, before the Great Recession, banks chose to build up branches to increase their supply of retail service. However, However, as the cost of providing a unit of retail service using internet banking is less than 2.5% as great as the cost of using branches, after the recession banks started to close branches and increased their rate of building up internet banking.

Branches will not disappear, though. Branches are used by banks to serve firms. The model shows that it is very profitable to keep branches and that the profits of having a branch in a large city are twice those of a bank in a small city. Therefore, after the recession, large banks close more branches in small cities compared to in large cities. However, the situation is very different for small banks. Although revenues are high from branches in large cities, the competition costs in large cities are also high. On average, both large and small banks have 10 branches in a large city but they have only 4 branches in a small city. Therefore, the competition costs in large cities are 2.5 times as high as in small cities. Most importantly, these competition costs account for 50% of banks' total costs of maintaining branches. Therefore, as small banks are not productive enough as to compete with large banks in large cities, they close a larger percentage of branches in large cities after the recession compared to large banks (the productivity of a small bank is as half as that of a large bank) compared to those closed by large banks because the productivity of a small bank is half that of a large bank. As small banks closed many branches, their marginal costs of having additional branch in small cities decrease, so they do not close as many branches in small cities as in large cities.

The model shows that restructuring will cost a bank 45% of its current profits. However, the recession lowers the cost of restructuring by at least 50%. Therefore, the restructure in 2010 accelerated large banks' adoption of internet banking since then. The model shows that, in 2016, the unit of internet banking is 47.3. However, suppose there is no restructure in 2010; the unit would be 30.3. This means that the restructuring increases the unit of internet banking in 2016 by 56%. The share of internet banking in 2016 would be 48% if there were no restructuring; it was 60% when restructuring happened in 2016. The average price of retail service in 2016 thus decreases by 37%, from 0.41 (without restructure in 2016) to 0.26 (with restructure in 2016) (The average price of retail service equals sum of the share of branch banking times the price of branch banking and the share of internet banking times the price of internet banking.) The decrease in the price of retail service comes from two parts: first, expensive branch banking is replaced by internet banking; second, internet banking itself becomes cheaper after the restructure. In 2016, the price of using a unit of branch banking is 0.62 and the price of using a unit of internet banking is 0.0074, which is less than 2% of that of branch banking. Because of the restructure, the share of internet banking in 2016 increases from 48% to 60%. If the share of internet banking had stayed at 48% instead of 60%, the average price of retail service would be 0.33. Therefore, the replacement of branches by internet banking itself contributes to 53% of the price drop. The drop of the price of internet banking thus accounts for 47% of the price reduction.

However, there are costs from the cleansing effect for firms in small cities. As banks replace branches with internet banking, some firms receive fewer loans. Without the cleansing effect and restructuring, in 2016, on average both large banks and small banks in small cities would have 4.1 branches in total. With the cleansing effect and restructuring, in 2016, on average both large banks and small banks in small cities would have 4 branches in total. Therefore, the cleansing effect reduces loans to firms in small cities by 2.5% in 2016.

We have three contributions to the literature. First, we use a difference in differences method to show that the cleansing effect–that is, branches replaced by internet banking–exists in the US commercial banking market, which is not empirically supported by previous literature (Dal Pont Legrand and Hagemann, 2017; Aghion *et al.*, 2015; Argente *et al.*, 2018; Barlevy, 2003; Eslava *et al.*, 2010; Foster *et al.*, 2016; Garcia-Macia *et al.*, 2016). We, therefore, support the conclusion from Hershbein and Kahn (2016), who find that more computer skills are demanded by employers after the Great Recession. In addition, we quantitatively evaluate the contribution from the cleansing effect to banks' adoption of internet banking. Second, we are the first to analyze the welfare effects from internet banking adoption and to contribute to the literature on e-commerce. Eslava *et al.* (2010) shows that the gain from e-commerce is equivalent to a 1.3% permanent increase in consumption by 2014. From our results, the effects can be large. The estimation results show that consumers' demand for retail service in 2016 is increased by more than 30% because banks adopt internet banking at a faster speed after the recession. Third, we explore some potential downsides of this creative destruction. Branches are valuable to business service, especially to small businesses (Nguyen, 2014). Many small businesses are located in small cities and, when banks close many branches in small cities, these small businesses can be more financially constrained than before.

3.1 Recession and Internet Banking Usage: Reduced-Form Evidence

In this section, We use a difference in differences regression design to show empirically that the Great Recession accelerated banks' adoption of internet banking. We use data from the Survey of Consumer Payment Choice, 2008-2013 and data from the US Bureau of Labor Statistics to test whether the recession from 2008 through 2010 accelerated bank's adoption of of internet banking. The data on internet banking usage is from the Survey of Consumer Payment Choice, 2008-2013. This data set contains repeated cross-section individual consumer data. This data set has information about a consumer's adoption of internet banking and his/her other demographic characteristics, including state of residence, income, age, marital status, education, gender, race and employment status. The recession data is from the US Bureau of Labor Statistics. This data set has information on the monthly unemployment rate of each US state. We define a state as heavily hit by the recession if it had an increase in unemployment above the median level of 5.3% from from January 2008 through January 2010. In the data, we can only see if the income level belongs to a certain range, not the absolute dollar amounts. I define high-income consumers as consumers with annual income more than 100,000 dollars. In the data set, about 10% of consumers have high income. The variable education is defined as 1 if the consumer has less than a 1st grade education; as 2 if the consumer completed 1st, 2nd, 3rd, or 4th grade; as 3 if the consumer completed 5th or 6th grade; as 4 if the consumer completed 7th or 8th grade; as 5 if the consumer completed 9th grade; as 6 if the consumer completed 10th grade; as 7 if the consumer completed 11th grade; as 8 if the consumer attended 12th grade but received no diploma; as 9 if the consumer has a high school diploma or the equivalent (for example, a GED); as 10 if the consumer has some college but no degree; as 11 if the consumer has an associate degree in a college occupational/vocational program; as 12 if the consumer has an associate degree in a college academic program; as 13 if the consumer has a bachelors degree (for example, BA, AB, or BS); as 14 if the consumer has a masters degree; as 15 if the consumer has a professional school degree (for example, MD, DDS, DVM, LLB, JD); and as 16 if the consumer has a doctoral degree (for example, PhD, EdD). A white consumer is indicated as 1. Employment status is defined as 1 if the consumer is employed and otherwise as 0. Marital status is defined as 1 if married and otherwise as 0. Gender is defined as 1 if male and otherwise as 0. In Table 3.4, I compare the income, age, marital status, education, gender, race, and employment status of the people surveyed from the hit states and the not-hit states. In Table 3.4, I compare the income, age, martial status, education, gender, race, employment status of the surveyed people from the hit states and the not hit states. I do not find significant difference between these two groups with respect to demographic characteristics and their adoption of internet banking before the crisis. Before the recession, all the states had about 70% of consumers using internet banking to make payments; after the recession, 78% of consumers used internet banking to make payments in the states hit hard by the recession and 74% of consumers used internet banking to make payments in the states not hit hard by the recession.

The empirical design uses a difference in differences approach. The treatment group is those states with an increase in the unemployment rate above the median level during the Great Recession. The control group includes other states. The period before treatment is from 2008 through 2010 and the period after treatment is from 2010 to 2013. We compare the results from the Probit model and the Logit model. The dependent variable in the regression is a dummy that indicates whether the consumer has adopted internet banking. The key independent variable is a cross of two dummies: the first one indicates whether the state where the consumer resides was hit heavily by the recession and the second one indicates the years after 2010. I include a consumer's income, age, marital status, education, gender, race and employment status and year-fixed effect in the regression. The regressions show that in the states that are heavily hit by the recession, there is a larger increase in the adoption of internet banking. However, the limitation in the data set is that we cannot separate the supply from the banks and the demand from the consumers. One possibility is that the recession lowers consumer's income and therefore, consumers use more internet banking, which is cheaper than branches. This concern is excluded by the result that consumers with income higher than 100 thousand dollars per year are more likely to adopt internet banking. Another concern is that the recession is not exogenous. Banks in the states hit hard by the recession have worse performance and tighter liquidity. This worse banking condition makes it more difficult for firms hit harder to survive. Therefore, we see more layoffs in these states. This concern will not affect our empirical results. In the paper, we are trying to show that it is cheaper to restructure the production line within banks when banks have lower profits, The regression is specified as

$$Internet\_banking\_adoption_{jit} = \beta_0 + \beta_1 recession_{it} \times year\_after\_2010_t$$

$$+controls_{jit} + \epsilon_{jit}$$

where $Internet\_banking\_adoption_{jit}$ is whether consumer j at state i has adopted internet banking at time t, $recession_{it}$ is a dummy variable whether state i is hit hard by the recession at time t, $year\_after\_2010_t$ is a dummy variable whether time t is after year 2010, and $controls_{jit}$ include the consumer's demographic characters. The results of the regressions are in Table 3.5

3.2 Model

The model is built on Koenders *et al.* (2005); Berger *et al.* (2012); Hendricks (2011). Two forces prevent banks from increasing the adoption of internet banking and the closing branches. Banks have adjustment costs in adopting internet banking and closing branches. These costs are identified in the literature as contracting, training, recruitment, and firing (Caballero and Hammour, 1996; Aghion *et al.*, 2015; Dal Pont Legrand and Hagemann, 2017; Hershbein and Kahn, 2016). When banks have increasing marginal costs of adjustment, they must adjust the units of branches or internet banking more slowly. This convexity in banks' cost function abstracts the role financial constraint plays in a bank. During recessions, banks have lower returns from branches and internet banking. As the marginal costs of adjustments do not decrease, banks will adjust less in order to reduce their costs. (Using Colombian establishment-level data, Eslava *et al.* (2010) present empirical evidence that the exit margin is distorted in times of financial constraints in a manner consistent with the model of Barlevy (2003).). A bank can restructure the production units so as to reduce the adjustment costs of internet banking to zero, but it needs to give up a proportion of profits of current period. In reality, the restructure can be setting up new positions, changing the production lines and re-matching positions with workers. These changes will distract managers' and workers' focus from producing and, therefore, are very costly. However, after these changes, a bank can have lower costs of recruiting and contracting with workers who can perform better at internet banking-related positions. As these costs are procyclic, banks prefer to restructure during recessions. However, over time, with the popularity of internet and smartphones, internet banking becomes more convenient for consumers. Therefore, banks may like to restructure as early as possible and may not wait until a recession.

The model also explains why large and small banks behave differently in large and small cities. Banks can sell their service at higher prices in larger cities than in small cities. Hence, banks are willing to open more branches in large cities. Therefore, it is more competitive and more expensive for banks to expand in large cities than in small cities. As large banks can produce more at the same cost, they gain more by opening branches in large cities than do small banks. Small banks, with low productivity, will find that the high costs of expansion are difficult to bear; therefore, small banks, small banks will open fewer new branches in large cities compared to large banks. When the technology changes reduce the price of retailing service and the costs of building up internet banking, the marginal benefits of bank branches decrease. As the marginal costs of maintaining branches increase, banks will close branches to decrease those costs. Large banks will keep their branches in large cities and close branches in small cities because large banks have higher marginal benefit from branches in large cities than in small cities. On the contrary, small banks will find the high costs of maintaining branches in large cities are harder to bear than before because of the decrease in marginal benefits. In addition, the competition in small cities is much reduced because of the exit of large banks. Therefore, small banks will close a higher percentage of branches in large cities than in small cities, compared to large banks.

Model Details

Periods $t = 1, 2, ...$ Two cities, a large city (LC) and a small city (SC), each with productivity A_x, $x = L, S$. Two banks, a large bank (LB) and a small bank (SB), each with productivity m^j, $j = LB, SB$. We assume that the productivity of the large bank is greater than that of the small bank, i.e. $m^{LB} > m^{SB}$. A firm at city x produces profits by its technology equal to

$$A_x b_x - r_x b_x$$

where b_x is the amount of bank service (bank product) used and r_x is the price of bank loan. The assumption is that both large banks and small banks provide identical loans at the same prices in each city.

A bank maximizes expected profits. A bank has two methods of delivering products/service (used interchangeably) to its customers. It can either use a branch or use internet banking to deliver its products/services. A bank also has two types of customers: retail customers and business customers (firms). Retail customers need retail service while firms need business service from banks. A bank produces 1 unit of retail service with a unit of branch or with a unit of internet banking. Thus, retail customers can either be served by a branch or by internet banking. A bank also produces 1 unit of business service with a unit of branch. Thus, firms (business customers) can only be served by a branch.

