ESSAYS ON BANKING, CAPITAL MARKETS, AND FINTECH

by

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ABSTRACT OF THE DISSERTATION

Essays on Banking, Capital Markets, and FinTech

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Dissertation Director:

Joseph Hughes

This dissertation focuses on issues of banking, capital markets, and FinTech in China and the U.S. The first chapter discusses the slow recovery of small business lending in the U.S. after 2008 financial crisis. I provide one mechanism for how regulatory burden imposed by Dodd-Frank Act of 2010 and the regulatory relief plan in 2014 impacted the incentives for banks lending to small businesses. The second chapter investigates how the new investors contributed to the stock market bubbles in 2007 and 2015 in China. The third chapter studies the adoption of mobile payment in rural China.

The first chapter contributes to the continuing debate on the costs and benefits of the Dodd-Frank Act of 2010, focusing on small business loans. Instead of

attempting to directly measure the costs and benefits, I propose an alternative approach, measuring how the new regulations altered the capital market incentives for bank lending to small businesses. The events triggering the market's response were (1) the passage of the Dodd-Frank Act of 2010 and (2) the regulatory relief plan announced in 2015. By matching the Federal Reserve's Call Reports, Summary of Deposits, and Y9C Reports with Compustat data, I constructed a dataset of the top-tier publicly traded bank holding companies, spanning the years 2001–2017 to identify the market effects of the Dodd-Frank Act. Overall, the capital market responded by increasing the incentives for community banks to expand their small business loans and for large banks to reduce theirs. After 2010, large banks' lending recovered so sluggish that in spite of increased incentives for community banks to increase lending following the Federal Reserve's 2015 regulatory relief plan, the volume of newly originated small business loans never fully recovered from the recession.

The second chapter studies the phenomenon that naïve investors are attracted to the market as asset prices soar. This chapter presents previously unused data on the aggregate number of newly opened brokerage accounts in China and investigates the role of new investors in bubble formation. I find that new investors, attracted by the intensive trading activities of others, drove the Chinese stock market bubbles in 2007 and 2015, supporting the Greater Fool theory of bubbles. Their insensitive to the stock price changes during the bubble periods made them more likely to be the "greater fools." Applying the method of residual orthogonalization , I build a data-driven structural model system, where shocks from the new accounts variable could explain 40-55% of Chinese stock return variations.

The third chapter focuses on the acceptance of mobile payment in rural China. Together with my coauthor, I analyze a large-scale survey data which provides detailed household information and the usage of mobile payment in rural China. By

applying a hurdle model with 2SLS, we find that consumers who have better access to bank services are more likely to accept mobile payment as they might have gained financial literacy. However, after adoption, the less frequently consumers visit banks due to distance or social reasons, the more they use mobile payment to supplement bank services. Younger, better educated households with higher income and more smart phones are more likely to adopt and use mobile payment. At aggregate level, regions with higher acceptance level of mobile payment enjoy higher GDP with better development in bank and FinTech services.

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Special thanks to my parents and my khers. Without your love and support, I could not have survived those painful and tough times.

Dedication

For my parents, Yuanyu and Kaijun, and my mentor X

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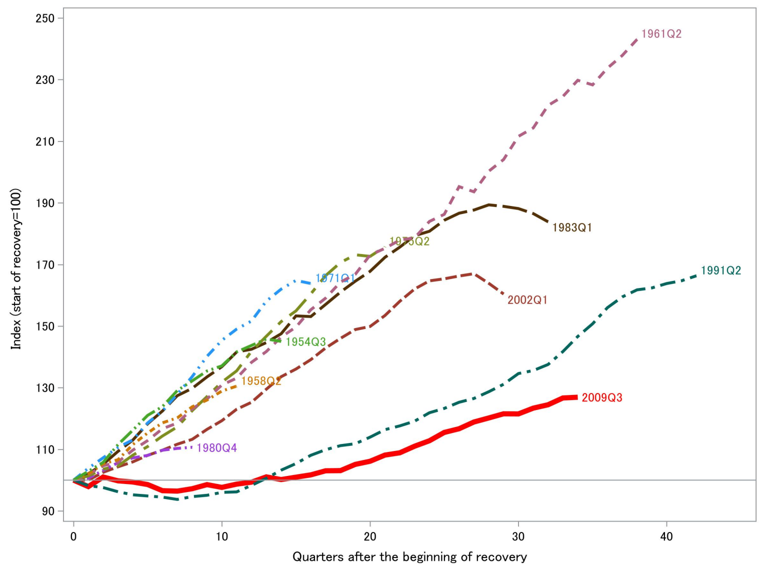
Chapter 1

Squeezing Small Business Lending: Dodd-Frank's Capital Market Incentives

1.1 Introduction

The recovery pace of the U.S. bank credit for the recent recession "has been the slowest of any recession since the early 1960s" (Liu and Tai, 2016), as shown in Figure 1.1. Within the private sector, small businesses have particular difficulty in getting bank credits because they presumably have higher risks and lack formal accounting information. Nevertheless,since small businesses usually have no access to debt or equity markets, small business loans (SBL) by banks, is one of their primary funding sources. Ten years after the 2008 financial crisis, the bank credit flowing to small businesses has recovered slowly, remaining below pre-crisis levels both in absolute amounts and relative to total assets (Figure 1.2). This has contributed to the slow recovery of employment and wage growth (Chen, Hanson, and J. C. Stein, 2017), business formation (Bordo and Duca, 2018), entrepreneurial activities (Bord, Ivashina, and Taliaferro, 2018), and investment and output(Klein, 2014). This raises the question of why SBL recovered so slowly this time.

Figure 1.1: Bank Credit to Private Non-Financial Sector during Recoveries



Source: BIS, FRED, and NBER.

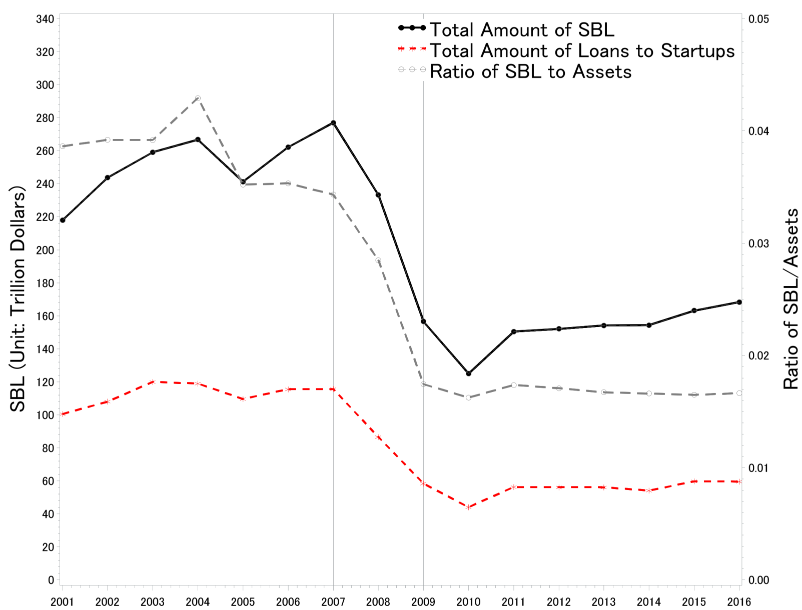
Notes: The data is collected and adjusted by BIS and retrieved from FRED. The private non-financial sector includes households, non-financial businesses, and non-profit institutions serving households. The data captures the outstanding amount of credit at the end of each quarter. The original unit of private credit is billions USD, but all series are adjusted by setting the level in the first quarter after the recession as 100.

In addition to the weak credit demand,[1] the credit rationing from large banks has been considered as a main cause for the slow recovery of SBL (Chen, Hanson, and J. C. Stein, 2017; Bord, Ivashina, and Taliaferro, 2018; Nguyen, 2019). Another widely discussed factor is Dodd-Frank Act of 2010 (Bordo and Duca, 2018; Acharya, Berger, and Roman, 2018), which imposed heightened supervisions and annual Federal Reserve-conducted stress tests for large banks with assets above

[1] *The Federal Reserve Report to the Congress on the Availability of Credit to Small Business (2017)* stated that credit conditions for SBL were increasingly accommodative during the recovery but small business demand for credit was weak. Their main argument was that, in surveys of National Federation of Independent Business (NFIB), small business investment plans (planned capital outlays and anticipated business expansions) recovered very slowly. However, it is difficult to identify whether the the slow recovery of SBL was due to a lack of credit demand or insufficient credit supply, without comprehensive loan-level data.

$50 billion. Although not directly targeted by the Act, some community banks also have been complaining about the compliance costs imposed by Dodd-Frank regulations (American Bank Association, 2012). At the same time, other surveys and interviews of community bankers showed the opposite views, for example, "(Dodd-Frank Act is) not considered a serious problem because banks already have established regulatory compliance programs." (Conference of State Bank Supervisors, 2017). How to measure the regulatory burdens and the effects becomes a crucial question, especially with the data limitation.[2]

Figure 1.2: Annual New Originations of Small Business Loans by U.S. Banks during 2001-2017



Source: the Community Reinvestment Act and the U.S. Bureau of Labor Statistics.

Notes: SBL is defined as business loans with originated amounts less than $1 million. Startups here are defined as firms with gross annual revenues less than $1 million. Both SBL and loans to startups are adjusted for inflation, using the price level in 2001 as benchmark.The total assets in CRA, which I use to calculate the ratio of SBL to assets, are the values of total assets in Call Reports of the previous year.

[2]Currently, there is no direct measure of regulatory compliance costs, but some studies used crude proxies, such as the number of employees, the salary, and the consulting fees.

In this chapter, I address the problem of slow recovery of SBL since the 2008 financial crisis by measuring how the new regulations imposed by Dodd-Frank Act of 2010 altered the capital market incentives for banks to lend to small businesses. The idea is that shareholders or investors have more information about the profitability of certain assets, according to the theory of market discipline, and how shareholders evaluate the impact of changes in regulations would affect bankers' lending strategy, assuming that they would maximize shareholders' value. If the capital market or shareholders consider certain types of loans as becoming more/less profitable due to changes in policies or macroeconomic conditions, banks would have more/less financial incentives to make these loans at the margin.

First, in a year-by-year analysis, small or community banks (with assets of less than $10 billion) have incentives to increase their SBL both before the recent financial crisis and after the 2015 Regulatory Relief Plan for Small Banks. For a 1 p.p. increase in the ratio of SBL/assets, their Tobin's Q ratio is expected to increase at least 0.5 p.p. on average. Similar trends are found when measuring the effects of replacing large business loans or non-business loans with SBL. On the opposite, regional and large banks (with assets of more than $10 billion) were penalized by the capital market for SBL during the crisis and following the Dodd-Frank Act of 2010. Although the trend is clear, some results are not significant because I have to group the regional (with assets of between $10 and $50 billion) and large banks (with assets of more than $50 billion) due to the relative small number of them.

The next section focuses on large banks and examines whether policy changes have contributed to the divergence between large banks and smaller banks (with assets of less than $50 billion) in terms of capital market incentives to lend to small businesses. Because Dodd-Frank Act of 2010 was designed to target *large* banks and then Federal Reserve announced to ease regulatory burdens for *smaller* banks effective in 2015, the capital market is expected to react differently to banks in different sizes. Using fixed effect model on panel data spanning 2001–2017, I find that, while smaller banks have been encouraged to lend more to small businesses, large banks were penalized for SBL and the penalty would triple once a large bank is labeled as a systemically important bank (SIB). For a 1 p.p. increase in the ratio of SBL/assets, Tobin's Q of a SIB would decrease about 3 p.p. on average. One possible explanation is that SIBs are under stress tests which usually put SBL under higher risk assessment and thus shareholders would predict that SIBs with increasing share of SBL are more likely to fail the stress test. The failure of stress tests is not desirable for shareholders because the consequence would be a limitation on a SIB's dividend and share buyback plan.

During the post-Act era, the capital market continued to encourage smaller banks to increase SBL, which was mainly driven by the surged incentives following the regulatory relief plan of 2015. Smaller banks which were relieved from some reporting and examination burden would expect a 0.6 to 0.8 p.p. increase in Tobin's Q ratio for a 1 p.p. increase in SBL/assets. The disincentives for large banks to lend to small businesses have increased about 50% since 2015. This might be because the capital market reassessed the competitiveness of large and smaller banks in lending to small businesses, given that only smaller banks qualify for regulatory relief policies.

This chapter contributes to the literature in three aspects. First, this research fills the gap of studies on U.S. SBL recovery after the recent recession. Most of the related research[3] is on Euro Area, which is due to more comprehensive loan-level datasets. Compared with other studies on SBL by U.S. banks, my study complements the literature by telling the story from the perspective of capital market incentives. Chen, Hanson, and J. C. Stein (2017) found that counties with an initial high presence of big banks experienced a large decline in SBL and business establishments, leading to slower employment and wage growth, but they did not explain the reasons. My study confirms one of their hypotheses that financial regulations played an important role in the large decline in SBL by big banks. While Bordo and Duca (2018) found that Dodd-Frank Act hampers SBL and business formation speed, my result supports their results by suggesting another transmission mechanism.

Second, this chapter contributes to the discussion about the role played by banks of different sizes in financing small businesses, given that existing empirical studies have shown conflicting results. Since the recent financial crisis, large banks have been playing increasingly important roles in SBL (DeYoung, Glennon, and Nigro, 2008, Berger, Goulding, and Rice, 2014, and Berger, Cerqueiro, and Penas, 2014). Prager and Wolken (2008) found that 70% of small businesses cited a big bank as their primary financial institution, but only 25% cited a community bank, and 5% cited a nonbank institution. Jagtiani and Lemieux (2016) added that SBL by community banks has been declining for more than ten years, but large banks and nonbank financial institutions have been playing an increasing role in SBL. However, Berger, Bouwman, and D. Kim (2017) found that small

[3]For example, Artola and Genre (2011) confirmed the financing crunch across firms in the Euro zone and found that small and young firms suffered more when credit standards were tightened. Kremp and Sevestre (2013) claimed that the decline of small businesses' access to bank loans in France is due to a decrease in credit demand, not credit rationing of banks. Despite the tighter bank lending standard, they believe that French small businesses were not strongly affected by credit rationing after 2008. B. Ozturk and Mrkaic (2014) analyzed the factors affecting the access to finance of SME in Euro area. They found that higher bank funding costs, larger firms' debt/asset ratio, smaller and younger firms, and less subsidized funding would lead to less credit access for small businesses.

banks still have comparative advantages in alleviating small business financial constraints compared to large banks, especially during the crisis when large banks had liquidity shocks. Although only focusing on publicly traded banks, this study supports Berger, Bouwman, and D. Kim (2017) from a capital market perspective that SBL was considered by shareholders as a profitable asset for smaller public banks throughout my sample period of 2001–2017, even during the 2008 financial crisis. Contrarily, large banks have been penalized by the capital market for increasing SBL since Dodd-Frank Act, as regulatory constraints have turned SBL into nonprofitable and risky asset for large banks from shareholders' view.

Third, my research offers an alternative method to measure the effects of regulatory compliance costs. A common practice is to use non-interest expense items in call reports as proxies for regulatory compliance costs, but the proxies are crude. For example, Hogan and Burns (2019) use employees' salary expenses as a proxy of compliance costs, but it is impossible to separate compliance staff's salary from others.[4] Moreover, some banks do not report detailed non-interest expenses in Call reports, so some items, such as advisory and consulting fees, are not available for every bank data. Therefore, direct measures of regulatory compliance costs are not reliable. By interacting time-series policy dummy with SBL and size dummy, my study teases out the effects of regulatory compliance on financial performance of banks in different sizes.

The remaining parts of this chapter are organized as follows. In section 2 and 3, I introduce the background of Dodd-Frank Act, data, and the identification strategy. Section 4 presents empirical results from year-by-year analysis and panel regressions, and section 5 discusses robustness checks. Section 6 concludes and

[4]Although in Conference of State Bank Supervisors (2017), community banks were asked what portion of expenses are used for compliance, in a interview conducted by FDIC in 2012, community bankers reported that it is too costly to track compliance costs so they can not estimate the exact amount.

places this study in the context of literature.

1.2 Background

1.2.1 The Dodd-Frank Act and Regulatory Burden

The Dodd–Frank Wall Street Reform and Consumer Protection Act of 2010 was passed to target the systemically important financial institutions whose excess leverage and growth were believed to be the major cause of the crisis in 2008. To prevent future crises, the Act requires certain large banks with assets more than $50 billion to submit to annual stress tests administered by the Federal Reserve. One of the unintended consequences of the stress tests might provide disincentives for large banks to lend to small businesses.

Although Dodd-Frank regulations target large banks, many researchers and bankers have claimed that Dodd-Frank Act imposes "daunting new compliance, operational, and record-keeping burdens on all banks...make it significantly harder for banks, particularly community banks, to serve their communities and help grow the economy" (American Bank Association, 2012). Specifically, several studies argued that the increased fixed regulatory compliance cost would discourage banks to make SBL.

In another survey conducted by the Mercatus Center of George Mason University on 200 community banks in 2013, 90% of participants reported increased compliance cost and 83% reported more than 5% increase, and 10% of participants anticipated mortgage products and services to be cut and 5% have done so (Peirce, Robinson, and Stratmann, 2014). But the Government Accountability

Office (2015) criticized this survey, because “the survey was based on a convenience sample of small banks and was conducted prior to the effective dates of some of the rules covered in the survey.” Nevertheless, the Government Accountability Office (2015) reported that representatives from community banks, credit unions, and industry associations confirmed the overall increased compliance burden, including training staff, allocating time for regulatory compliance issues, and updating compliance systems.

However, other surveys and interviews for community bankers showed opposite opinions towards regulatory burdens. FDIC conducted interviews with 9 community bankers in 2012 to ask about regulatory compliance costs.[5] Most participants reported that no *one* regulation or practice had a significant effect on their overall business model and strategic direction, but the *cumulative* effects of all regulatory requirements built up over time caused them to increase staff over the past 10 years for regulatory compliance and the associated duties. They had not cut any products or services because of regulatory compliance, except for overdraft protection and certain high-risk mortgage products. They did not actively track the regulatory compliance costs, because it is too time-consuming, costly, and difficult to separate from normal operational costs. Despite this, a national survey asked community bankers to estimate the percentage of compliance costs due to specific regulations in 2017. The result showed that the Bank Secrecy Act[6] accounted for more than 20% of total compliance costs and call report requirements accounted for 7.7%, but Dodd-Frank regulations were not even mentioned by bankers. They explained that Dodd-Frank regulations “are not considered a serious problem because banks already have established regulatory compliance programs” (Conference of State Bank Supervisors, 2017).

[5] `https://www.fdic.gov/regulations/resources/cbi/report/cbsi-b.pdf`

[6] require banks to report cash transactions of more than 10k and suspicious activities to control money laundry or fraud

Which provision in Dodd-Frank Act is *directly* related to SBL? I found only one[7] – Section 1071 "Small Business Data Collection" amended the Equal Credit Opportunity Act which additionally requires financial institutions to ask borrowers if their business is minority or women owned or if it is a small business and to compile and maintain a record of the information. This record contains many details[8] In interviews conducted by the Government Accountability Office (2012), 12 of 16 officials from state associations, community banks, and credit unions expected section 1071 to negatively affect SBL. Particularly, they expected increasing compliance and other costs and being forced to develop standardized criteria for SBL to avoid being penalized by regulators.[9] Although some surveys and interviews showed that bankers have been concerned about section 1071, in fact it has never been implemented and has been reclassified "from pre-rule status to longer-term action status" in the fall 2018 rulemaking agenda[10] of Consumer Financial Protection Bureau.