Let $B^j_{x,t}$ denote the number of branches of bank j in city x at time t. The cost of branches for bank j is:

$$c^j_{B,t} \;=\; c_0(\textstyle\sum_x B^j_{x,t})^2 + c_1 \sum_x(\sum_j B^j_{x,t})B^j_{x,t}$$

The first term of the cost captures the decreasing returns to scale in banks' production technology and the second part captures the increasing cost of branch expansion due to competition in a city between two banks. The cost of internet banking is:

$$c^j_{I,t} \;=\; c_I I^j_t$$

for bank j with I^j_t units of internet banking in period t. We use the subscript B to denote branches and I to denote internet banking, respectively.

A bank faces increasing marginal costs to adjust its production units. That is, $\frac{\phi_B}{2}\sum_x\left(\Delta B^j_{x,t}\right)^2$ represents the additional investments in increasing the number of branches for a bank j at time t across all cities x and $\frac{\phi_I}{2}\left(\Delta I^j_t\right)^2$ for the increase in internet banking for bank j at time t. The bank has the option of restructuring its internet banking system by forgoing a portion of its profits this period. By doing so, it eliminates all the adjustment costs for increasing its internet banking capacity in the future. That is, by restructuring its internet banking system, ϕ_I is reduced to 0 for all future periods. However, it will lose λ proportion of its profits of this period. This generates a trade-off between restructuring during normal times when profits are high versus restructuring during recessions when profits are low. By incurring a higher cost of restructuring during normal times, the bank might be able to deliver retail service through internet banking at a lower cost to its customers (compared to branch banking). We discuss additional details of the retail service demand while defining the retail consumer's problem.

Bank j's Problem

The bank maximizes its profits by choosing whether to restructure its internet banking system, R_t^j. $R_t^j = 1$ means restructuring in period t and otherwise, 0; its units of branches and internet banking, $\{B_{LC,t}^j, B_{SC,t}^j, I_t^j\}$,

$$\max_{\{B_{LC,t}^j, B_{SC,t}^j, I_t^j, R_t^j\}} (1-\lambda R_t^j)\Bigg\{ m^j (p_{B,t}(B_{LC,t}^j + B_{SC,t}^j) + p_{I,t}\ I_t^j) + m^j \sum_x r_x B_{x,t}^j$$

$$-\frac{c_0}{2}(\sum_x B_{x,t}^j)^2 - \sum_x c_1(\sum_j B_{x,t}^j) B_{x,t}^j$$

$$-c_I I_t^J - \frac{\phi_B}{2}\sum_x \left(\Delta B_{x,t}^j\right)^2 - \frac{\phi_I}{2}\left(\Delta I_t^j\right)^2 \Bigg\} +$$

$$\beta\Bigg\{ R_t^j V^R(B_{LC,t}^j, B_{SC,t}^j, I_t^j, B_{LC,t}^{-j}, B_{SC,t}^{-j}, I_t^{-j})$$

$$+(1-R_t^j)V^{NR}(B_{LC,t}^j, B_{SC,t}^j, I_t^j, B_{LC,t}^{-j}, B_{SC,t}^{-j}, I_t^{-j})\Bigg\}$$

where V^R is the continuation value after restructuring and V^{NR} is the continuation value if there is no restructuring. The subscript -j denotes all competitor banks of bank j. In the model, a bank can only restructure once. That is, $R_t = 0$, if there is $j > 0$ such that $R_{t-j} = 1$. In addition, the small bank will never restructure given the assumptions. Suppose the small bank restructures before the large bank. When the small bank finds it profitable to restructure, the large bank will it profitable to restructure too, given its assumed productivity advantage over the small bank. When (after) the large bank restructures, the small bank will find find it unprofitable to further build up internet banking because of the ability of the large bank to set the internet banking price as low as possible to eliminate profits for the small bank, while it continues to be profitable due to its higher productivity. Therefore, the small bank will not restructure.

Consumer's Problem

In the model, there is a representative retail consumer. The retail service demand is:

$$D_t = D/(p_{B,t}^{\rho} + p_{I,t}^{\rho})^{\frac{1}{\rho}}$$

where $p_{B,t}$ is the price for retail service provided by a branch (assumed to be the same in both the large city and the small city) and $p_{I,t}$ is the price for retail service provided by internet banking (again, common to both cities), both prices at time t and D is a parameter and $\frac{1}{1-\rho}$ is the constant elasticity of substitution between the two retail services. Banks are price takers in a competitive market. Thus, the retail service product is homogeneous across both cities and the type of banks and can be supplied by either the small bank or the large bank either through a branch or through internet banking. Recall, in contrast, that the business service demand b_x is different in each city because firms utilization the funds depends on the productivity in each city. The business service demand can also be supplied by either the small bank or the large bank at the same market clearing price. Thus, banks' differences in productivity deliver different revenues for the products (while the costs are assumed to be the same across the banks).

The consumer maximizes his/her utility by choosing whether to use internet banking or branches. The consumer's utility of using internet banking is given following Berry *et al.* (1995)

$$U_{I,t} = \gamma_0 + \gamma_1 \frac{p_{I,t}}{p_{B,t}} + \gamma_2 x + \epsilon$$

the consumer's utility of using branches is given by

$$U_{B,t} = \gamma_0^{'} + \gamma_1^{'} \frac{p_{I,t}}{p_{B,t}} + \gamma_2^{'} x + \epsilon^{'}$$

where γ_0, γ_1, γ_2, $\gamma_0^{'}$, $\gamma_1^{'}$, and $\gamma_2^{'}$ are parameters, x is the consumer's probability of access to smartphones, and ϵ and $\epsilon^{'}$ are the type-I errors that follow an extreme value distribution. During our sample period, consumer's use of smartphones for internet banking service increased dramatically from a near-zero base. Thus, there is a demand-induced increase in internet banking services that must be explicitly disentangled before drawing any conclusions about the bank's incentive to supply these services. (The share population with smartphones increased from 13% to 77% from 2009 through 2017 and the shares of internet banking users increased from 30% to 76% from 1998 through 2016. Data source: Consumers and Mobile Financial Services and The World Bank.)

The consumer will choose internet banking if and only if

$$U_{I,t} > U_{B,t}$$

That is

$$\gamma_0 + \gamma_1 \frac{p_{I,t}}{p_{B,t}} + \gamma_2 x + \epsilon > \gamma_0^{'} + \gamma_1^{'} \frac{p_{I,t}}{p_{B,t}} + \gamma_2^{'} x + \epsilon^{'}$$

Then

$$Q_{I,t} = \int_{-\infty}^{\infty} \int_{(\gamma_0^{'} - \gamma_0) + (\gamma_1^{'} - \gamma_1) \frac{p_{I,t}}{p_{B,t}} + (\gamma_2^{'} - \gamma_2) x + \epsilon^{'}}^{\infty} dF(\epsilon) dF(\epsilon^{'})$$

where $F(\epsilon) = exp(-exp(-\epsilon))$, $F(\epsilon^{'}) = exp(-exp(-\epsilon^{'}))$, the cumulative density function of the extreme value (Type-I) distribution (See the details in appendix).

Therefore the probability of choosing internet banking, $Q_{I,t}$, is the logistic distribution:

$$\frac{exp\left\{(\gamma_0 - \gamma_0^{'}) + (\gamma_1 - \gamma_1^{'})\frac{p_{I,t}}{p_{B,t}} + (\gamma_2 - \gamma_2^{'})x\right\}}{1 + exp\left\{(\gamma_0 - \gamma_0^{'}) + (\gamma_1 - \gamma_1^{'})\frac{p_{I,t}}{p_{B,t}} + (\gamma_2 - \gamma_2^{'})x\right\}}$$

Redefine $\gamma_0 - \gamma_0^{'} = \gamma_0$, $\gamma_1 - \gamma_1^{'} = \gamma_1$, $\gamma_2 - \gamma_2^{'} = \gamma_2$, then $Q_{I,t}$ is

$$\frac{exp\left\{\gamma_0 + \gamma_1\frac{p_{I,t}}{p_{B,t}} + \gamma_2 x\right\}}{1 + exp\left\{\gamma_0 + \gamma_1\frac{p_{I,t}}{p_{B,t}} + \gamma_2 x\right\}}$$

Equilibrium

The competitive equilibrium is defined as a price for retailing service (both branch banking and internet banking), $p_{B,t}$ and $p_{I,t}$, prices for firm service at each location, r_L, r_S, banks' choices on the number of branches at time t in both cities, the level of internet banking and the decision to restructure at time t, $\{B^j_{LC,t}, B^j_{SC,t}, I^j_t, R^j_t\}_{j=LB,SB}$, such that

(1) Banks' choices $\{B^j_{LC,t}, B^j_{SC,t}, I^j_t, R^j_t\}_{j=LB,SB}$ and the continuation values, V^R and V^{NR} solve the banks' optimization problems.

(2) Given banks' choices $\{B^j_{LC,t}, B^j_{SC,t}, I^j_t, R^j_t\}_{j=LB,SB}$, and the price of retailing service provided by branches, $p_{B,t}$, the retailing market for bank branch is cleared,

$$(1 - Q_{I,t})D_t = \sum_{j=LB,SB} m^j(B^j_{LC,t} + B^j_{SC,t}) \tag{3.1}$$

where $Q_{I,t}$ is the probability the consumer chooses internet banking.

(3) Given banks' choices $\{B^j_{LC,t}, B^j_{SC,t}, I^j_t, R^j_t\}_{j=LB,SB}$, and the price of retailing service provided by internet banking, $p_{I,t}$, the retailing market for internet banking is cleared,

$$Q_{I,t}D_t = \sum_{j=LB,SB} m^j I^j_t \tag{3.2}$$

(4) Given banks' choices $\{B^j_{LC,t}, B^j_{SC,t}, I^j_t, R^j_t\}_{j=LB,SB}$, and the price of firm service, $\{r_x\}$, the market of firm service is cleared (firms make zero profits),

$$r_x = A_x$$

for $x = LC, SC$

Unexpected Recession

The starting period in the model is the year 1998. The Great Recession is captured in the model as an unexpected, negative shock to banks' productivity, a shock that occurs in the $t = t_r$ period of the model. As the shock is unexpected by banks and lasts for only one time period, the banks' policy function before and after the shock will not change. The banks' decisions are affected by the shock, only in the period when the shock occurs.

In the recession, the productivity of both large and small banks are reduced by a fraction v. Bank j's problem at period $t = t_r$ is

$$\max_{\{B^j_{LC,t_r}, B^j_{SC,t_r}, I^j_{t_r}, R^j_{t_r}\}} (1-\lambda R^j_{t_r})\Bigg\{(1-v)m^j(p_{B,t_r}(B^j_{LC,t_r}+B^j_{SC,t_r})+p_{I,t_r}\ I^j_{t_r})$$

$$+(1-v)m^j\sum_x r_x B^j_{x,t_r}$$

$$-\frac{c_0}{2}(\sum_x B^j_{x,t_r})^2-\sum_x c_1(\sum_j B^j_{x,t_r})B^j_{x,t_r}-c_I I^J_{t_r}-\frac{\phi_B}{2}\sum_x\left(\Delta B^j_{x,t_r}\right)^2-\frac{\phi_I}{2}\left(\Delta I^j_{t_r}\right)^2\Bigg\}+$$

$$\beta\Bigg\{R^j_{t_r}V^R(B^j_{LC,t_r}, B^j_{SC,t_r}, I^j_{t_r}, B^{-j}_{LC,t_r}, B^{-j}_{SC,t_r}, I^{-j}_{t_r})+$$

$$(1-R^j_{t_r})V^{NR}(B^j_{LC,t_r}, B^j_{SC,t_r}, I^j_{t_r}, B^{-j}_{LC,t_r}, B^{-j}_{SC,t_r}, I^{-j}_{t_r})\Bigg\}$$

where V^R is the continuation value after restructuring and V^{NR} is the continuation value before restructuring. In the model, a bank can only restructure once. That is, $R_t = 0$, if there is $j > 0$, $R_{t-j} = 1$.

3.3 Estimation

We use method of moments to identify the values of a set of key parameters in the model, so that the model can explain banks' opening and closing of branches and adoption of internet banking before and after the Great Recession.