Therefore, many provisions in Dodd-Frank Act might cumulatively affect banks' ability to lend to small businesses. For community banks, one possible channel is through the new regulations related to mortgage lending, because some small business owners often use their homes as a financial source, not only for 1–4 family real estate loans, but also as additional collateral for SBL. Community bankers usually accept this collateral, but "now that this collateral avenue will be HMDA (the Home Mortgage Disclosure Act) -reportable, we (bankers) are going to be less likely to utilize that source of equity, which ultimately reduces

[7]This was also confirmed by some officials from federal agencies, state regulatory associations, and industry associations in (Government Accountability Office (2012))

[8]Such as the census tracts of principal place of business, the type and purpose of the loan, the number and the received data of the application, the type of action and the date, race, sex, and ethnicity of principal owners, and etc.

[9]However, 11 of the 16 officials stated that it was too soon to tell the overall impact of Dodd-Frank Act on their SBL, and two said that Dodd-Frank Act would have no impact.

[10]`https://www.consumerfinance.gov/about-us/blog/fall-2018-rulemaking-agenda/`

the availability of small business credit" (Conference of State Bank Supervisors, 2017). For SIBs, one possible channel is through the stress tests which would put SBL in higher risk assessment. To pass the test, SIBs do not have incentives to hold more SBL in their asset portfolios.

Quantifying regulatory burdens is a challenge not only for banks but also for regulators. To solve the problem that "while they (FDIC officials) have heard concerns about an increase in compliance burden, they have not been able to quantify compliance costs", the Government Accountability Office (2015) used data from Call Reports to construct indicators of the cumulative compliance costs associated with the Dodd-Frank Act, including numbers of employees per $1 million assets, non-interest expenses as a percentage of assets, and earnings as a percentage of assets. They found that the cumulative compliance costs have not increased since the financial crisis. McCord and Prescott (2014) also confirmed that "the increase is relatively small and, more importantly, the size of these expenses is just too small to have a big effect on bank profitability." There are also studies showing opposite results.[11]

Nevertheless, these measures are crude and inaccurate, because it is difficult to distinguish the parts related to regulatory compliance and parts for operations.[12] The limitation of data constrains our ability to accurately measure regulatory

[11] For an example, Cyree (2016) found lower pretax return on assets, lower loans per employee, lower technology and fixed-asset expenditures, and higher percentage change in employees and salaries-to-assets in panel regressions after the passage of Dodd–Frank Act. For another example, Hogan and Burns (2019) divided noninterest expenses into salary expenses and non-salary expenses. They found that although salary expenses grew faster after Dodd-Frank Act for both large and small banks, small banks have been bearing higher total noninterest expenses and salary related expenses and non-salary related expenses after the Act.

[12] The Conference of State Bank Supervisors (2017) conducted a national survey of more than 600 community banks and estimated compliance costs as a percentage of each expense category. On average, the salary and benefits of compliance staff account for 10–12% of total salary expenses; accounting and auditing for compliance purpose accounts for 38–42% of expenses of accounting and auditing; consulting and advisory expenses related to regulatory compliance accounts for 42–47% of total such expenses. Yet, these survey results have large variance, as the median values are dramatically smaller than the mean values.

compliance cost and its effects. Therefore, the changes of capital market incentives could be a better way to measure effects of regulatory burdens imposted by policy changes.

1.2.2 The Regulatory Relief Plan for Smaller Banks

Around 2015, a series of rules (see Table 1.A.1) were made to provide regulatory relief for smaller banks. Hunter (2015) provided a summary of the relief plan. First, the plan calls for improving the efficiency of supervisory activities by (a) reducing examination intensity and frequency on low-risk community (assets under \$10 billion) and regional banks (assets of \$10-50 billion), (b) more off-site supervisory activities, (c) developing technological tools for off-site and on-site supervisory activities, and (d) training community bank examiners. Second, the plan calls for expanding the Small Bank Holding Company Policy Statement to cover 89% of all BHCs and 81% of all savings and loan holding companies to a) increase debt limit for transferring ownership, and b) be excluded from consolidated capital requirements. Third, BHCs and savings and loan holding companies (assets under \$1 billion) are exempted from quarterly Y-9C reports and instead required to file simpler Y-9SP reports semiannually, and savings and loan holding companies with assets of less than \$500 million are exempted from reporting regulatory capital data in Y-9SP reports.

Despite that the Conference of State Bank Supervisors (2017) stated that "signs of actual regulatory relief were not yet apparent in our survey results" and "inferred compliance costs for community banks increased from \$4.5 billion in 2014 to \$5.0 billion in 2015 and then to \$5.4 billion in 2016." Therefore, it is crucial to measure the effects of the relief plan.

At the same time, heightened capital and risk requirements were imposed on larger BHCs with assets of $50 billion or more, which might intensify the divergence between SIBs and non-SIBs. For example, Basel III has implemented regulatory capital rules and minimum liquidity coverage ratio for large BHCs. To implement Dodd-Frank Act, guidelines for heightened standards for SIBs are effective from late 2014. Details are provided in Table 1.A.2.

1.2.3 Systemically Important Banks

To compare the divergence of lending behaviors between SIBs and non-SIBs, I summarize the list of SIBs in Table 1.B.1 in Appendix, based on the list of large BHCs participated in the Supervisory Capital Assessment Program (SCAP), Comprehensive Capital Analysis and Review (CCAR), and Dodd-Frank Act stress test (DFAST) in 2009–2019 in Federal Reserve reports[13] and the list of large holding companies collected by NIC National Information Center[14]. The SIB list includes 19 "old" SIBs[15] which participated in the 2009 SCAP and have remained in the list since then and 20 "new" SIBs[16], including 12 foreign banks[17] operating

[13] The list of CCAR reports: `https://www.federalreserve.gov/publications/comprehensive-capital-analysis-and-review-publications.htm`; the list of DFAST reports: `https://www.federalreserve.gov/publications/dodd-frank-act-stress-test-publications.htm`

[14] `https://www.ffiec.gov/npw/Institution/TopHoldings`

[15] They are Ally Financial, American Express, Bank of America, Bank of NY Mellon, BB&T, Capital One, Citigroup, Fifth Third Bank, Goldman Sachs, JPMorgan Chase, Keycorp, MetLife (dropped out after 2012), Morgan Stanley, PNC Financial, Regions, State Street, SunTrust Banks, US Bancorp, and Wells Fargo.

[16] Eight domestic BHCs added to the list are CIT group, Comerica, Discover, Huntington, M&T Bank, Northern Trust, Citizens, and Zions.

[17] They are BNP Paribas (BancWest), BBVA, BMO, Barclays, Credit Suisse, Deutsche Bank, HSBC, RBC, Santander, TD group, UBS, and MUFG. Due to the changes of institution type and other reasons, these foreign SIBs often use different RSSD ID in Call reports and Y9C reports and some also changed ID. In addition, the ID matching list by NY Fed which I use to link market value with bank information does not include foreign banks. Therefore, I have to manually fix their ID changes and match their market values with their bank information. See my data manual for details.

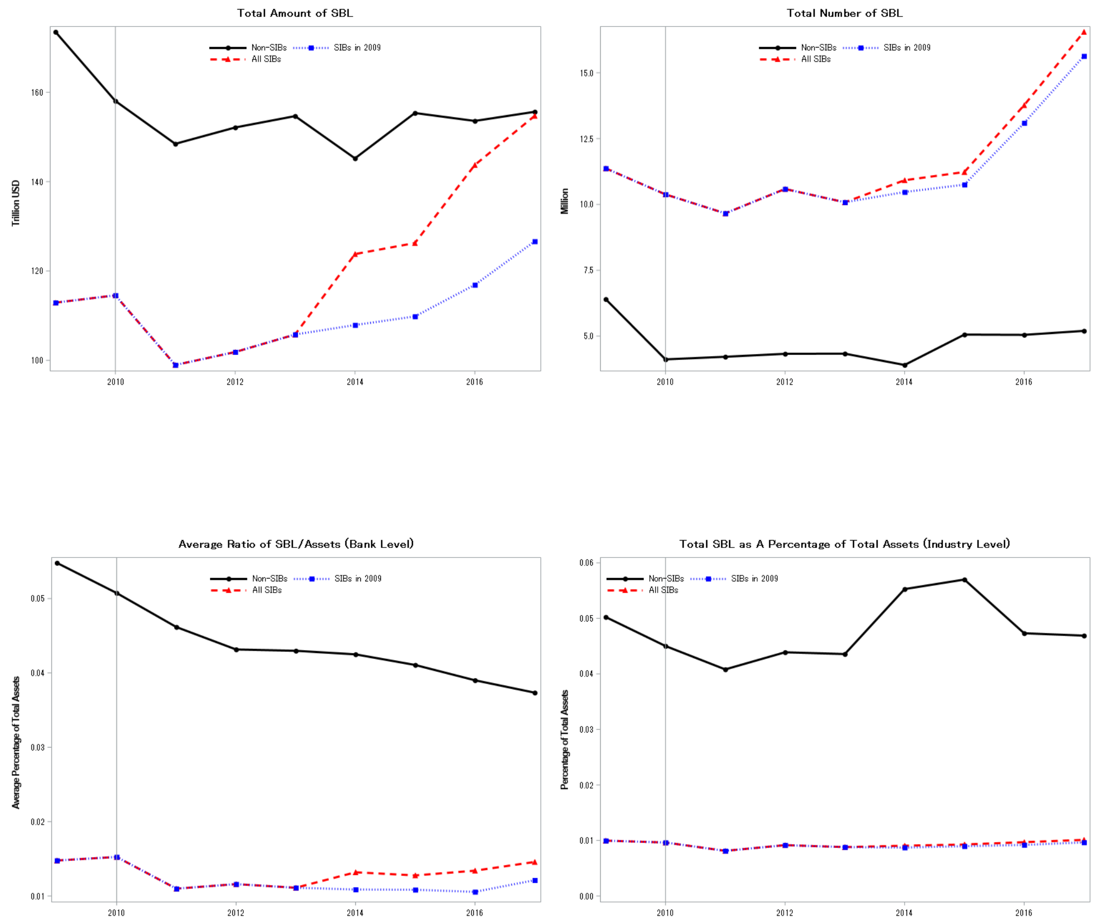
in the U.S., which joined after 2014.[18] The scattered plots of SBL made by SIBs are in Figure 1.B.1.

At aggregate level, SIBs contributed to the recovery of SBL more than non-SIBs did, especially after 2015, as shown in Figure 1.3. Although more than half of the total SBL was made by smaller banks, SIBs have been increasing loans to small businesses since 2011. SIBs have contributed to half of the total SBL in the U.S., within which the additional \$13 trillion of SBL were made by the 19 "old" SIBs which participated in the 2009 SCAP and \$28 trillion of SBL were made by the "new" SIBs which joined in the list after 2014. In 2009–2015, about 10 million outstanding SBLs were originated by SIBs, twice of the number by small BHCs. In 2017, SIBs made about 5 million more SBL, in which 1 million were made by "new" SIBs and 4 million were contributed by "old" SIBs. This implies that "old" SIBs mainly originated SBL of smaller amount than "new" SIBs did.

After scaled by total assets, SBL by SIBs and non-SIBs both remained relatively stable at levels of 1% and 4-5% respectively, as shown in Figure 1.3. At bank level, the average ratio of SBL/assets for non-SIBs declined from more than 5% in 2009 to below 4% in 2017 and, similarly, "old" SIBs decreased their SBL shares from 1.5% in 2009 and 2010 to slightly above 1% in recent years. "New" SIBs have been maintaining the average ratio of SBL/assets at more than 1.5%, pushing up the average ratio for all SIBs to 1.45% in 2017. But at industry level, SIBs have been holding 1% of their portfolio as SBL since 2009 without much variations, while the SBL shares of smaller BHCs have varied between 4% and 5.5%. These constant ratios of SBL/assets, combined with the consolidation of smaller banks and the increase in assets of SIBs, contributed to the trends shown in Figure 1.3.

[18]Note that there is a group of banks which have more than \$50 billion in assets but have never submitted to the annual stress test: SVB Financial (1031449), E Trade (3412583), Charles Schwab (1026632), and Synchrony (4504654).

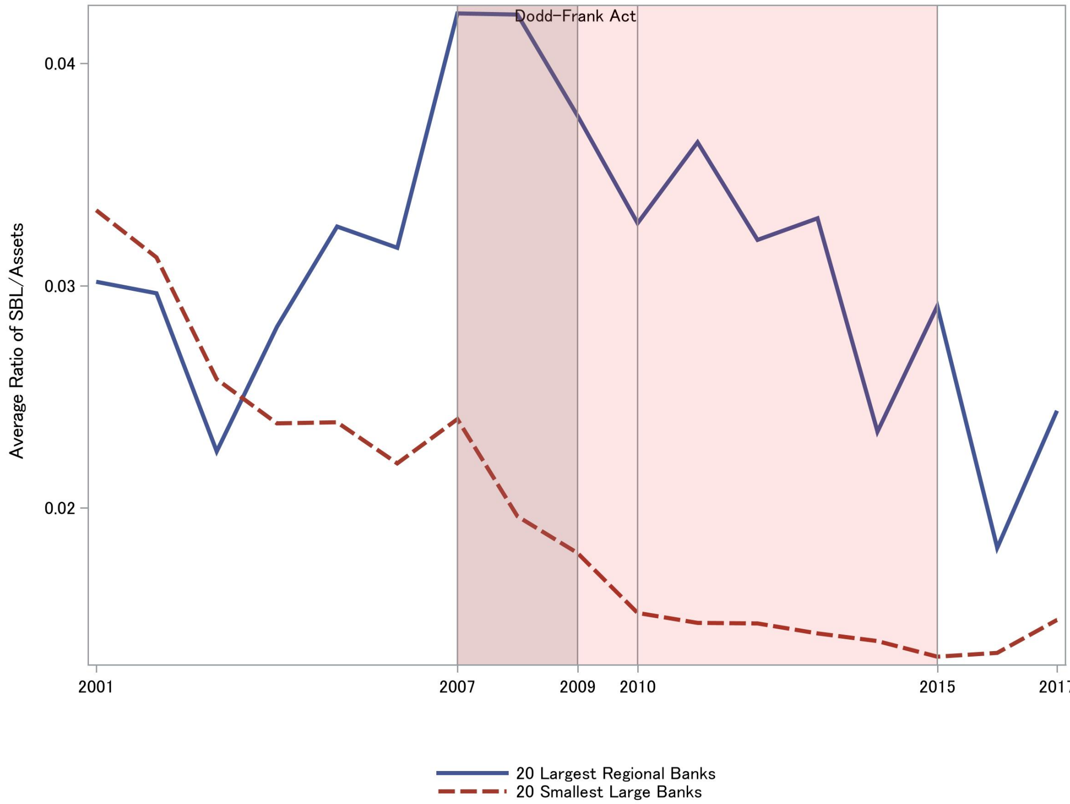
Figure 1.3: Aggregate and Average SBL: SIBs vs. non-SIBs in 2009-2017



*Source: Call reports; Y9-C reports; Federal Reserve Board. SIBs in 2009 refers to the 19 "old" SIBs participated in the 2009 SCAP. Since 2014, about 15 more "new" BHCs have been added to the list of SIBs and submitted to heightened supervision. Non-SIBs refers to smaller BHCs which filed Call reports and Y9-C reports. The bank-level average ration of SBL/Assets is calculated as the arithmetic mean of individual bank's SBL scaled by its total assets. The industry level average refers to the aggregate amount of SBL in the banking industry scaled by the total assets of the industry.

To briefly examine whether the $50 billion asset threshold has changed the lending behavior of large banks, I select 20 regional banks and 20 large banks

Figure 1.4: SBL by Banks with Assets Around $50 Billion Threshold



*I select 20 regional banks and 20 large banks with assets around the threshold and plot the average ratio of SBL/assets. I conduct the Wilcoxon two sample test and the area is filled with pink shade when the results are statistically significant.

with assets around the threshold and plot the average ratio of SBL/assets, as shown in Figure 1.4. Although initially falling behind, 20 largest regional banks more focus on SBL than 20 smallest large banks do. The difference is statistically significant in the Wilcoxon two sample test and maintains about 1—2% during 2007—2015, as indicated by the pink area.

1.3 Data and Identification

1.3.1 Data Description

This chapter uses BHC-level data from Federal Reserve Y-9C reports, market value data from Wharton Research Data Service (WRDS) Compustat, SBL data from Consolidated Report of Condition and Income for FDIC-insured institutions (Call Reports), branch-level bank deposit data from Summary of Deposit, and state-level GDP data from Bureau of Economic Analysis.[19] The time period of interest is 2001-2017, covering before, during, and after the financial crisis. Although I have updated the data to 2018, this chapter does not include year 2018 due to the possible effects of the deregulation law in 2018. Except for SBL data, other data are collected at the end of each year during 2001-2017.

Federal Reserve Y-9C data are collected quarterly for all domestic holding companies with certain level of consolidated assets.[20] The BHC accounting items collected are liabilities, assets, revenues, different types of loans, capital, interests, cost of funding, and non-performing loans.

The market values for BHCs are collected from WRDS Compustat. The market value of assets is proxied by the sum of the market value of equity and the book value of liabilities, and the market value of equity is calculated as the product of stock prices and outstanding shares by the end of each fourth quarter.

Because regulators do not collect data on SBL, I extract the small commercial

[19]Data manual in Appendix 1.C

[20]Before 2006, banks with more than $150 million in consolidated assets were required to file Y9C. In 2006, the asset-size threshold was raised from $150 million to $500 million; in 2015, it was further raised to $1 billion; in 2018, it was increased to $3 billion. This leads to the decline of the number of observations. Details in Appendix.

and industrial (C&I) loans as a proxy for SBL from the Schedule RC-C Part II in Call Reports. FDIC-supervised banks are required to report the number and amount of *outstanding* of C&I loans with original amounts of $100,000 or less, more than $100,000 through $250,000, and more than $250,000 through $1,000,000 respectively.[21] This chapter uses the total amount of outstanding C&I loans under $1 million as the amount of SBL.[22] Due to the data limitation of SBL before 2010, Call Reports in second quarters are used for each year. So SBL data is 6-month leading other variables. A summary of average amount of SBL and the ratio of SBL/assets by banks of different sizes is shown in Table 1.1.

Summary of Deposits provides bank branch-level data on deposits for FDIC-insured banks. This data is used for three purposes. First, the Herfindahl-Hirschman index (HHI), as a measure of market concentration, is calculated by taking square of market share of each BHC's deposits in the market and then summing up to the state-level. The county-level HHI can be calculated using zip codes of branches.[23] Second, I calculate each BHC's share of deposits in each operating counties as weights to get weighted HHI. Similarly, using the state-level GDP data from the Bureau of Economic Analysis, I calculate the weighted average GDP growth rate for each holding company to control the economic fundamentals. Third, SOD contains the relationship structure of banks with their BHCs, which can be extracted and used to sum all the bank-level data can be summed up to top-tier holding company level.