3.3.1 Data

We use US individual bank branch level data from 1998 to 2017 from the Summary of Deposits (SOD) which is an annual survey of branch office deposits maintained by the Federal Deposit Insurance Corporation (FDIC). This data set contains the information about bank branches, including location (state, county, city), deposits in the branch, bank name, and bank holding company name.The starting date of 1998 corresponds to the period when internet banking is tracked by the Pew Research Center. We define large banks as those banks that belong to a bank holding company with total deposits in the top 20% of the deposit distribution every year, and small banks as the other remaining banks. In our sample, on average, there are about 144,980 bank-year data points, 7,249 banks every year and, of these, on average 1,450 are classified as large banks. We define large cities as metro areas that contain a core urban area population of 50,000 or more (following the definition used by FDIC) and small cities as all other cities. Internet banking is defined as both online banking and mobile banking. The data about online banking and mobile banking is from the following sources: Survey of Consumers' Use of Mobile Financial Services (2012-2016) conducted by the Federal Reserve Board, Digital Banking Consumer Survey done by PwC, Emarketer, and Bank of America. The number of internet banking users increased by 35 times, from 10 million users in 1998 to 360 million users in 2017. The market share of internet banking is calculated as the percent of bank service users who use internet banking to sum of the percent of bank service users who use internet banking and the percent of bank service users who use branches (some percent of users in the survey claim to use neither of these services). This data is obtained from the Survey of Consumers' Use of Mobile Financial Services (2012-2016) and used as target moments for the model.

The market share of internet banking (online and mobile users) increased from 52% to 57% from 2012 to 2015, corresponding to a decline in branch banking from 48% to 43% during the same period. The share of smartphone users as a proportion of the population in the US has increased dramatically from 13% in 2009 to 77% in 2017. A vast majority of these smartphone users also use banking services on their phones. Thus an increasing share of internet banking users comprises mobile users during this period. We explicitly model this demand-driven increase in internet banking in our calculations to estimate the effect of the bank supply of these services and the effect of technology shocks on this supply.

3.3.2 Computation Method

We compute banks' policy functions, price function and the value functions. We begin by enumerating the F.O.C of the problem. The F.O.C of the bank's problem is (1) F.O.C with respect to $B^j_{x,t}$, $\forall$ x=LC,SC *and* j=LB,SB

$$m^j p_{B,t} + m^j r_x - c_0(\sum_x B^j_{x,t}) - c_1 \sum_j B^j_{x,t} - c_1 B^j_{x,t} - \phi_B(B^j_{x,t} - B^j_{x,t-1})$$
$$+\beta\phi_B(B^j_{x,t+1} - B^j_{x,t}) = 0$$

(2) F.O.C with respect to I^j_t, $\forall$ j=LB,SB

$$m^j p_{I,t} - c_I - \phi_I(I^j_t - I^j_{t-1}) + \beta\phi_I(I^j_{t+1} - I^j_t) = 0 \tag{3.3}$$

From these six equations (four for the first F.O.C. and two for the second F.O.C) we can solve for the six unknowns, $B^j_{x,t}$ and I^j_t. However, the above equations show that $B^j_{x,t}$ and I^j_t depend on their future values, $B^j_{x,t+1}$ and I^j_{t+1} respectively. We simplify the computation by assuming linear policy functions. (Since the seminal papers of Kydland and Prescott (1982) and King *et al.* (1988), it has become commonplace in macroeconomics to approximate the solution to non-linear, dynamic, stochastic, general equilibrium models using linear methods. Linear approximation methods are useful to characterize certain aspects of the dynamic properties of complicated models ((Schmitt-Grohé and Uribe, 2004)).) That is, banks' decisions $B^j_{x,t}, I^j_t$, are linearly correlated with state variables $B^j_{x,t-1}, B^j_{-x,t-1}, B^{-j}_{x,t-1}, I^j_{t-1}, I^{-j}_{t-1}$.

$$B^j_{x,t} = \alpha^j_{x,0} + \alpha^j_{x,1} B^j_{x,t-1} + \alpha^j_{x,2} B^j_{-x,t-1} + \alpha^j_{x,3} B^{-j}_{x,t-1} + \alpha^j_{x,4} I^j_{t-1} + \alpha^j_{x,5} I^{-j}_{t-1} \tag{3.4}$$

$$I^j_t = \theta^j_0 + \theta^j_1 I^j_{t-1} + \theta^j_2 I^{-j}_{t-1} \tag{3.5}$$

The values for $\alpha^j_{x,k}$ and θ^j_h are calculated by iterations. At a set of starting values of $\alpha^j_{x,k}$ and θ^j_h, we compute banks' choices $B^j_{x,t}, I^j_t$. Then, we estimate the two regressions specified above (using the computed values of $B^j_{x,t}, I^j_t$ in the first iteration as data) to update $\alpha^j_{x,k}$ and θ^j_h. Using the updated values of $\alpha^j_{x,k}$ and θ^j_h, we can now estimate a new series of bank's choices over time, $B^j_{x,t}, I^j_t$. We iterate the above two steps until the values of $\alpha^j_{x,k}$ and θ^j_h change little between iterations. The convergence of $\alpha^j_{x,k}$ and θ^j_h and the high R^2 for each regression guarantee that the banks' optimal choices can be explained by state variables in a stable and linear fashion.

We begin by conjecturing values for $p_{B,t}$ and $p_{I,t}$, the prices of the branch and internet retail services. These prices will have to clear the equilibrium condition (that equates the demand and supply of these services, outlined in equations 2.1 and 2.2) and the six F.O.C.'s for each period, enumerated above.

- Step 1: We first find the values for α and θ in equations 3.3 and 3.4. We begin the process with a conjecture for α and θ

- Step 2: With a given α and θ from Step 1, we find the value of $p_{B,t}$ and $p_{I,t}$. We begin the process with a conjecture for $p_{B,t}$ and $p_{I,t}$

  - We replace $B^j_{x,t+1}$ in equation 3.1 using the policy function given by equation 3.3 and replace I^j_{t+1} in equation 3.2 using the policy function given by equation 3.4.

  - We use equations 3.1 and 3.2 to solve $B^j_{x,t}$ and I^j_t and thus calculate the supply of the branch and internet banking retail service across cities and banks. Summing up both these services across all cities and banks provides us with the aggregate supply that equals aggregate demand of the representative consumer (assuming the system is in equilibrium).

  - Using the aggregate demand function of the representative consumer (equation 2.1 and 2.2 in which D_t is replaced with equation x.y), we can solve for the prices $p_{B,t}$ and $p_{I,t}$. We then compare these two solved prices with our conjectured prices at the beginning of this step.
  - We then update the values for $p_{B,t}$ and $p_{I,t}$ and repeat Step 2. We continue this iteration process until the the successive values of $p_{B,t}$ and $p_{I,t}$ converge to a pre-specified tolerance.

- Step 3: We now re-estimate the regressions in equation 3.3 and 3.4 (adding the new estimated values of $B^j_{x,t}$ and I^j_t to the sample) and update the values of α and θ. We then use the new values of α and θ and repeat Step 2. We stop when successive values of α and θ converge to a pre-specified tolerance.

The computation of value functions uses the contraction mapping theorem by iteration as the standard. However, there are two differences from the standard steps. The first difference is that we first compute the banks' continuation value after restructuring (which occurs only once in the model) and, using these values to solve for the banks' choices of restructuring, compute the banks' continuation values before restructuring. At each set of values of the state variables (the branch and internet banking choices of the banks and their competitors), banks compare the benefit and cost of restructuring and make decisions accordingly. The second difference is that we assume the policy function is a linear function of the state variables (equations 3.3 and 3.4) rather than re-solving the market clearing conditions at each set of values of state variables, when computing the value functions.

3.3.3 Estimation Results

We use the simulated method of moments to identify the values of parameters in the model. The parameter in the adjustment costs of bank branches ϕ_B is identified from how fast banks closed branches from 2010 through 2016. The parameter in the adjustment costs of internet banking ϕ_I is identified from the percentage change in internet banking users from 1998 to 2009. The parameter that captures competition of large and small banks c_1 is identified from the difference in changes of bank branches in metropolitan areas and nonmetropolitan areas from 1998 through 2009. The parameter that measures banks' marginal costs of maintaining branches c_0 is identified from the difference in the number of branches opened by large banks between large and small cities from 1998 through 2009. The cost of internet banking c_I is identified from the increase of internet banking after 2010. The parameters of consumers' preferences γ_1, γ_2 are identified from the share of internet banking from 2012 through 2015. In the data, we see that the number of internet banking users increased faster after the recession; therefore, banks chose to restructure during the recession. The parameter that measures the costs of restructuring λ is identified from this fact. The parameter measures the degree of recession v is jointly identified from the restructure choices and the number of branches in 2010. The discounting factor β is set to .97. The value of ρ is normalized to 1. (We can normalize this parameter to 1 because the consumer's preference y1 already captures the substituting rate of internet banking and branches.) The parameter γ_0 is normalized to 0. The parameter D is normalized to 50. The values of parameters are in Table 3.2 and the comparison of data and model moments is in Table 3.3.

The model does a reasonable job in explaining the data. We set the first period of the model to the year 1998 in the data. That is, we take the average number of branches of a large bank, of a small bank in a large city, and of a small bank in a small city in 1998 as the starting values of the model. The number of branches increases/decreases gradually at a linear trend; therefore, we do not need to match all the points in each year period. We just need to match the critical points that include the number of branches in 2009 (when the number of branches peaked), the number of branches in 2010 (when the recession decreased banks' productivity), the number of branches in 2016 (the last period in the data), the increased percentage of internet banking from 1998 through 2009 (the time periods before the restructure) and the increased percentage of internet banking from 2010 through 2016 (the time periods after the restructure). The first group of moments is the number of branches for a large bank in a large city, a large bank in a small city, and a small bank in a small city in 2009. In the model, in 2009, the number of branches for a large bank in a large city is 8.4 (vs 8.24 in the data); the number of branches for a large bank in a small city is 2.41 (vs 2.56 in the data); the number of branches for a small bank in a large city is 2.17 (vs 2.27 in the data); the number of branches for a small bank in a small city is 1.83 (vs 1.71 in the data). The second group of moments is the number of branches for a large bank in a large city, a large bank in a small city, and a small bank in a small city in 2010. In the model, in 2010, the number of branches for a large bank in a large city is 7.87 (vs 8.91 in the data); the number of branches for a large bank in a small city is 1.9 (vs 2.25 in the data); the number of branches for a small bank in a large city is 2.22 (vs 2.59 in the data); the number of branches for a small bank in a small city is 1.73 (vs 1.7 in the data).The third group of moments is the number of branches for a large bank in a large city, a large bank in a small city, and a small bank in a small city in 2016. In the model, in 2016, the number of branches for a large bank in a large city is 8.31 (vs 8.57 in the data); the number of branches for a large bank in a small city is 2.22 (vs 2.49 in the data); the number of branches for a small bank in a large city is 2.1 (vs 1.98 in the data); the number of branches for a small bank in a small city is 1.78 (vs 1.62 in the data).The fourth group of moments includes the percentage of increase of internet banking from 1998 through 2009 and from 2010 through 2016. From 1998 through 2009, the unit of internet banking increased by 13 times (vs 14 times in the data) and from 2010 through 2016, the unit of internet banking increased by 0.97 times (vs 0.9 times in the data).

The estimation of the model shows that the cost of building up branches is one-eighth the cost of building up internet banking before the Great Recession. That is why, before the Great Recession, banks chose to build up branches to increase their supply of retail service. However, However, as the cost of providing a unit of retail service using internet banking is less than 2.5% as great as the cost of using branches, after the recession banks started to close branches and increased their rate of building up internet banking.

Branches will not disappear, though. Branches are used by banks to serve firms. The model shows that it is very profitable to keep branches and that the profits of having a branch in a large city are twice those of a bank in a small city. Therefore, after the recession, large banks close more branches in small cities compared to in large cities. However, the situation is very different for small banks. Although revenues are high from branches in large cities, the competition costs in large cities are also high. On average, both large and small banks have 10 branches in a large city but they have only 4 branches in a small city. Therefore, the competition costs in large cities are 2.5 times as high as in small cities. Most importantly, these competition costs account for 50% of banks' total costs of maintaining branches. Therefore, as small banks are not productive enough as to compete with large banks in large cities, they close a larger percentage of branches in large cities after the recession compared to large banks (the productivity of a small bank is as half as that of a large bank) compared to those closed by large banks because the productivity of a small bank is half that of a large bank. As small banks closed many branches, their marginal costs of having additional branch in small cities decrease, so they do not close as many branches in small cities as in large cities.

The model shows that restructuring will cost a bank 45% of its current profits. However, the recession lowers the cost of restructuring by at least 50%. Therefore, the restructure in 2010 accelerated large banks' adoption of internet banking since then. The model shows that, in 2016, the unit of internet banking is 47.3. However, suppose there is no restructure in 2010; the unit would be 30.3. This means that the restructuring increases the unit of internet banking in 2016 by 56%. The share of internet banking in 2016 would be 48% if there were no restructuring; it was 60% when restructuring happened in 2016. The average price of retail service in 2016 thus decreases by 37%, from 0.41 (without restructure in 2016) to 0.26 (with restructure in 2016) (The average price of retail service equals sum of the share of branch banking times the price of branch banking and the share of internet banking times the price of internet banking.) The decrease in the price of retail service comes from two parts: first, expensive branch banking is replaced by internet banking; second, internet banking itself becomes cheaper after the restructure. In 2016, the price of using a unit of branch banking is 0.62 and the price of using a unit of internet banking is 0.0074, which is less than 2% of that of branch banking. Because of the restructure, the share of internet banking in 2016 increases from 48% to 60%. If the share of internet banking had stayed at 48% instead of 60%, the average price of retail service would be 0.33. Therefore, the replacement of branches by internet banking itself contributes to 53% of the price drop. The drop of the price of internet banking thus accounts for 47% of the price reduction.