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[21] In Schedule RC-C Part II, banks are also asked whether all C&I loans have original amounts of $100,000 or less. If the answer is yes, then the total amount of C&I loans is counted as SBL.

[22] Although, according to FDIC Small Business Lending Survey (2018), this proxy of C&I loans under $1 million in the Call Report failed to capture larger C&I loans and loans secured by residential real estate that were also borrowed by small businesses, it is still the best available measure of sbl. Detailed discussion in Appendix.

[23] According to FDIC Small Business Lending Survey (2018), banks usually view local banks of similar size as major competitors and local banks of other size as frequent competitors. Therefore, county-level HHI is a better proxy for market competition than state-level HHI.

Table 1.1: SBL by Banks of Different Sizes
(unit: million dollars)

Year	All Banks	Large	Regional	Large Community	Small Community
2001	32.81	4101.13	846.08	157.18	27.2
2002	34.46	4129.73	897.43	154.14	26.37
2003	34.57	3874.09	815.22	140.71	25.2
2004	36.14	3764.31	716.47	140.02	24.85
2005	37.59	4343.64	699.29	134.19	24.83
2006	38.61	4323.67	686.89	133.81	38.62
2007	43.27	5695.01	691.99	131.22	39.37
2008	51.81	5707.06	674.55	130.3	39.77
2009	50.36	5034.89	623.41	119.04	38.33
2010	49.42	5077.12	584.31	111.66	35.44
2011	42.49	4664.92	560.2	101.99	31.59
2012	42.83	5246.72	541.89	97.32	30.24
2013	45.21	5197.48	533.7	98.51	30.42
2014	48.24	5298.57	556.77	101.4	30.09
2015	52.46	5161.54	631.628	104.93	40.66
2016	57.61	5388.11	571.56	103.95	35.62
2017	62.4	5539.44	637.95	100.59	35.36

Source: Call Reports.
Note: The sample has 19003 observations, larger than that used in regressions.

Depending on the size of consolidated assets, banks are categorized into regional and large banks[24] (with more than \$10 billion assets), and community banks (including large community banks with assets of \$1-10 billion and small community banks with less than \$1 billion assets)[25]. The cross-sectional regression is conducted for each bank category during 2001–2017, which can demonstrate the divergence between large and smaller banks in capital market incentives.

Table 1.2: The Summary Statistics for Key Variables (N=6331)

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Tobin's Q	1.057	0.069	0.616	1.534
SBL/Assets	0.05	0.039	0	0.422
Business-Loan/Assets	0.109	0.074	0	0.579
Total-Loan/Assets	0.682	0.133	0.012	0.966
Log(Assets)	14.76	1.675	11.94	21.67
Liquid-Assets/Assets	0.261	0.121	0.016	0.952
Noninterest-Income/Revenue	0.19	0.132	-1.129	0.977
Nonperforming-Loan/Assets	0.02	0.023	0	0.316
Deposits/Funding	0.905	0.095	0.107	1
GDP	0.041	0.014	-0.025	0.119
HHI	0.19	0.084	0.061	0.895

[1] The sample period spans 2001-2017.
[2] All variables are at BHC level.

Table 1.2 provides a summary of key variables. When combining the data, many observations are dropped, due to different reporting requirements from different data sources and the limited number of publicly-traded BHCs. This is a limitation of the dataset. My sample data is an unbalanced panel. The sample selection cannot be assumed exogenous, because only publicly-traded BHCs which filed Y9-C and Call reports are included. The fact that smaller banks which were not required to file regulatory reports or not publicly traded are not in my sample probably underestimated the effects of regulatory burden.

[24]It would be ideal to create a category of large banks, but the number of banks with more than \$50 billion assets is too small, which hampers the estimation process.

[25]Due to the dramatic decline of number of small community banks in recent years, it is better to combine small community banks with large community banks for estimation purpose.

This chapter also collects the branch-level SBL data in CRA Disclosure Reports during 2001-2017 for robustness check. This SBL is different in definition and reporting requirements from Call Reports.[26] The branch-level data is summed up to holding company level according to the link implied by the Summary of Deposit. The data would be used for a robustness check. The plotted SBL data for banks in different sizes are in Figure 1.D.1, Figure 1.D.2, Figure 1.D.3, and Figure 1.D.4 in the Appendix.

1.3.2 Univariate Analysis

Before running regressions, I check the univariate relation between SBL and financial performance of banks in different sizes. Table 1.3 provides the average Tobin's Q ratio for banks with different levels of SBL and bank assets. To construct this table, I rank BHC-year data based on the ratio of SBL/assets and the size of assets and then divide by the 25th, 50th, and 75th percentile. I calculate the average value of Tobin's Q ratio for each group of large, regional, and community banks respectively. For community banks, financial performance and lending to small businesses are positively correlated, while for large and regional banks, SBL and financial performance are roughly negatively correlated.

To better illustrate the relationship between financial performance and SBL of large and community banks, I plot the average financial performance of banks dedicated most and least to SBL, as shown in Figure 1.5. First, I ranked large banks by their ratio of SBL/assets, and then plot the average value of Tobin's Q ratio for the top 10 and bottom 10. The bottom 10 large banks making least

[26] Note that SBL data from CRA are flow data while SBL from Call Reports are stock data. To some extent, the newly originated SBL amount in CRA can better demonstrate the recovery of small business credit availability.

Table 1.3: Bank Financial Performance by Small Business Lending and Bank Size

	Average Financial Performance(Tobin's Q)		
Quantile of SBL	Large	Regional	Community
P0 – P25 (smallest)	1.095	1.100	1.044
P25 – P50	1.057	1.076	1.052
P50 – P75	1.050	1.072	1.059
P75 – P100 (largest)	1.079	1.076	1.060

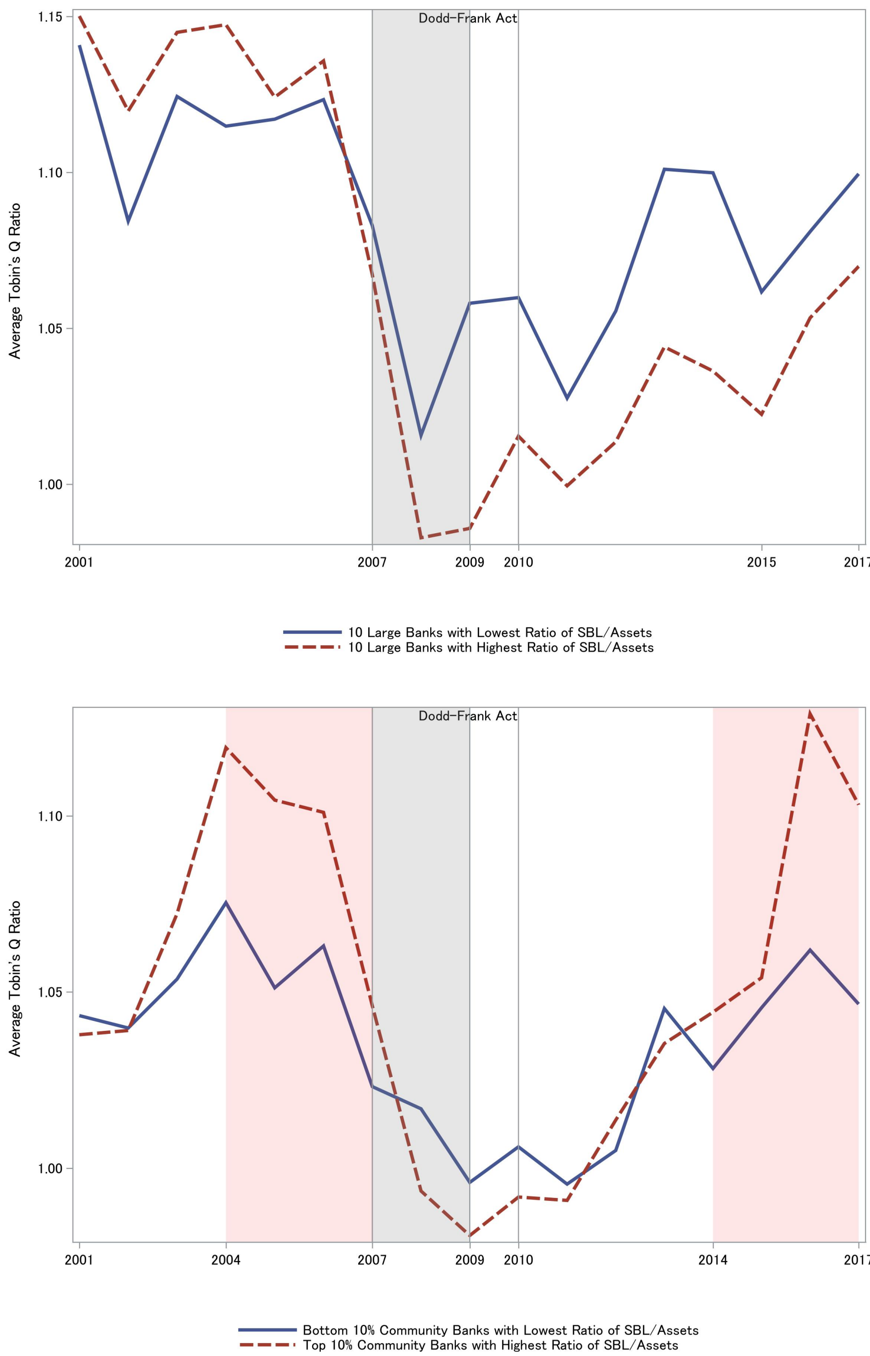
[1] Banks in different sizes are ranked by their ratio of SBL/assets and grouped by 25th, 50th, and 75th percentiles. I calculate the average value of Tobin's Q ratio for each group.