However, there are costs from the cleansing effect for firms in small cities. As banks replace branches with internet banking, some firms receive fewer loans. Without the cleansing effect and restructuring, in 2016, on average both large banks and small banks in small cities would have 4.1 branches in total. With the cleansing effect and restructuring, in 2016, on average both large banks and small banks in small cities would have 4 branches in total. Therefore, the cleansing effect reduces loans to firms in small cities by 2.5% in 2016.

3.4 Conclusions

In this paper, we study the cleansing effect of the Great Recession. We first use a difference in differences empirical framework to show that, in states hit hard by the recession, consumers adopted more internet banking. We exclude the concern that recession lowers consumers' income and, thus, they adopt cheaper methods of banking. Therefore, we conclude that the recession makes banks accelerate their adoption of internet banking. Next, we use a structural model to quantify the costs of restructuring and to evaluate the welfare implications of the cleansing effect for retail consumers and firms in large and small cities. We find that the price of retail service is lowered by about 37%; however, firms in small cities receive fewer loans from banks.

Table 3.1: Description of Parameters and Variables

This table shows the description for each parameter and variable.

Parameter	**Description**
c_1	competition costs
c_0	marginal costs of branches
c_I	marginal costs of internet banking
ϕ_B	adjustment costs of branches
ϕ_I	adjustment costs of internet banking
A_L	large city's productivity
A_S	small city's productivity
m^{LB}	large bank's productivity
m^{SB}	small bank's productivity
λ	restructure costs
v	negative shock to banks' productivity
γ_0	preference parameter
γ_1	consumer's price sensitivity
γ_2	preference with smart-phone effect
$B^j_{x,t}$	bank j's branches at city x at time t
	serve firms at city x and retail customers at both cities
I^j_t	bank j's internet banking at time t
	serve retail customers at both cities
R^j_t	bank j's restructuring choice at time t

Table 3.2: Values of Parameters and Targeted Moments

This table shows the values for each parameter.We use the simulated method of moments to identify the values of parameters in the model. The parameter in the adjustment costs of bank branches ϕ_B is identified from how fast banks closed branches from 2010 through 2016. The parameter in the adjustment costs of internet banking ϕ_I is identified from the percentage change in internet banking users from 1998 to 2009. The parameter that captures competition of large and small banks c_1 is identified from the difference in changes of bank branches in metropolitan areas and nonmetropolitan areas from 1998 through 2009. The parameter that measures banks' marginal costs of maintaining branches c_0 is identified from the difference in the number of branches opened by large banks between large and small cities from 1998 through 2009. The cost of internet banking c_I is identified from the increase of internet banking after 2010. The parameters of consumers' preferences γ_1, γ_2 are identified from the share of internet banking from 2012 through 2015. In the data, we see that the number of internet banking users increased faster after the recession; therefore, banks chose to restructure during the recession. The parameter that measures the costs of restructuring λ is identified from this fact. The parameter measures the degree of recession v is jointly identified from the restructure choices and the number of branches in 2010. The discounting factor β is set to .97. The value of ρ is normalized to 1. The parameter $gamma_0$ is normalized to 0.

Parameter	**Description**	**Value**	**Moments**
c_1	competition between banks	.2	large and small
		(.0015)	banks' branch growth (reduction) rate
c_0	marginal costs of branches	.28	large and small
		(.0018)	banks' branch growth (reduction) rate
c_I	marginal costs	.00004	banks' internet banking
	of internet banking	(.0032)	growth rate

Parameter	Description	Value	Moments
ϕ_B	adjustment costs of branches	2.4	branch closure after 2010
		(.0016)	
ϕ_I	adjustment costs of internet banking	18	internet banking growth rate
		(.13)	
A_{LC}	large city's productivity	2.02	large cities' branches
		(.016)	
A_{SC}	small city's productivity	1.03	small cities' branches
		(.0036)	
m^{LB}	large bank's productivity	2.54	large banks' branches
		(.0071)	
m^{SB}	small bank's productivity	1.36	small banks' branches
		(.0011)	
γ_0	normalized	0	
γ_1	price sensitivity	-2.5	increase in internet banking
		(.013)	
γ_2	smart-phone effect	.45	share of internet banking
		(.0047)	
v	negative shock to banks' productivity	.5	branches in 2010
			and restructure choices
λ	restructure costs	.45	banks' restructure choices

Table 3.3: Comparison of Moments in the Data and in the Model

This table shows the values for data moments and model moments. The model does a reasonable job in explaining the data. We set the first period of the model to the year 1998 in the data. That is, we take the average number of branches of a large bank, of a small bank in a large city, and of a small bank in a small city in 1998 as the starting values of the model. The number of branches increases/decreases gradually at a linear trend; therefore, we do not need to match all the points in each year period. We just need to match the critical points that include the number of branches in 2009 (when the number of branches peaked), the number of branches in 2010 (when the recession decreased banks' productivity), the number of branches in 2016 (the last period in the data), the increased percentage of internet banking from 1998 through 2009 (the time periods before the restructure) and the increased percentage of internet banking from 2010 through 2016 (the time periods after the restructure).

Panel A: Bank Branches

moment	**data**			**model**		
	2009	2010	2017	2009	2010	2017
large bank						
branches in a large city	8.24	8.92	8.57	8.4	7.87	8.31
branches in a small city	2.56	2.59	2.50	2.41	2.22	2.22
small bank						
branches in a large city	2.27	2.25	1.98	2.17	1.90	2.1
branches in a small city	1.71	1.70	1.62	1.83	1.74	1.78

Panel B: Internet Banking				
data				
	from 1998 to 2009		from 2010 to 2017	
Increase in the amount	14.3		.9	
	2012	2013	2014	2015
share of internet banking (%)	52.3	55.4	55.6	56.5
model				
Increase in the amount	from 1998 to 2009		from 2010 to 2017	
	14.2		0.97	
share of internet banking (%)	2012	2013	2014	2015
	58.9	59.1	59.1	59.6

Table 3.4: Summary of Statistics

This table compares the statistics of the states hit by recession and the states not hit by recession. We define a state as heavily hit by the recession if it had an increase in unemployment above the median level of 5.3% from from January 2008 through January 2010. In the data, we can only see if the income level belongs to a certain range, not the absolute dollar amounts. I define high-income consumers as consumers with annual income more than 100,000 dollars. In the data set, about 10% of consumers have high income. The variable education is defined as 1 if the consumer has less than a 1st grade education; as 2 if the consumer completed 1st, 2nd, 3rd, or 4th grade; as 3 if the consumer completed 5th or 6th grade; as 4 if the consumer completed 7th or 8th grade; as 5 if the consumer completed 9th grade; as 6 if the consumer completed 10th grade; as 7 if the consumer completed 11th grade; as 8 if the consumer attended 12th grade but received no diploma; as 9 if the consumer has a high school diploma or the equivalent (for example, a GED); as 10 if the consumer has some college but no degree; as 11 if the consumer has an associate degree in a college occupational/vocational program; as 12 if the consumer has an associate degree in a college academic program; as 13 if the consumer has a bachelors degree (for example, BA, AB, or BS); as 14 if the consumer has a masters degree; as 15 if the consumer has a professional school degree (for example, MD, DDS, DVM, LLB, JD); and as 16 if the consumer has a doctoral degree (for example, PhD, EdD). A white consumer is indicated as 1. Employment status is defined as 1 if the consumer is employed and otherwise as 0. Marital status is defined as 1 if married and otherwise as 0. Gender is defined as 1 if male and otherwise as 0. In Table.6, I compare the income, age, marital status, education, gender, race, and employment status of the people surveyed from the hit states and the not-hit states.

2008-2010		
	states hit by recession	states not hit by recession
age	46.6	44.7
education	10.5	10.5
percent of high income	0.14	0.14

male	0.48	0.48
white	0.73	0.75
married	0.6	0.65
employed	0.78	0.82
internet banking adoption	0.7	0.7

2011-2013

	states hit by recession	states not hit by recession
age	47.2	46.7
education	10.6	10.5
percent of high income	0.19	0.21
male	0.47	0.49
white	0.75	0.74
married	0.62	0.63
employed	0.59	0.63
internet banking adoption	0.74	0.78

Table 3.5: Recessions and Internet Banking Usage

Internet banking usage		
	Probit Model	Logit Model
Crisis hit	.066***	.12***
	(.007)	(.012)
High income	.20***	.39***
	(.006)	(.011)
Education	.16***	.28***
	(.001)	(.002)
Age	−.013***	−.021***
	(.0001)	(.0002)
White race	.31***	.52***
	(.004)	(.007)
Male	−.014***	−.029***
	(.004)	(.006)
Employed	.28***	.48***
	(.005)	(.008)
Married	.33***	.55***
	(.004)	(.007)
Pseudo R-square	0.12	0.12
Number of Observations	576,395	

Chapter 4

TECHNOLOGICAL CHANGE AND SMALL BUSINESS LENDING

This paper evaluates the negative effects of information technology (IT) improvements on small business lending and what can be done to combat this trend if necessary. Three challenges lie in the identification. First, in the data, we cannot see the demand for small business loans and banks' willingness to lend to small business borrowers. Therefore, it is hard to establish casual effect between IT improvements and decline of lending to small businesses. Second, a bank's costs of IT is a choice variable for the bank as well as lending to small businesses. These two variables are probably affected by the same unobserved characters of the bank. For example, when a bank faces pressure from Stress Test, it may decrease lending to risky small business borrowers. Thus, the bank has lower information processing costs for a dollar of loans as banks have economy of scale in processing larger loans. Third, the decomposition of two mechanisms suggested will give quantitative answers to a question that has attracted much attention, but remains unsolved in the literature: to what degree, the consolidation has contributed to the decline of small business lending. As the consolidation may also be caused by IT improvements, it is not easy to quantify the contribution from the consolidation without a theory or an instrument variable. Because of these identification problems, I evaluate the effect from IT improvement on small business loans with a general equilibrium structural framework. This framework can also be used to evaluate policies that may encourage small business lending.

I build a dynamic model of relationship banking. In the model, I distinguish between relationship lending and transaction lending. Transaction lending is an "arm's length" transaction based on hard information about a borrower. In comparison, relationship lending is based on a borrower's hard information as well as soft information. As noted by Liberti and Petersen (2017), hard information is machine readable and quantifiable, but soft information is usually subjective, and its collection and evaluation are usually not separable and is expensive to collect. Therefore I assume that it is expensive for banks to build relationships with borrowers. Small business borrowers are modeled as risky borrowers. Small borrowers are risky for banks because of insufficient credit histories and low credit scores (according to the 2017 Small Business Credit Survey). For banks, lending to small borrowers is less profitable than lending to established businesses (Mills and McCarthy, 2016). However, a bank can improve the returns from these borrowers by monitoring their cash flow and restructuring delinquent loans promptly (Bolton *et al.*, 2016). In the model, lending with additional monitoring through bank-borrower relationships is relationship lending. Consequently, risky small borrowers are more likely to receive relationship loans than transaction loans (Boot and Thakor, 2000) [1] . The dynamic features of the model are built on Hopenhayn (1992). In the model, banks decide to grow or exit according to the advancing rate of lending technology and the competition in the deposit market. The bank size distribution is thus endogenous to IT improvements.

The model suggests two mechanisms by which IT improvements can reduce the amount of small business lending: a substitution effect between transaction and relationship lending and a crowding-out effect between large and small banks. Liberti and Petersen (2017) find that IT improvements favor the collection of hard information

[1] This assumption is a simplification of the reality. It does not mean that lending to large corporations requires no bank-borrower relationships at all. The conclusion in the model still holds as long as lending to small businesses more depends on bank-borrower relationships, which is suggested by Chodorow-Reich (2013).

over soft information. I assume therefore that the cost of acquiring hard information decreases, but that the acquisition of soft information is as expensive as before [2] . As a consequence, banks' profits from transaction lending increase more than those from relationship lending. Banks thus decrease the share of relationship loans in their portfolios. The second effect is the crowding-out effect, in which larger banks with smaller shares of small business lending gain market share. IT improvement increases the lending capacity of large banks more than that of small banks. IT improvement also intensifies competition in the deposit market and increases the cost of deposits. Small banks that face high costs of staying in the market will become less profitable and choose to exit. Overall, the share of small business lending declines. In both situations, if banks cannot increase their lending capacity enough, lending to small businesses falls.