SBL as a percentage of total assets[27] have been outperforming the top 10 banks in financial performance since 2007. Before the recent financial crisis, the top 10 large banks maintained about 3%–6% of assets as SBL and enjoyed higher Tobin's Q ratio than those of the bottom 10, but they were also hurt more in the crisis partly because of the risky nature of SBL. I conduct the Wilcoxon two sample tests to examine the difference between the two groups, despite that the results are not statistical significant due to the small sample size, the trend of bottom SBL-making large banks performing better financially is robust to slight changes of the sample size.

Second, based on the ratio of SBL/assets, I rank community banks and plot the average Tobin's Q ratio for the top and bottom 10%. The financial performance of the top community banks, similar to that of top large banks, is more volatile than that of the bottom community banks, which is partly because the financial crisis is associated with higher default rate of SBL. However, top community banks have been outperforming bottom 10% in financial performance during pre-crisis era and later recovery period, with eight years with statistically significant difference as shown in pink shades. Both top and bottom community banks have mostly recovered their Tobin's Q ratio, but large banks have not.

[27] it often includes at least two Big4 banks: Citi Group and JPMorgan Chase.

Figure 1.5: Financial Performance Comparison



Note: I ranked 40 large banks which once labeled as SIB by their ratio of SBL/assets, and then plot the average value of Tobin's Q ratio for the top 10 and bottom 10 in the upper panel. Similarly, I rank community banks and plot the average Tobin's Q ratio for the top and bottom 10% in the lower panel. I conduct the Wilcoxon two sample test and the area is filled pink if the test result is statistically significant at 90% confidence level.

1.3.3 Methodology

The relationship of interest is how much financial incentives the capital market provided for banks to make SBL:

$$FinancialPerformance_{i,t} = \alpha + \tau_t + \beta \frac{SBL_{i,t-0.5}}{Assets_{i,t}} + \gamma' X_{i,t} + \epsilon_{i,t} \tag{1.1}$$

where $FinancialPerformance_i$ is proxied by the Tobin's Q ratio of BHC i in year t, $SBL_{i,t-0.5}$ is the outstanding amount of small business loan in 6 months before year t, $Assets_{i,t}$ is the amount of total assets, τ_t are year fixed effects, and $X_{i,t}$ is a vector of bank characteristics[28] and deposit-weighted fundamentals which include logarithm of book value of assets, share of liquid assets to total assets, share of non-interest income to total revenue, nonperforming loans-to-assets, ratio of deposits to total funding, ratio of equity to assets, and deposit-weighted HHI and GDP growth rate, as well as large business loan and non-business loan ratios, based on Hughes et al. (2019).

The underlying assumption for an unbiased OLS estimate for β is that $\frac{SBL_{i,t-0.5}}{Assets_{i,t}}$ is orthogonal to $\epsilon_{i,t}$. Generally, this assumption is likely to hold because the ratio of SBL to total assets half a year ahead is unrelated to other factors which might affect the financial performance of one BHC, conditioned on covariates. The concern of reverse causality is not valid, not only because the lending strategy cannot be caused by bank's financial performance 6 months later, but also because the change of lending strategy[29] should be based on the observation of

[28] For the concern of near-multicollinearity, it would not lead to estimation bias but would make all parameter estimates insignificant while joint significance of all regressors is upheld, which does not happen in my results.

[29] One possible channel could be that the enhanced financial performance due to stock market boom would lure banks to expand sizes. In order to conduct M&A activities, according to

incentives provided by the capital market.

I apply the year fix effects to eliminate the inter-temporal variation and focus on comparing banks within the same period of time. I choose to not include unit fix effects due to two reasons. First, there is not enough within-unit variation in SBL to allow for the unit fixed-effects estimation.[30] Second, when both unit and year fixed effects are used, the variation reduction would be even more severe and the coefficient would be a complicated weighted average of unit and year fixed effects.

To capture the impact of regulatory changes on SBL, I specify the pooled OLS regression and further add policy and size dummy variables interacting with SBL to estimate the capital market incentives for the periods under specific policy and for certain groups of banks. The panel estimation takes the form:

$$
\begin{aligned}
FinancialPerformance_{i,t} = {} & \alpha_0 + \alpha_t + \beta_1 \frac{SBL_{i,t-0.5}}{Assets_{i,t}} + \beta_2 \frac{SBL_{i,t-0.5}}{Assets_{i,t}} \\
& * PolicyDummy + \beta_3 \frac{SBL_{i,t-0.5}}{Assets_{i,t}} \\
& * SizeDummy + \beta_4 \frac{SBL_{i,t-0.5}}{Assets_{i,t}} \\
& * PolicyDummy * SizeDummy + \gamma' X_{i,t} + \epsilon_{i,t}
\end{aligned} \tag{1.2}
$$

where $PolicyDummy$ is a dummy variable, equals 1 in years under certain regulatory policies and 0 otherwise, and $SizeDummy$ is a dummy variable, equals 1 for large banks or with other conditions, and 0 otherwise. Other variables are

Community Reinvestment Act, banks need to meet certain levels of requirements for SBL. While this possible channel implies positive relationship between SBL and financial performance, my results show negative relationship for large banks, which further eliminates the possibility of this channel.

[30]Within-unit variation is usually smaller than the overall variation in the independent variable.

the same as those in regression (1). The cluster-robust standard deviations are calculated as clustering by each BHC.

To measure the marginal effect of a 1 p.p. increase in SBL/assets, I sum up coefficients. β_1 shows the effect for smaller banks before the regulation; $\beta_1 + \beta_2$ represents the effect for smaller banks under the regulation; $\beta_1 + \beta_3$ shows the effect for large banks before the regulation; $\beta_1 + \beta_2 + \beta_3 + \beta_4$ represents the effect for large banks under the regulation.

1.4 Results

1.4.1 Year-by-year Estimation

The year-by-year regression to measure the impact of increasing or substituting SBL on banks' financial performance is

$$FinancialPerformance_i = \alpha + \beta_1 \frac{SBL_i}{Assets_i} + \beta_2 \frac{LBL_i}{Assets_i} + \beta_3 \frac{NBL_i}{Assets_i} + \gamma' X_i + \epsilon_i \tag{1.3}$$

where $FinancialPerformance_i$ is proxied by the Tobin's Q ratio of BHC i in one year between 2001 and 2017, SBL_i is the outstanding amount of small business loans of BHC i, LBL_i represents large business loans which is calculated as total business loans (or commercial & industrial loans) subtracting SBL, and NBL_i represents total non-business loans which is calculated as total loans subtracting total business loans. I control for a set of bank characteristics in X_i, including logarithm of book value of assets, share of liquid assets to total assets, share of non-interest income to total revenue, nonperforming loans-to-assets, ratio of deposits to total funding, and ratio of equity to assets. I also control for GDP and HHI. GDP is the 5-year average growth rate of GDP in states where branches of one BHC operate weighted by its deposits in each state, HHI is county-level and weighted by one BHC's deposits in each county it operates.

The coefficients of interest are β_1 on the ratio of SBL-to-assets for each BHC, β_2 on the ratio of large business loans-to-assets, and β_3 on the ratio of total non-business loans-to-total assets. Specifically, β_1 measures the effect of an 1 p.p. increase in SBL ratio on financial performance. By subtracting β_2 from β_1, I measure the impact of replacing large business loans with SBL on financial performance. By subtracting β_3 from β_1, I measure the impact of replacing non-business loans[31] with SBL.

The baseline cross-sectional model was estimated for each year from 2001-2017 for banks with different sizes. Table 1.E.3, 1.E.1, and 1.E.2 in Appendix summarize the results of interest. Although some coefficients are not statistically significantly different from zero, there exist obvious divergences between large banks and smaller banks in capital market incentives, as shown in Figures 1.6, 1.7, and 1.8.

Decreasing SBL?

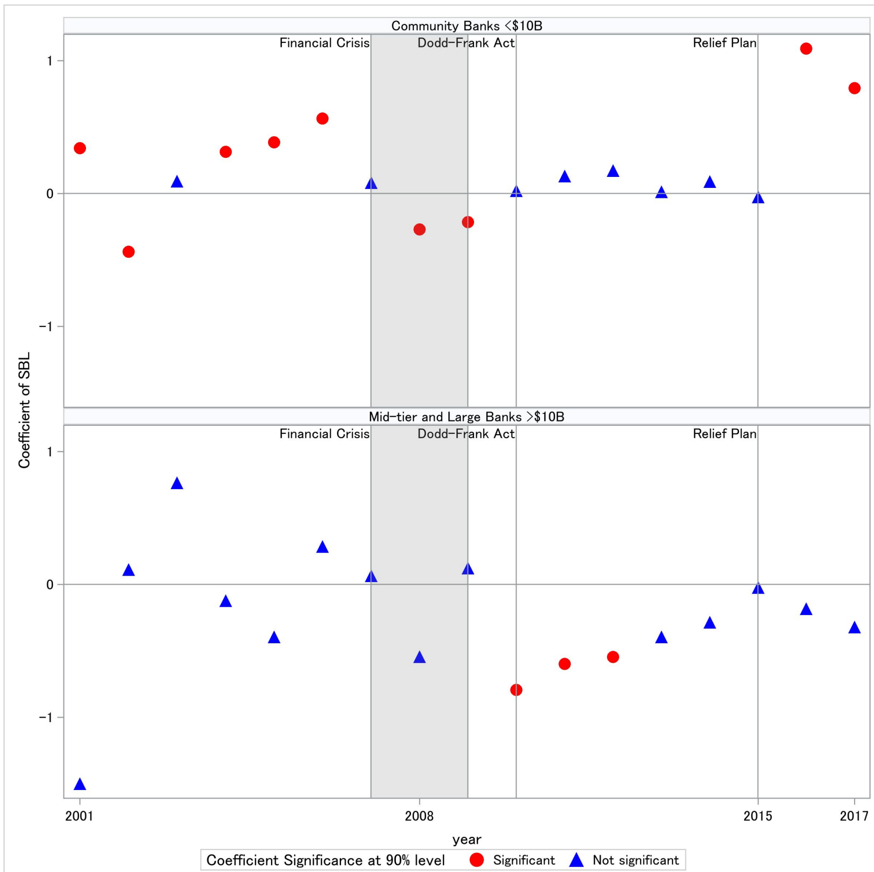
To measure the impact of a 1 p.p. increase in SBL/assets on banks' financial performance in each year, I plot the estimated coefficients of SBL ratio of community banks and regional & large banks,[32] as shown in Figure 1.6. Significantly

[31]Other types of loans include real estate loans, loans to other banks, loans to other financial institutions, agricultural loans, consumer loans, and loans to foreign governments.

[32]Since community banks are the majority of my sample, the results for all banks are driven by community banks' characteristics. I do not report the results for entire sample, as them are very similar to those of community banks.

positive coefficient represents that banks have incentives from the capital market to lend more to small businesses, because banks can improve their financial performance by increasing ratio of SBL/assets. Similarly, significantly negative coefficient represents that banks have incentives to reduce SBL.

Figure 1.6: Financial Incentive (Tobin's Q Ratio) on Increasing SBL/Assets



Note: The figure shows the coefficients of SBL ratio in repeated cross-sectional regressions (see Table 1.E.3) for community banks and larger banks, which represent capital market incentives for banks to increase SBL/Assets. Significant positive coefficient represents that banks have incentives from the capital market to lend more to small businesses, and significant negative coefficient represents incentives for banks to make less SBL. Blue triangles refer to no incentives from the capital market for SBL. Community banks are banks with consolidated assets of less than $10 Billion; regional banks refer to banks with consolidated assets of $10-50 Billion; large banks refer to banks with consolidated assets of more than $50 Billion.

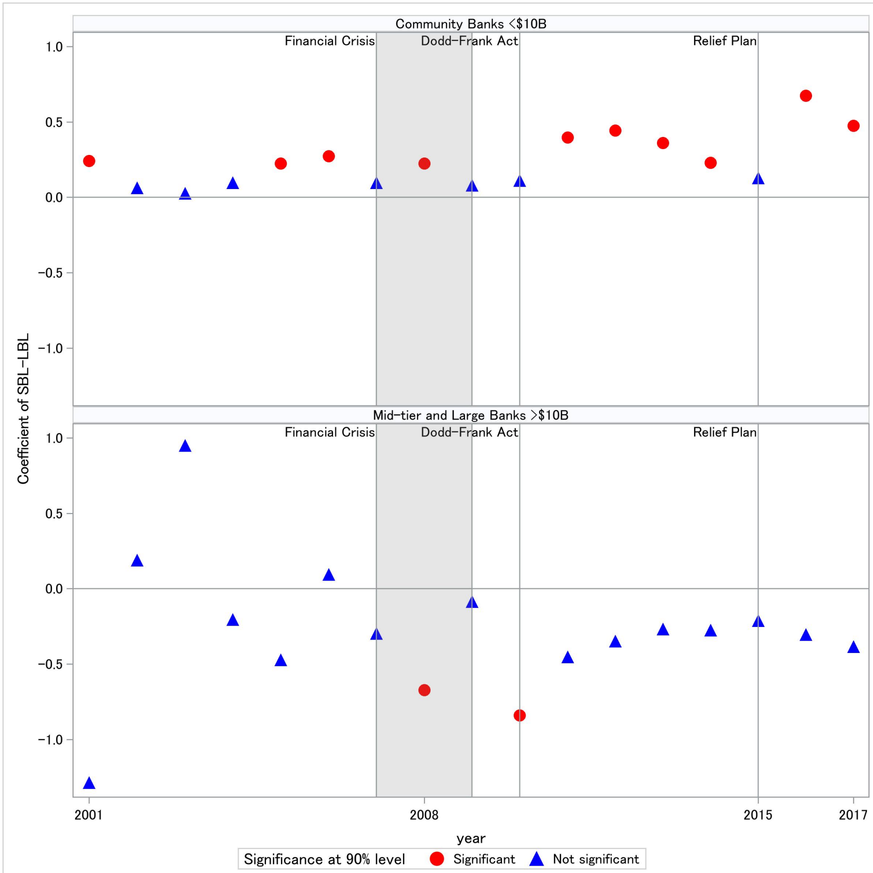
For community banks, the financial incentives have been mostly positive before the crisis and after 2015, implying that shareholders viewed SBL as a profitable opportunity for community banks during those periods. In 2008 and 2009, the capital market considered SBL as risky and nonprofitable assets for community banks, since small businesses are usually hit most and easier to bankrupt compared to large firms during recessions.

For regional & large banks, the coefficients were fluctuating and insignificant before 2010. After 2010 when Dodd-Frank Act was passed, the coefficients have turned to negative and were significant in 2010, 2011, and 2012. The coefficients were increasing during 2010-2015 but started to decline after 2015.

Replacing SBL with Large Business Loans?

To measure the impact of replacing large business loans with SBL on banks' financial performance for community banks and regional & large banks in each year, I plot the estimated coefficients of SBL ratio minusing those of large business loans-to-assets ratio, as shown in Figure 1.7. Significantly positive coefficient represents that banks have incentives from the capital market to replace large business loans with SBL, because banks can enhance their market value by increasing SBL and at the same time decreasing large business loans. Similarly, significantly negative coefficient represents that banks have incentives to replace SBL with large business loans.

Figure 1.7: Financial Incentive (Tobin's Q Ratio) on Replacing Large Business Loans with SBL



Note: The points show the difference between coefficients of SBL/assets ratio and coefficients of large business loans-to-assets ratio in the cross-sectional regressions (see Table 1.E.1), which represent financial incentives for banks to replace large business loans with SBL. Significantly positive coefficient represents that banks have incentives from the capital market to replace large business loans with SBL. Similarly, significantly negative coefficient represents that banks have incentives to replace SBL with large business loans. Blue triangles refer to no incentives from the capital market for replacement. The significance level is determined by the joint F-test. Community banks are banks with consolidated assets of less than \$10 Billion; regional banks refer to banks with consolidated assets of \$10-50 Billion; large banks refer to banks with consolidated assets of more than \$50 Billion.

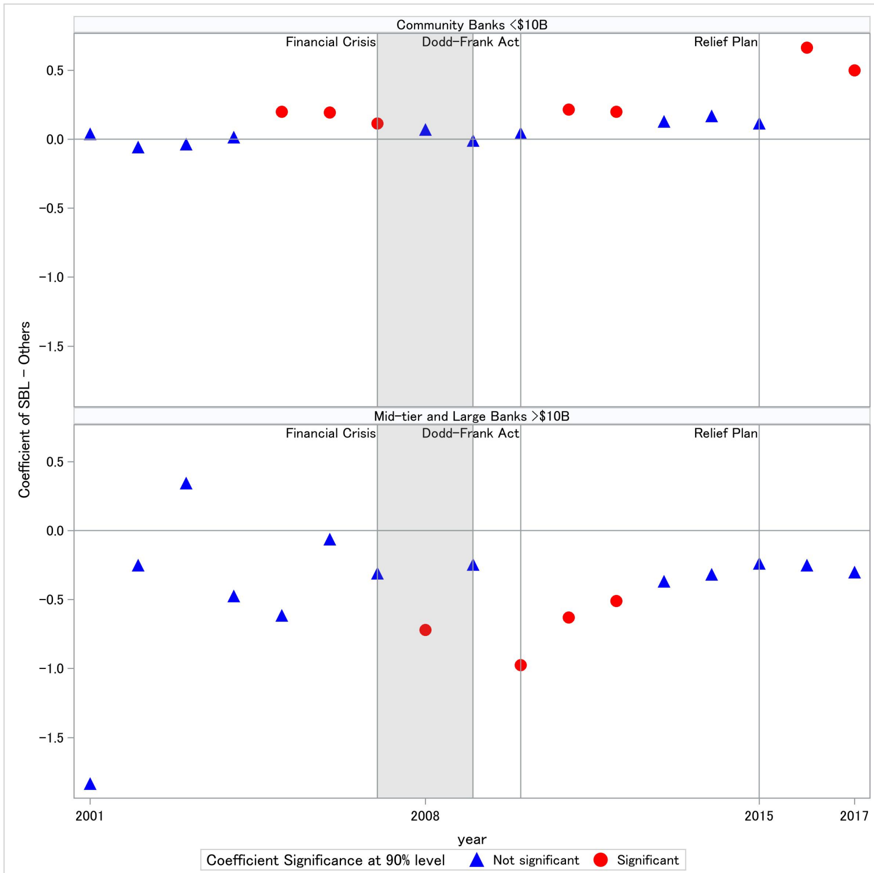
Consistently, community banks have financial incentives to replace large business loans with SBL. This implies that the capital market consider cutting the size of business loans would be more profitable for community banks, even in 2008. This could be explained by the comparative advantage of community banks for SBL.

For regional & large banks, the coefficients have been statistically insignificant before 2008 financial crisis and turned negative afterwards, except for year 2008 and 2010. If replacing 1% of SBL ratio with 1% of large business loans-to-assets, Tobin's Q ratio of regional & large banks would increase by more than 0.5 p.p. in 2008 and 2010–2012. This is probably due to the fact that large firms are less likely to default the loans compared to small businesses during recessions, which is easier to understand than the case of community banks.