I estimate the model with the U.S. individual commercial bank data from 2002 to 2007 and from 2012 to 2017 [3] . I find that the technological advancements contribute to 58% of the small business decline in the US. I identify a set of parameters for which the simulated moments from the model are quantitatively consistent with the observed behavior of U.S. commercial banks. I use the moments of banks' total loans from 2002 to 2017 to identify the advancement rate of lending technology. From this identification, I link IT improvements to bank productivity growth. Using the

[2] The assumption is a simplification of reality where the cost of acquiring hard information decreases faster than the cost of acquiring soft information. As is in Liberti and Petersen (2017), "Hard information is quantitative, easy to store and transmit in impersonal ways, and its information content is independent of the collection process. Technology has changed and continues to change the way we collect, process, and communicate information. This has fundamentally transformed the way financial markets and institutions operate. One of these changes is a greater reliance on hard relative to soft information in financial transactions. This has altered the design of financial institutions by moving decisions outside the traditional boundaries of organization."

[3] I exclude data during the recessions because my model cannot explain fluctuations in the banking sector. However, my model does show that IT improvements makes banks to issue transaction lending to riskier borrowers and thus increases the risk in the pool of transaction lending.

share and amount of small business loans in 2002, I identify the parameters of banks' technology for building relationships. The identification shows that there is an increasing marginal cost of building additional relationships. This finding is consistent with Chen *et al.* (2004), who find that financial institutions have decreasing returns to scale in non-routine tasks. The model does a reasonable job of fitting the data. The total bank loans increased from \$5.16 to 8.62 trillion from 2002 to 2017 (vs from \$5.11 to \$8.54 trillion in the data). The un-targeted moments in the data is the cost of processing a dollar amount of loans, which decreased by 16% from 2012 to 2017 in the model (vs 16% in the data). The share of small business loans is 6.7% for all banks, and 5.4% for large banks (with loan more than 1 billion dollars) in 2002 (vs 6.7% and 5.1% in the data); small business loans are \$346 billion in the model (vs \$340 billion in the data) in 2002. The estimated model shows that small business loans decreased from \$346 to \$322 billion dollars because of IT improvement from 2002 to 2017. This identification strategy solves the challenges mentioned above because I do not identify the values of each parameter by targeting at the moments about the change of small business loans.

The model shows that the substitution effect contributes to at least 63% of the decline in the model, while the crowding-out effect contributes to at most 37%. In the quantitative model, the costs of processing each dollar of a transaction loan decreased by 46%, from \$0.0144 in 2002 to \$0.0078 in 2017. This decrease is large in comparison with the average loan spread of about 3%. However, for each dollar of a relationship loan, the bank needs to pay at least an additional \$0.0066 to build relationships, so the cost of relationship lending is reduced by at most 31%. Because the returns to banks are larger from transaction lending than from relationship lending, they substitute from relationship loans to transaction loans. In the model, the loan share of large banks with loans totaling more than \$1 billion increased from 76% to 86% (vs from 81% to 90% in the data) from 2002 to 2017; the share of small business loans decreased from 6.7% to 3.6% for all banks, but for large banks (with loan more than 1 billion dollars), it decreased from 5.4% to 2% (vs 5.1% to 3% in the data) from 2002 to 2017. Because large banks have smaller shares of small business loans, lending to small businesses declines.

There are debates about the desirability and effectiveness of policies to encourage lending to small businesses. A structural framework can be better for conducting counter-factual policy analysis, compared to a reduced-form approach. With my quantitative structural model, I compare three policies: subsidizing lending to risky small borrowers; subsidizing small banks with fewer than 100 million dollars of loans; and reducing banks' staying costs. A dollar of subsidy of \$100 to small business lending increases small business lending by \$79 as this policy reduces the substitution effect. However, a dollar of subsidy of \$100 to small bank's lending increases small business lending by \$0 because, even if this policy decreases the crowding-out effect as is suggested by Berger *et al.* (2005), it increases the substitution effect. Bordo and Duca (2018) suggest that we should reduce the regulatory burden on banks to reduce the exit of small banks and to increase lending to small businesses. I find that when small banks' (with fewer than \$100 million loans) staying costs are reduced by \$1 out of \$100, lending to small businesses increases by \$0.002. Therefore the policy of reducing banks' regulatory burden (for example, the repeal of the Dodd-Frank Act) may increase lending to small businesses, but not that much.

The paper contributes to literature by providing a general equilibrium framework to evaluate the consequences of technological advances and banking policies.

The general equilibrium framework well addresses the competition among banks and banks' endogenous adoption of new technology, which are the challenges to relate IT improvement and banks' productivity growth. The general equilibrium framework allows me to better evaluate the casual relationship between the consolidation and the decline of small business lending when natural experiments are not available for empirical work (Berger and Udell, 2002). The framework also considers the rational expectations of banks and the competition among large and small banks when evaluating policies. Thereby, I arrive at quantitatively different results from previous empirical work.

The rest of the paper is organized as follows. Section I is the contributions to literature. Section II presents key statistical features of the U.S. commercial banking market. Section III contains the model. Section IV presents the estimation of the model. Section V shows implications of the model. Section VI concludes. Proofs and tables are in the Appendix.

4.1 Contributions to Literature

First, this paper contributes to the recent literature on the decline in small business lending. Two pioneering studies (Cortés *et al.*, 2018; Bordo and Duca, 2018) try to attribute this reduction to the increasing regulatory burden created by the Dodd-Frank Act, but they arrive at conflicting results. Bordo and Duca (2018) find that this policy makes it more difficult for small banks to survive, and that the increased regulatory burden has contributed to the decline in small business lending in the U.S. However, Cortés *et al.* (2018) do not find any positive correlations. Therefore it is not entirely clear why small business lending has declined. My paper offers an alternative explanation: improvements in information technology. I show that this factor may have contributed to a major part of the decline. Using this framework with IT improvements, I conduct policy experiments and find that when policy reduces the regulatory burden of small banks, lending to small businesses may increase little.

Second, this paper contributes to the literature on banking market consolidation and small business lending (Berger *et al.*, 1998; Strahan and Weston, 1998; Peek and Rosengren, 1995; Berger *et al.*, 2017). Berger *et al.* (2005) and Berger *et al.* (2017) find that small banks still play a significant role in lending to small business and suggest that consolidation in the U.S. banking market may contribute to the decline in small business lending (also refer to Berger and Udell (2002) for a summary of related research). However, other studies find that the exit of small banks decreases or does not affect lending to small risky borrowers. My study finds that the consolidation is only correlated with the decline in small business lending, but does not cause the decline. Both bank consolidation and the decline in small business lending are the result of IT improvements. Therefore, when we use a regression to establish a causal relationship between greater banking market concentration and the decline in small business loans, we may have the problem of omitted variables and establish a false causal relationship.

Third, this paper contributes to studies of technological improvements and productivity growth in the U.S. banking industry. Berger (2003) summarizes the difficulties of relating information technology improvements to observed productivity growth. First, firms may not adopt the best available technology. Second, productivity growth may not increase firms' profits, but instead benefit consumers through competition among firms. This study tackles this challenge by using a quantitative structural model that endogenizes the adoption of advanced technologies and competition among banks. I find that productivity in the banking sector grew by 46% from 2002 to 2017 due to IT improvements.

Fourth, this paper contributes to the literature on industry "shake-out." The research on industry shake-out suggests that with the introduction of cost-saving technology, small firms exit and large firms gain market share (Hopenhayn, 1992; Hayashi *et al.*, 2017). Hayashi *et al.* (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. When the technology used in transaction lending improves, there is a shake-out in the banking market. Consistent with this study, transaction loans to safe borrowers in my model are similar to ATMs, and these safe borrowers receive more loans. By enriching the previous framework of shake-out with an alternative product—relationship lending, and with alternative borrowers—risky borrowers, I find that shake-out can be welfare-decreasing for these risky borrowers. This finding is different from the conclusions of previous research as I introduce different production technologies that improve at different rates.

4.2 Model

In this section, I construct an infinite-horizon model with discrete time 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 \$1 dollar of 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 of the firm (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 thereby increase 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 accumulate assets in order to grow and can 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 when IT improves. As banks gain economy of scale in accumulating assets, IT improvements allow larger banks to grow faster and gain market share. Because IT improvements also intensify the competition in the deposit market and increase the cost of deposits, smaller banks cannot afford to stay and may choose to exit.

I do not model borrowers' behaviors or choices. Some may argue that improvements in IT allow borrower to search more efficiently for the best loan offers, and that therefore advanced information technology will promote 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 leads to more efficient matching between banks and borrowers.

4.2.1 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 the borrower. If the bank chooses to lend to the borrower, the bank decides by relationship or transaction lending. On date 2, the bank receives the return from its loan. On date 3, after seeing its cost to stay for the next period, the bank decides whether to stay in the market and decides the amount of its assets for the next period.

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

Types of securities are risky bank loans and riskless deposits. A bank issues a loan of $1 to finance a borrower's project. The borrower and his project exist for one period. Borrowers differ in the delinquency rates of θ, $\theta \in [0, 1]$. If the borrower repays on time, the payoff to the bank is R_H, the sum of principal and interest. 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 borrower's project and receives the liquidation value, R_L. In relationship lending, the bank can restructure the debt and receives a higher return, R_R, $R_R > R_L$. I abstract from 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' risk, the results of the model will not change. As information technology improves, banks will increase their loan rates to risky borrowers and these risky borrowers will not be able to profit from borrowing from banks. Similarly, risky borrowers who receive relationship loans will still be hurt by 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. When the deposit rate increases, the supply of deposits increases.

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.

On date 1, banks use their assets to determine the delinquency rates of borrowers at no cost. The number of borrowers evaluated by a bank is determined by banks' technology and the bank's assets in this period. The rationale behind this number is an optimal decision by the bank. The bank decided on the amount of its assets for this period in the previous period and cannot make any changes thereafter. Given a bank's assets and the current technology, the bank decides how many borrowers to evaluate. The bank will make the maximum profit if it uses all of its assets to evaluate borrowers. 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 $M_t = e^{\lambda} M_{t-1}$. The parameter M_0 measures banks' technology at period 0 and λ measures the advancement of bank's technology of each period.

A bank chooses whom to lend to and whether to use a relationship or transaction loan based on the delinquency rates of borrowers. If a bank makes a relationship loan to a borrower, 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 builds, where $c(L^S) = \frac{1}{F(\omega+1)}(L^S)^{\omega}$, L^S is the number of relationships that the bank builds, ω captures the elasticity between marginal costs of building relationships and the number of relationships, and F measures the average costs of building relationships. In the data, large banks have smaller shares of small business loans (relative to total loans), therefore, $\omega > 0$. Hence in the model, banks have greater decreasing return to scale of lending to small business borrowers, compared to lending to large corporations. This is equivalent to say that banks have some fixed costs of making loans.

The process of building relationships is as follows: the bank manager sends loan officers to collect soft information about a borrower, such as his managerial ability, the condition of his business, and his reputation among neighbors. With this information collected, the loan officer can better monitor the cash flow from the borrower's project. During the process, a loan officer may neglect his responsibilities. 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 them as efficiently as managers who monitor only a few loan officers. In this case the manager needs to give his loan officers even more incentives. 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' subjective judgments. Building relationships to acquire borrowers' soft information is a task of this type.

On date 2, a bank earns its profits from all the loans he finances. If a borrower repays on time, the bank receives R_H, , the sum of principal plus interest. If the borrower is delinquent on the debt, the bank decides whether to liquidate his project or restructure his debt. In transaction lending, the bank liquidates the project and receives the liquidation value, R_L. In relationship lending, the bank has the option to restructure the debt and receives R_R, a higher amount than the liquidation value. Think about two types of loans: a mortgage loan and a loan to a high-tech start-up. For both, if the borrower repays on time, the lender receives the principal and interest. In the case of a mortgage, after issuing the loan, the lender seldom has contact with the borrower; if the borrower does not repay on time, the lender will repossess the house and sell it, usually at a discounted price. In the case of a loan to a high-tech start-up, after issuing the loan, the lender will contact the firm's CEO frequently so as to monitor the firm's cash flow, innovation activities, and management decisions. If the firm does not repay the bank on time, the lender usually knows the reason for the delinquency. If the bank and the firm's 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 of its money back. This process is debt restructuring, which increases banks' returns.

On date 3, after the cost of staying, e_t, is known, the bank decides whether to stay and decides 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, δ_z is the depreciation rate of assets, A and γ are constant parameters, and $0 < \gamma < 1$. The parameter A, the bank's assets, z_t and the technology for assessing borrowers determine the bank's return from the investment of g_t. The money used for investment is borrowed from future profits. The model assumes that banks can borrow from another debt market besides deposit market to finance its investment in IT. Banks with more assets, has larger returns from this investment. When making the investment on productive assets, banks need to trade off the cost of this borrowing and the benefit to its continuation value, which depends on the current level of its assets. As a result, when the technology for evaluating borrowers is improving, the return gaps between large and small banks increase. Large banks benefit more from technological improvements than small banks. The process by which banks accumulate assets can also be seen as a process of banks utilizing new technology. Large banks are assumed to be better at utilizing new technology than small banks.

People find that large banks have usually been first to adopt advanced technologies and benefit more from the adoption (Berger, 2003). For example, the transaction website adoption rate varied greatly by bank size. By the end of 2001, 100% of the largest banks (banks with over $10 billion in assets) had transaction websites, while 29.1% of the 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, θ, the bank decides whether to lend to him. If the bank chooses to lend to him, it decides whether to issue a relationship or a transaction loan. Second, after it sees the cost of staying in the market, the bank decides whether to stay in the market. Last, if the bank decides to stay, it determines its assets for the next period.

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

s.t.

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

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

Competitive Equilibrium

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

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

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

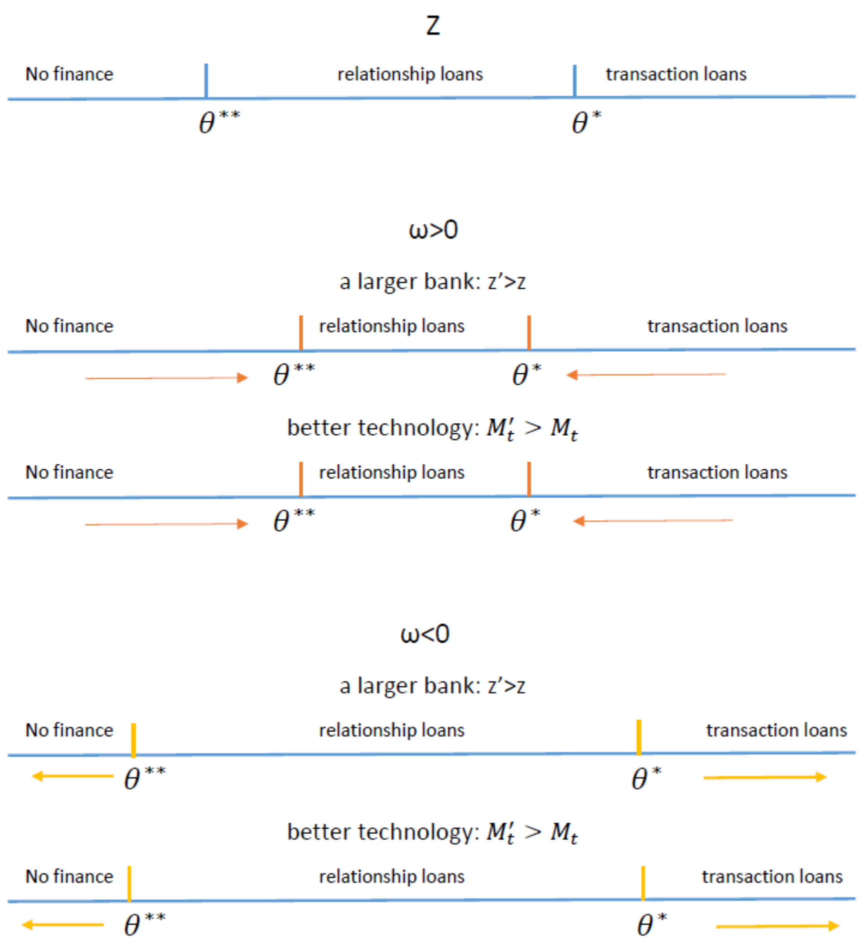
$$\int_{z_t} \int_{\theta} M_t z_t^{\alpha} (I^R(\theta, z_t) + I^T(\theta, z_t)) dU(\theta) d\Omega_t = S^{-1}(r_t^*)$$

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

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

Intuitions: The additional expected return from a relationship, $\theta(R_R - R_L) - c$, Therefore, if a borrower's project is too safe, the additional return from a relationship exceeds the cost of building the relationship. So, there is a θ^* such that the cost and the return are equal. On the other hand, when a project is too risky, its expected return is less than the cost of financing it, so there is a θ^{**} such that the bank will not finance projects with a delinquency rate of $\theta > \theta^{**}$. In first case where banks have increasing marginal costs of building relationships, when a bank has more assets, it can evaluate more borrowers; if the bank chooses to build more relationships,

Figure 4.1: Shifts of Two Thresholds



This figure shows that there are two thresholds that determine a bank's transaction lending and relationship lending. From left to right, borrowers become safer with lower delinquency rates. For the bank with assets z, there exists two thresholds $\theta^* < \theta^{**}$, such that if the borrower has a delinquency rate of θ that $\theta < \theta^*$, the bank finances him with transaction lending; if the borrower has a delinquency rate of θ that $\theta^* \leq \theta \leq \theta^{**}$, the bank finances him with relationship lending; and if the borrower has a delinquency rate of θ that $\theta > \theta^{**}$, the bank will not finance him. When a bank's has increasing marginal costs of building relationships ($\omega > 0$) and its assets increase, its risk tolerance for transaction loans increases and its risk tolerance for relationship loans decreases (that is, θ^* increases and θ^{**} decreases); when a bank's has decreasing marginal costs of building relationships ($\omega < 0$) and its assets increase, its risk tolerance for transaction loans decreases and its risk tolerance for relationship loans increases (that is, θ^* decreases and θ^{**} increases).

the bank's cost of building relationships increases. This increase reduces the surplus from relationships, and the bank may extend transaction loans to riskier borrowers who received relationship loans before; in this case, θ^* shift to the left. In addition, the bank's return from the riskiest borrowers, who received relationship loans before, becomes negative. Therefore the bank will no longer lend to these borrowers; in this case θ^{**} shift to the right. The explanation is similar when banks have better lending technology. In the second case where banks have decreasing marginal costs of building relationships, the conclusions are on the contrary.

The proposition qualitatively implies that as information technology improves and banks become more efficient in evaluating borrowers, high-risk borrowers will receive fewer loans; those that do receive loans are more likely to receive transaction loans. The model also implies that transaction loans are associated with a riskier pool of borrowers with IT improvements.

4.3 Estimation

I estimate 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 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. Cross-sectionally, larger banks have a smaller share of small business lending. The model does a very good job of explaining the change of bank size distribution from 2002 to 2017 and the dollar amount of small business loans and the share of small business loans for all banks and for large banks (with loans more than $1 billion) in

2002. The estimation strategy solves the identification challenges mentioned in the introduction [4] . I do not estimate the model by targeting at the moments about the change of small business lending from 2002 to 2017; Instead, I simulate the estimated model to evaluate to what extent, technological improvement can change the supply of small business lending. By doing so, I separate the effect from supply side.

4.3.1 Data

The data are from the Federal Deposit Insurance Corporation (FDIC), Statistics on Depository Institutions (SDI). The data are all reported in June of each year. I use data from 2002 to 2017 and exclude data from 2008 to 2011, the years of the so-called Subprime Crisis. First, since I do not introduce economic fluctuations in the model, I cannot explain the data during a crisis using this model. Second, the market for small business lending is far from securitized in comparison with mortgage lending. The collapse of the loan securitization market may not have affected lending to small businesses. Third, the decline in lending to small businesses may not come from the demand side. Although during a crisis many small firms exit, the demand for loans by small businesses is never satisfied. According to 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 made no small business loans. These banks usually are small and specialized in a type of lending, such as mortgages or agricultural loans.

[4] First, in the data, we cannot see the demand for small business loans. Without a good instrument variable for the supply of small business lending, it is hard to establish casual effect between IT improvements and decline of lending to small businesses. Second, a bank's costs of IT is a choice variable for the bank as well lending to small businesses.

A bank's total loans in the model are measured by total loans and leases net of unearned income [5] . I assume that the loan size distribution does not change much. Some argue that the development of the securitization market allowed non-jumbo mortgage loans to become more liquid and that, as a result, banks issue more non-jumbo mortgage loans and fewer jumbo mortgages. The average loan size would thus become smaller. However, this change would have little effect on the loan size distribution, as jumbo mortgages account for less than 2% of all mortgages. Relationship loans are measured as 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 to 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 the securitization market, these loans can be easily securitized and sold. Loans in delinquency are loans that are past due by more than 30 days, interest is unaccrued, and the loans are charged off. Table 4.1 shows the definition of each variable. Table 4.2 shows the summary of statistics.

The cost of data processing is from Compustat, Bank Fundamental Annual. This data set had 3,200 banks (in each year) from 2012 to 2017. The average total loans of these banks is $28,025 million. However, in the FDIC data set, the average loan amount for a bank is $7,880 million. These banks are larger than the average U.S.

[5] 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

bank. In the model, banks do not differ from productivity of processing information in a given year even though larger banks have slightly larger marginal costs of evaluating hard information. Therefore, the information costs per dollar loans are very similar across all banks in a given period. The data processing costs represent total costs and fees incurred in processing banks' data, including the costs of computer services, technology, and software. The data show that, from 2012 to 2017, the data processing costs per dollar of loans decreased by 16%. The costs for a dollar of loans equal to the information expenses divided by bank total loans in dollar amount. This is not a perfect measure of bank's costs of processing information for a dollar of loans. Perfectly, we should use the information costs divided by the dollar amount of newly originated loans. However, I cannot see how many loans are originated in a given year. In the data, bank total loans increase at a quite constant rate and thus, the flow of loans is probably a constant proportion of the stock of loans. In the estimation, I only need to care about by what percentage, the information costs for a dollar of loans has decreased. Therefore, the measure I use is a good proxy for banks' costs of information for a dollar of loans.

4.3.2 Estimation Method and Results

I estimate the model using the simulated method of moments. I select the values of parameters to match the key moments in the data with the simulated ones from the model. For each group of parameters, I compute the optimal choices of each bank and the deposit interest rate in the equilibrium in each period. The initial period in the model is the year of 2002. The solution to the banks' problems is provided in Appendix. 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 totaling more than $1 billion, the average of banks' total loans for banks in the top 25% percent , the average of banks' total loans for banks in the bottom 25% percent , the dollar amount and the share of small business loans in 2002, the share of small business loans by the top 25% of banks in 2002, the loan delinquency rates in 2002 and 2017, and the average amount and standard variations of total loans of entry banks from 2002 to 2007 and from 2012 to 2017. I put three restrictions in the estimation. First, the average bank's productive assets increase over time because the value of bank software increases over time. Second, the ratio of the standard deviations of bank loans to the sum of loans increases over time. Third, the ratio of the average dollar amount of loans by banks in the top 25% to the average dollar amount of loans by banks in the bottom 25% increases over time. These specifications are consistent with the data observations.

The estimation is to identify the parameters in a bank's technology for evaluating borrowers' delinquency rates, M_0, λ, α,the parameters in a bank's technology for building relationships, F, ω, the parameters in the deposit supply function, n_r, the parameters in the technology used by banks to accumulate assets, δ_z, A, γ, the distribution of the staying costs, μ, σ, the parameters that characterize the returns from the projects, R_H, R_L, R_R, and the parameters that characterize the asset distribution of newly entered banks, μ_z, σ_z. I estimate 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, 1.0375. Assets depreciating rate δ_z is set to 0.004. The discounting factor β is set to 0.996. The number of newly entered banks (B) are calculated as total de nova banks from 2003 to 2007 and from 2012 to 2017 to the number of years, 89.

I explain the identification of each parameter in this paragraph. The first period of the model is estimated to the year of 2002. The initial distribution of banks' productive assets is identified from the mean and the standard deviation of bank total loans in 2002. The parameter α is identified from the growth rate of the standard deviation of total loans during 2002 to 2017: a larger α increases the growth rate. The parameter α measures the economy of scale in a bank. Overtime, the distribution of banks' productive assets becomes more dispersed. When banks have greater economy of scale to do lending, the standard deviations increases more from 2002 to 2017. The parameter M_0 is identified from the difference of total loans between large banks (with loans more than \$1 billion) and small banks (with loans fewer than \$1 million): a larger M_0 increases the difference. The parameter M_0 measures the initial level of lending technology. As better lending technology favors larger banks, thus a larger M_0, a larger difference. The parameter F is identified from the total amount of small business loans: a larger F increases the amount of small business loans. The parameter F measures the average costs of building relationships, a larger F, a smaller costs and thus, more relationship loans. The parameter ω is identified from the share of small business loans for all banks and for large banks: a larger ω increases the difference between these two shares. The parameter ω measures the elasticity between the marginal costs of building relationships and the number of relationships. With a larger ω, large banks have greater decreasing return to scale in building relationship loans, and then, compared to small banks, they have smaller shares of small business loans. The parameter λ is identified from the increase of total loans from 2002 to 2017: a larger λ increases the loan growth rates; this parameter measures the advancement rate of technology. The parameter γ is identified from the change of loan share of large banks: a larger γ increases the growth rate of the market concentration; this parameter measures banks' economy of scale in accumulating productive assets. The parameter A is identified from the difference in the change of total loans for banks at the top and bottom 25%: a smaller A increases the difference. The parameter n_r is identified by the delinquency rates: a larger n_r decreases the delinquency rates; a larger supply elasticity of deposits, a larger deposit rate with the same amount of deposits, and therefore, a lower delinquency rate. The parameter μ_z, σ_z are identified from the mean and standard deviation of total loans of newly entered banks. Other parameters are identified jointly. The standard errors are calculated using the method in Bazdresch *et al.* (2018). Table 4.3 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, for the years 2002–2017, total loans increase from \$5.16 to \$8.6 trillion (vs \$5.11 to \$8.54 trillion in the data). For the same period, the standard variations of bank loans increase from \$8.69 to 16.2 billion (vs \$8.78 to \$24.6 billion in the data). The loan delinquency rates decrease from 2.33% to 2.3% (vs 2.37% to 2.14% in the data) from 2002 to 2017. The average bank loans of banks in the top 25% increase from \$2.36 to \$4.92 billion (vs \$2.43 to \$6.58 billion in the data) from 2002 to 2017. The average bank loans of banks in the bottom 25% increase from \$14.7 to \$38.6 million (vs \$20.7 to 31.5 million in the data) from 2002 to 2017. The loan share of large banks with loans totaling more than \$1 billion increases from 76% to 85% (vs 81% to 90% in the data) from 2002 to 2017. The share of relationship lending (small business lending) decreases from to 6.7% to 3.7% (vs from 6.6% to 3.5% in the data); for large banks (with loan more than 1 billion dollars), it decreased from 5.4% to 2% (vs 5.1% to 3% in the data) from 2002 to 2017. The dollar amount of relationship lending decreases from \$345 billion to \$322 billion (vs from \$340 billion to \$301 billion in the data) from 2002 to 2017. The probability of being a small bank with asset below \$100 million decreased by 17% (vs 18% in the data) from 2002 to 2017. The mean of loans of newly entered banks is \$671 million in the model (vs \$675 million in the data); the standard variation of loans of newly entered banks is \$5.7 billion in the model (vs \$5.1 billion in the data).

The most important untargeted moment is the cost of data processing per dollar of loans issued. In the model, it shrinks by 15.8% (the cost of processing hard information in the model is equal to the aggregate bank productive assets divided by bank total loans) from 2012 to 2017. In the data, it shrinks by 16%.

4.3.3 Comparative Analysis

The comparative analysis provides intuition for my identification of each parameter. 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 in the top 25%) to average loans of small banks (banks in the bottom 25%), defined as r_{2t}, where $t = 1, ..., 12$. I increase M_0 from 1339 to 1636, increase α from .89 to .9, decreases from 1.09 to .88, increase μ_0 from 21 to 21.2, and increase σ_0 from

.4 to .42 (Table 4.4). Only an increase of μ_0 can increase $\frac{r_{2,12}}{r_{2,1}}$ and only an increase of σ_0 can increase $\frac{r_{1,12}}{r_{1,1}}$.

To identify the parameters in the second group, I need to use the moments of loan delinquency rates, the number of small banks with loans totaling less than \$100 million, and the loan share of banks with loans totaling more than \$1 billion. I increase F from 148 to 181, decrease ω from .0279 to .0259, increase R_R from .55 to .56, and decrease n_r from .152 to .15 (Table 4.5). Only an increase of $-n_r$ can increase the loan delinquency rate in 2017; only an increase of F can decrease the loan share of large banks with loans more than 1 billion dollars in 2017; an 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 λ from .0365 to .043, decrease γ from .31 to .29, and increase A from .36 to .38 (Table 4.6). Only a decrease of γ can increase $\frac{r_{1,12}}{r_{1,1}}$ and only an increase of A can increase $\frac{r_{2,12}}{r_{2,1}}$.

4.4 Counter-factual and Policy Experiments

In this section, I conduct one decomposing analysis and three policy experiments. I decompose the effects of the substitution mechanisms and the crowding-out mechanisms. I find that the first mechanism contributes to 63% of the decline in small business loans in the model. Consistent with the results from the decomposing analysis, the policy experiment shows that to encourage lending to small businesses, policy should subsidize lending to small businesses rather than subsidize small banks.

4.4.1 Decomposing the Effects from Two Mechanisms

In this experiment, I decompose the relative importance from substitution effect and crowding out effect. The model shows that the cost of processing hard information in a loan application for \$1 million decreased from \$720 in 2002 to \$389 in 2017. As in the model, a bank on average approves 5% of loan applications it evaluates. Therefore, per dollar transaction loan, a bank saves \$0.66 cents (that is, $\frac{720-389}{1000000} \div 5\%$). This number is large if we compare it to the average loan spread, about \$3 cents. It also means that the cost of bank transaction lending is reduced by 46%. However, for each dollar of a relationship loan, the bank needs to pay at least an additional \$0.0066 (that is, $\frac{1}{F(1+\omega)}$) to build the relationship, so the cost of relationship lending is reduced by at most 31%. Since technological improvements benefit transaction lending more than they do relationship lending, banks replace relationship loans with transaction loans. In the model, because large banks are less constrained in their ability to issue more loans, large banks benefit more from technological improvements than small banks and crowd out small banks. The quantitative model infers that a bank with an additional \$1,000 of productive assets can produce at most \$1,726 in higher returns (that is, $(0.05\alpha(M_{12} - M_1) + 0.05\alpha(M_{12} - M_1)A\gamma(1 - \gamma))(R_H - r))$ as a result of improved IT.

To decompose, I keep the substitution effect and shut down the crowding-out effects between large and small banks. I keep the distribution of bank productive assets the same in each year. Under this condition, small business loans decrease by \$15 billion dollars, rather than the \$24 billion in the benchmark model. I thus conclude that the substitution effect accounts for at least 63% of the decline.

4.4.2 Policy Experiments

Using the quantitative model, I experiment with three policies to encourage lending to small borrowers and compare their effects on small business loans in 2017. Table 4.7 compares the effects from different policies.

In the first policy experiment, I subsidize banks with 1% of their loan amounts, when lending to borrowers with delinquency rates greater than or equal to 5%. This policy reduces the substitution effects. According to the U.S. Small Business Administration, from 2002 to 2009 more than 90% of small business loans (in dollar amount) had a delinquency rate greater than 5%, and in the model all relationship loans have a delinquency rate greater than 4.9%. The benchmark model shows that loans to all borrowers with delinquency rates greater than or equal to 5% decreases from $159 billion to $90 billion; while other borrowers receive more loans from 2002 to 2017. Thus the model indicates that many risky small businesses receive fewer loans than before, and this reduction in lending to risky small businesses leads to a decline in small business lending. Therefore I only subsidize lending to risky borrowers. In comparison with the benchmark model, a borrower with a delinquency rate greater than or equal to 5% receives 4 times more loans in 2017 (from $90 to $428 billion), and other borrowers also receive more loans under this policy. This subsidy costs $4.28 billion dollars in 2017. A dollar of subsidy to small business lending increases small business lending by $79. 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 of less than \$100 million) with 1% of their loan amounts in order to reduce their exit rate. This policy targets at the crowding-out effect. In comparison with the benchmark model, this policy does not increase relationship loans. This is because this policy gives small banks an incentive to grow. When these small banks grow, they reduce their share of relationship loans to small businesses. This policy costs \$796 million in 2017 without an increase in small business lending. A dollar of subsidy to small banks increases small business lending by \$0. Berger *et al.* (2005) suggests that instead of subsidizing small business lending directly, we should subsidize the intermediaries that have a comparative advantage in relationship lending. My study shows that if we do not consider the general effects and the substitution effects, this policy will increase lending to small business loans by \$10 for \$1 subsidy of \$100 to small banks' loans. However, when we consider these two effects, this policy does not have any effect on lending to small business loans.

In the last policy experiment, I decrease small banks' costs of staying by 1% (small banks: banks with loans of less than \$100 million). This experiment is to see whether lending to small businesses will increase if policy decreases small banks' regulatory burden. I find that lending to small businesses in 2017 increases from \$322 to \$343 billion under this policy. This policy costs \$10,475 billion. Therefore, \$1 of decrease in banks' regulatory burden increases small business lending by \$0.002.

4.5 Conclusions, Implications and Future Work

I study the effects of IT improvements on small business lending in a quantitative structural framework. The framework includes a dynamic model of relationship banking, an estimation 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 of explaining some key features of the U.S. commercial banking market: the increasing market concentration, the exit of small banks, and the difference in the share of small business loans among large and small banks. The model shows that when the data processing costs per loan dollar decline by 2.5% annually, lending to small businesses declines 1% annually. This decline may lead to an annual loss of 50,000 jobs according to Chen *et al.* (2017). The findings in this paper add insight to the debate over how to encourage lending to small businesses. They imply that policy should subsidize small risky borrowers, not small banks, even though small banks may have a comparative advantage in relationship lending. This research also implies that even if the repeal of Dodd-Frank Act can decrease the regulatory burden on banks, lending to small businesses may increase little.

Conducting a welfare analysis of the reallocation of bank loans from small to large firms can be very interesting and meaningful; however, it will complicate the model too much and is away from the focus of this paper. I will address this question in my next paper, in which we study how the reallocation of bank lending can increase the monopsony power in local labor market and therefore, decrease workers' wage income.

Table 4.1: Definitions of Variables

The table shows how I measure the model variables in the data. I use net total loans and leases in the data to measure the variable of total loans in the model. I use commercial and industrial loans less than $1 million dollars in the data (i.e. small business loans) to measure the variable of relationship loans in the model. I use sum of loans past due, unaccrual and charged-off to net total loans and leases in the data to measure the variable of delinquency rate in the model.

Definitions in the Data	**Variables in the Model**
net total loans and leases	total loans
commercial and industrial loans less than 1 million dollars	relationship loans
sum of loans past due, unaccrual and charged off/net total loans and leases	delinquency rate

Table 4.2: Summary of Statistics

The table shows the summary of statistics. In the paper, I only use the data of banks that have small business loans. Most US commercial banks have lending to small businesses. Very specialized banks may not issue loans to small businesses. I also exclude data from 2008 to 2011, which is the Great Recession. All the numbers are in millions of constant 2017 U.S. dollar. I use total loans and leases in the data to measure total loans. I use commercial and industrial loans less than $1 million dollars in the data to measure small business loans. I use sum of loans past due, unaccrual and charged-off as delinquent loans.

2002-2007, 2012-2017, No.of banks= 78,190

Variables	**Mean**	**Std**	**Min**	**Max**
total loans	1,052	16,800	9	940,000
small businesses loans	47	447	0	29,800
delinquent loans	31	759	0	82,300
total interest and fee income on loans	37	593	0	38,400

Table 4.3: Values of Parameters and Targeted Moments

This table shows the values for each estimated parameter and the moments that used to identify the values of each parameter. The sample period is 2002-2017, excluding 2008-2011, with 78,190 banks. Estimation is done with the simulated method of moments. The standard errors are calculated using the method from Bazdresch *et al.* (2018) (in parentheses). I choose structural model parameters by matching the moments from the dynamic general equilibrium model to the corresponding moments from these data. The model is solved by value-function iteration. The estimation is to identify the parameters in a bank's technology for evaluating borrowers' delinquency rates, M_0, λ, α,the parameters in a bank's technology for building relationships, F, ω, the parameters in the deposit supply function, n_r, the parameters in the technology used by banks to accumulate assets, δ_z, A, γ, the distribution of the staying costs, μ, σ, the parameters that characterize the returns from the projects, R_L, R_R, and the parameters that characterize the asset distribution of newly entered banks, μ_z, σ_z. I estimate period 0 in the model to the year of 2002. In the first period, incumbent banks have assets z that are from the distribution of $log - gamma(\mu_0, \sigma_0)$.

Parameter	Description	Value	Moments
M_0		1,339	total loans of large and small banks
	parameters in the technology	(0.80)	
α	of evaluating borrowers' credit	.89	market concentration
		(0.0003)	
F		148	
	parameters in the technology	(0.1)	small business loans:
ω	of building relationships	.0279	shares and amounts in each year
		(0.00005)	

R_L	liquidation value	.34	share of small business loans
		(0.0001)	
R_R	return from restructured debt	.553	delinquency rates
		(0.0002)	
λ	measure of technological	.0365	annual loan growth rates
	improvement	(0.00007)	
γ		.31	market concentration
	parameter in assets	(0.0013)	
A	accumulation technology	.36	
		(0.0002)	
μ	mean of the log of	5	probability of being a small bank
	the staying costs	(0.013)	
σ	std of of the log of	7.8	
	the staying costs	(0.0008)	
μ_z	mean of the log of	27.5	mean of loans of new born banks
	assets of new born banks	(0.037)	
σ_z	std of the log of	.3	std of of loans of new born banks
	assets of new born banks	(0.0002)	
μ_0	4*log of assets of incumbent banks	21	total loans: mean
		(0.021)	
σ_0		.4	total loans: std
		(0.0008)	
n_r	parameter in deposit	.152	delinquency rates
	supply function	(0.00007)	

Table 4.4: Moments Comparison I

The table shows the results when I change the values of some parameters. In the baseline model, $M_0 = 1,339, \alpha = .89, \mu_0 = 21, \sigma_0 = .4$. In the table, the ratio of loan standard variation to total loans, is defined as $r_{1,t}$ and the ratio of average loans of large banks (banks in the top 25%) to the average loans of small banks (banks in the bottom 25%), is defined as $r_{2,t}$, where $t = 1, ..., 12$.

Parameter	$\frac{r_{1,12}}{r_{1,1}}$	$\frac{r_{2,12}}{r_{2,1}}$
$M_0 = 1,636$	.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

Table 4.5: Moments Comparison II

The table shows the results when I change the values of some parameters. In the baseline model, $F = 148, \omega = .0279, R_R = .553, n_r = .152$. In the table, the delinquency rate, the number of small banks, and the loan share of large banks are the average of these moments for each year. Small banks are banks with loans totaling less than $100 million dollars, and large banks are banks with loans totaling more than $1 billion.

Parameter	**Delinquency Rate**	**No. of Small Banks**	**Loan Share of Large Banks**
$F = 181$	.0208	3,541	80.7%
$\omega = .0259$	.0227	3,224	81.3%
$R_R = .56$	.0226	2,771	84.3%
$n_r = .15$	.0233	2,514	80.9%
baseline	.023	2,790	80.8%

Table 4.6: Moments Comparison III

The table shows the results when I change the values of some parameters. In the baseline model, $\lambda = .0365, \gamma = .31, A = .36$. In the table, the ratio of loan standard variation to total loans, is defined as $r_{1,t}$ and the ratio of average loans of large banks (banks in the top 25%) to the average loans of small banks (banks in the bottom 25%), is defined as $r_{2,t}$, where $t = 1, ..., 12$.

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

Table 4.7: Policy Comparisons

In the table, I compare the effects from different policies, including the increase in dollar amount of small business loans, the delinquency rates and the policy effects without general equilibrium effects or substitution effects. In the first policy, I subsidize small banks with loans less than \$100 million. In the second policy, I reduce the staying costs of small banks with loans less than \$100 million. In the last policy, I subsidize loans to borrowers with delinquency rates equal to or greater than 5%. In the data, these loans are small business loans.

\$1 Subsidy of \$100 to	**Increase in Small Business Lending**	**Delinquency Rate**	**No Substitution or GE Effect**
small banks	\$0	2.29%	\$10
small banks' staying costs	0.2 cents	2.28%	0.02 cents
loans with delinquency rates $\geq$ 5%	\$79	2.34%	

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APPENDIX A

APPENDIX

A.1 MATHEMATICAL APPENDIX FOR CHAPTER 3

Proofs One

In the part, we prove that the small bank has no incentive to restructure. When the small bank finds it profitable to restructure, $j = S$

$$\lambda(m^S p_t(B^{SB}_{LC,t} + B^{SB}_{SC,t} + I^{SB}_t) + m^{SB} \sum_x r_x B^S_{x,t} - c_0(\sum_x B^S_{x,t})^2 -$$

$$c_1 \sum_x (\sum_j B^{SB}_{x,t}) B^{SB}_{x,t} - c_I I^{SB}_t - \frac{\phi_B}{2} \sum_x \left(\Delta B^S_{x,t}\right)^2$$

$$-\frac{\phi_I}{2} \left(\Delta I^{SB}_t\right)^2) + \beta(V^{NR}(B^{SB}_{LC,t}, B^{SB}_{SC,t}, I^{SB}_t, B^{LB}_{LC,t}, B^{LB}_{SC,t}, I^{LB}_t) -$$

$$V^R(B^{SB}_{LC,t}, B^{SB}_{SC,t}, I^{SB}_t, B^{LB}_{LC,t}, B^{LB}_{SC,t}, I^{LB}_t)) = 0$$

Define

$$G(m|m = m^{SB}) = \lambda(m^{SB} p_t(B^{SB}_{LC,t} + B^{SB}_{SC,t} + I^{SB}_t) + m^{SB} \sum_x r_x B^{SB}_{x,t}$$

$$-c_0(\sum_x B^{SB}_{x,t})^2 - c_1 \sum_x (\sum_j B^{SB}_{x,t}) B^{SB}_{x,t}$$

$$-c_I I^{SB}_t - \frac{\phi_B}{2} \sum_x \left(\Delta B^S_{x,t}\right)^2 - \frac{\phi_I}{2} \left(\Delta I^{SB}_t\right)^2) +$$

$$\beta(V^{NR}(B^{SB}_{LC,t}, B^{SB}_{SC,t}, I^{SB}_t, B^{LB}_{LC,t}, B^{LB}_{SC,t}, I^{LB}_t)$$

$$-V^R(B^{SB}_{LC,t}, B^{SB}_{SC,t}, I^{SB}_t, B^{LB}_{LC,t}, B^{LB}_{SC,t}, I^{LB}_t))]$$

$$\frac{\partial G(m)}{\partial m} = (p_t(B^{SB}_{LC,t} + B^{SB}_{SC,t} + I^{SB}_t) + \sum_x r_x B^{SB}_{x,t})\lambda + \beta(\frac{\partial V^{NR}}{\partial m} - \frac{\partial V^R}{\partial m})$$

$$< p_t(B^{SB}_{LC,t} + B^{SB}_{SC,t} + I^{SB}_t) + \sum_x r_x B^{SB}_{x,t})[\lambda(1 + \frac{\beta}{1-\beta}) - \frac{\beta}{1-\beta}$$

when $\lambda(1 + \frac{\beta}{1-\beta}) - \frac{\beta}{1-\beta} < 0$, $\frac{\partial G(m)}{\partial m} < 0$. That means,

$$\lambda(m^{LB} p_t(B^{LB}_{LC,t} + B^{LB}_{SC,t} + I^{LB}_t) + m^{LB} \sum_x r_x B^{LB}_{x,t} - c_0(\sum_x B^{LB}_{x,t})^2 -$$

$$c_1 \sum_x (\sum_j B^{LB}_{x,t}) B^{LB}_{x,t} - c_I I^{LB}_t - \frac{\phi_B}{2} \sum_x \left(\Delta B^{LB}_{x,t}\right)^2$$

$$-\frac{\phi_I}{2} \left(\Delta I^{LB}_t\right)^2) + \beta(V^{NR}(B^{LB}_{LC,t}, B^{LB}_{SC,t}, I^{LB}_t, B^{SB}_{LC,t}, B^{SB}_{SC,t}, I^{SB}_t) -$$

$$V^R(B^{LB}_{LC,t}, B^{LB}_{SC,t}, I^{LB}_t, B^{SB}_{LC,t}, B^{SB}_{SC,t}, I^{SB}_t)) \leq 0$$

That is, the large bank will restructure.

When the large bank restructures, the price of internet banking will be set to $p_{I,t} \leq \frac{c_I}{m^{SB}}$, where the small bank finds it unprofitable to add internet banking; therefore, the small bank will not restructure.

Proofs Two

$$Q_{I,t} = \int_{-\infty}^{\infty} \int_{(\gamma_0^{'}-\gamma_0)+(\gamma_1^{'}-\gamma_1)\frac{p_{I,t}}{p_{B,t}}+(\gamma_2^{'}-\gamma_2)x+\epsilon^{'}}^{\infty} dF(\epsilon)dF(\epsilon^{'})$$

where $F(\epsilon) = exp(-exp(-\epsilon))$, $F(\epsilon^{'}) = exp(-exp(-\epsilon^{'}))$

$$= \int_{-\infty}^{\infty} \left(\int_{(\gamma_0^{'}-\gamma_0)+(\gamma_1^{'}-\gamma_1)\frac{p_{I,t}}{p_{B,t}}+(\gamma_2^{'}-\gamma_2)x+\epsilon^{'}}^{\infty} exp(-\epsilon)exp(-exp(-\epsilon))d\epsilon \right)$$

$$exp(-\epsilon^{'})exp(-exp(-\epsilon^{'}))d\epsilon^{'}$$

Note

$$exp(-\epsilon)exp(-exp(-\epsilon))d\epsilon = d\left(exp(-exp(-\epsilon)) \right)$$

So $Q_{I,t}$

$$= \int_{-\infty}^{\infty} \left(1 - exp(-exp(-((\gamma_0^{'} - \gamma_0) + (\gamma_1^{'} - \gamma_1)\frac{p_{I,t}}{p_{B,t}} + (\gamma_2^{'} - \gamma_2)x + \epsilon^{'}))) \right)$$

$$exp(-\epsilon^{'})exp(-exp(-\epsilon^{'}))d\epsilon^{'}$$

Because

$$\int_{-\infty}^{\infty} aexp(-\epsilon)exp(-aexp(-\epsilon))d\epsilon = 1$$

$Q_{I,t}$

$$= 1 - \int_{-\infty}^{\infty} exp(-exp((\gamma_0 - \gamma_0^{'}) + (\gamma_1 - \gamma_1^{'})\frac{p_{I,t}}{p_{B,t}} + (\gamma_2 - \gamma_2^{'})x - \epsilon^{'}))$$

$$exp(-\epsilon^{'})exp(-exp(-\epsilon^{'}))d\epsilon^{'}$$

$$= 1 - \int_{-\infty}^{\infty} exp(-\epsilon^{'})exp\left(-exp(-\epsilon^{'})(1+exp((\gamma_0-\gamma_0^{'})+(\gamma_1-\gamma_1^{'})\frac{p_{I,t}}{p_{B,t}}+(\gamma_2-\gamma_2^{'})x)) \right) d\epsilon^{'}$$

Because

$$\int_{-\infty}^{\infty} aexp(-\epsilon)exp(-aexp(-\epsilon))d\epsilon = 1$$

$$= 1 - \frac{1}{1 + exp\left\{(\gamma_0 - \gamma_0') + (\gamma_1 - \gamma_1')\frac{p_{I,t}}{p_{B,t}} + (\gamma_2 - \gamma_2')x\right\}}$$

Because

$$\int_{-\infty}^{\infty} exp(-\epsilon)exp(-aexp(-\epsilon))d\epsilon = 1/a$$

and here,

$$a = 1 + exp((\gamma_0 - \gamma_0^{'}) + (\gamma_1 - \gamma_1^{'})\frac{p_{I,t}}{p_{B,t}} + (\gamma_2 - \gamma_2^{'})x)$$

So $Q_{I,t}$

$$= \frac{exp\left\{(\gamma_0 - \gamma_0') + (\gamma_1 - \gamma_1')\frac{p_{I,t}}{p_{B,t}} + (\gamma_2 - \gamma_2')x\right\}}{1 + exp\left\{(\gamma_0 - \gamma_0') + (\gamma_1 - \gamma_1')\frac{p_{I,t}}{p_{B,t}} + (\gamma_2 - \gamma_2')x\right\}}$$

Note:

$$\int_{-\infty}^{\infty} aexp(-\epsilon)exp(-aexp(-\epsilon))d\epsilon$$

$$= \int_{-\infty}^{\infty} d\Big(exp(-aexp(-\epsilon))\Big) = 1$$

A.2 MATHEMATICAL APPENDIX FOR CHAPTER 4

A.2.1 *Proof of Theorem 1*

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 θ^{**}, θ^* :

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

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

Solve θ^{**} 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, θ^* is larger. Similarly, I solve θ^{**} and I find that when z increases, θ^{**} is smaller.

A.2.2 *Model Computation*

Banks' choice of relationship and transaction loans in each period is a static problem. In the first step, I compute banks' choice 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 steps 1-3 until the deposit interest rates converge.

The computation of dynamic programming takes four steps. In the first step, I compute banks' value function at the initial assumed deposit interest rate, $\{r_t\}_{t=1,2,...,}$. I apply the contraction mapping theorem. I start by making an initial guess about 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. [1] 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.

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