Replacing SBL with Non-business Loans?

To measure the impact of replacing non-business loans with SBL on banks' financial performance for community banks and regional & large banks in each year, I plot the estimated coefficients of SBL/assets ratio subtracting those of non-business loans/assets ratio, as shown in Figure 1.8. Significantly positive coefficient represents that banks have incentives from the capital market to replace non-business loans (such as residential or commercial real estate loans and consumer loans) with SBL, because banks can enhance their market value by increasing SBL and at the same time decreasing non-business loans. Similarly, significantly negative coefficient represents that banks have incentives to replace SBL with non-business loans.

Figure 1.8: Financial Incentive (Tobin's Q Ratio) on Replacing Non-business Loans with SBL



Note: The points show the result of coefficients of SBL ratio minus non-business loan ratio in the cross-sectional regressions (see Table 1.E.2), which represent financial incentives for banks to to replace non-business loans with SBL. Significantly positive coefficient represents that banks have incentives from the capital market to replace non-business loans with SBL. Similarly, significantly negative coefficient represents that banks have incentives to replace SBL with non-business loans. Blue triangles refer to no incentives from the capital market for replacement. The significance is determined by the joint F-test. Community banks are banks with consolidated assets of less than $10 Billion; regional banks refer to banks with consolidated assets of $10-50 Billion; large banks refer to banks with consolidated assets of more than $50 Billion.

Similar to the case in Figure 1.7, community banks have financial incentives to replace non-business loans with SBL before 2008 financial crisis and after 2015, implying that the capital market consider SBL would be more profitable than other types of loans for community banks. For regional & large banks, the coefficients have been mostly negative and statistically insignificant, except for year 2008 and 2010–2012. The trends in Figure 1.8 is similar to those shown in Figure 1.7, which is probably because SBL is riskier than not only large business loans but also other types of loans.

In summary, the capital market evaluates lending strategies differently based on the asset size of banks. Overall, the capital market considers SBL as a profitable asset for community banks but an unimportant or nonprofitable asset for regional & large banks. Before the recent recession, community banks had incentives to increase SBL/assets and replace large business loans or other types of loans with SBL, but for regional & large banks, their lending strategy related to SBL did not affect their financial performance, which might be due to the relatively lower share of SBL to assets in regional and large banks, as shown in Figure 1.D.2 and Figure 1.D.4 in the Appendix. During and after the recent crisis, shareholders started to evaluate SBL in regional & large banks as risky and nonprofitable and thus regional & large banks have incentives to decrease SBL or replace it with other loans to improve financial performance. The disincentives during the crisis could be explained by the risky nature of SBL, yet the disincentives in the post-crisis era should be related to Dodd-Frank Act. For community banks, the lack of incentives during 2010–2015 could also be related to the regulatory burden imposed by Dodd-Frank Act and the revival after 2015 should be due to the relief plan for smaller banks. These results motivate the panel estimation for policy effects in the next section.

1.4.2 Panel Estimation – Effects of Regulation Changes

In year-by-year regressions, I have to measure the capital market incentives for regional and large banks together due to the small number[33] of large banks. This section focuses more on large banks, especially the ones under stress tests – SIBs. Panel regressions can capture regulatory policy effects.

The Effects of Dodd-Frank Act

To evaluate how Dodd-Frank regulations alter capital market incentives to lend to small businesses, I create a time-series dummy variable *DFA*, which equals 1 from 2010 when the Act was signed. To demonstrate the divergence between large and smaller banks, I include another dummy variable *LARGE*, which equals 1 for BHCs with consolidated assets of more than \$50 billion,[34] and 0 for community and regional banks.[35] I also create a dummy variable SIB which equals to 1 when one BHC is labeled as a SIB and under stress test *currently at year t*.[36] This is to capture the effects that Dodd-Frank Act imposes heightened restrictions on large banks. Table 1.4 summarizes results from pooled OLS estimation using data spanning 2001-2017. To better compare the different effects of Dodd-Frank Act on capital market incentives for large banks and smaller banks, I summarize the marginal effect of a 1 p.p. increase in SBL at the lower panel.

Model (1) and (2) show that capital market has been encouraging community

[33] The sample sizes for each regression are summarized in Table 1.E.1, Table 1.E.2, and Table 1.E.3.

[34] Excluding those with assets more than \$50 billion but have never been labeled as SIBs

[35] Note that even if one BHC was not listed as a SIB in a specific year, as long as it has been labeled as SIB before, then it is assigned 1 for LARGE variable.

[36] Because the list of SIBs is available only after 2009, I use the dummy for SIBs for the convenience of comparison with pre-crisis period.

Table 1.4: Large vs. Small Banks Before and After Dodd-Frank Act

This table reports results of pooled OLS regression of Tobin's Q on ratio of SBL/assets and its interaction with dummy variables. Coefficients are estimated using annual BHC level data spanning 2001-2017. SBL is defined as business loans with original amount of $1 million or less. DFA is a dummy variable and equals 1 from 2010 onward and 0 before 2010. LARGE is a dummy variable and equals 1 for large banks which were once labeled as systematically important bank and 0 otherwise. SIB is a dummy variable and equals 1 when a large bank is labeled SIB and under stress test. Bank controls include nonperforming loans, consumer loans, residential real estate loans, commercial real estate loans, ratio of liquid assets to total assets, ratio of non-interest income to revenue, and ratio of deposits to all funding. All loan variables are scaled by assets. Fundamental controls are weighted state-level 5-year GDP growth rate and weighted county-level Herfindahl-Hirschman index. All standard errors are clustered at individual BHC level. The joint effect is tested by using heteroscedasticity consistent covariance.

	Tobin's Q				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
SBL/Assets	0.171*	0.174*	0.174*	0.143	0.159
(a)	(0.097)	(0.098)	(0.098)	(0.099)	(0.1)
(SBL/Assets)*SIB			-3.098***		
(b)			(0.522)		
(SBL/Assets)*LARGE		-1.172***			-0.57
(c)		(0.375)			(0.375)
(SBL/Assets)*DFA				0.134*	0.106
(d)				(0.077)	(0.075)
(SBL/Assets)*DFA*LARGE					-2.325***
(e)					(0.522)
Bank Controls?	YES	YES	YES	YES	YES
Year FE?	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES
Obs.	6331	6331	6331	6331	6331
Adj.R^2	0.463	0.470	0.470	0.464	0.477
	Marginal Effect of 1 p.p. Increase in SBL/Assets:				
SIBs			-2.919***		
(a+b)			(130.69)		
Large Banks		-0.998***			
(a+c)		(25.78)			
During DFA				0.277***	
(a+d)				(20.87)	
Large Banks before DFA					-0.411*
(a+c)					(3.83)
Non-SIB during DFA					0.265***
(a+d)					(19.35)
SIB during DFA					-2.63***
(a+c+d+e)					(118.4)

[1] Clustered standard errors in parenthesis under estimated coefficients; Chi-Square values for joint effect using heteroscedasticity consistent covariance in parenthesis under marginal effect.
[2] *** stands for p<0.01; ** stands for p<0.05; * stands for p<0.1.
[3] Data are collected from Call Reports, Y-9C Reports, WRDS Compustat, Summary of Deposit, and Bureau of Economic Analysis.

and regional banks but penalizing large banks for lending to small businesses. A 1 p.p. increase in SBL/Assets ratio is associated with a 1.172 p.p. drop of Tobin's Q ratio for large banks, compared with a 0.174 p.p. increase for smaller banks. What's worse, when a large bank is *actually* labeled as a SIB and submit to stress test and heightened regulations, the penalty grows almost 3 times larger (from -0.998 to -2.919), as shown in model (2) and (3).

Model (4) and (5) further confirm the hypothesis that Dodd-Frank regulations changed capital market incentives for large banks to lend to small businesses. During the period under Dodd-Frank Act, banks overall enjoyed positive and enhanced capital market incentives: a 0.277 p.p. increase in financial performance for a 1 p.p. increase in SBL ratio in model (4), which is mainly driven by smaller banks. Large banks under Dodd-Frank regulations would expect a 2.63 decline in Tobin's Q ratio for a 1 p.p. increase in SBL ratio, drop from a decrease of 0.411 before the Act.

The worsen financial incentives for large banks can be explained by the heightened supervision standards imposed by Dodd-Frank Act. Since SBL is under higher risk assessment in stress tests, investors or shareholders would expect SIBs holding increasing amount of SBL are more likely to fail the test and thus suffer from the limits on dividend policy. But the improved financial incentives for smaller banks under the Dodd-Frank Act, as shown in model (5) in Table 1.4, are counter-intuitive, because many community banks complaint about the compliance costs contributed by Dodd-Frank regulations. Whether the relief plan for smaller banks in 2015 improved the capital market incentives and then drove up the incentives for post-Act period? The revival of financial incentives on SBL lending strategy for community banks after 2015 in the previous section also suggests a change in incentives.

The Impact of the Relief Plan of 2015

To further examine the effects of policy change for Dodd-Frank Act, this section focuses on SBL made by the large banks and their financial performance during 2010–2017. I create a time-series dummy variable *DFA2*, which equals 1 starting from 2015 and 0 before 2015, because in late 2014, the Federal Reserve announced to relieve the regulatory burden of Dodd-Frank Act for smaller banks from 2015. The dummy variable *DFA2* divided the sample period into two parts: before and after the relief policies. If this plan did relieve the regulatory burdens for smaller banks, then we would see an increase of financial incentives on SBL for smaller banks.

Table 1.5 lists pooled OLS estimation effects of bank financial performance on SBL share and its interaction with dummy variables *LARGE* and *DFA2*. To better compare the divergence between large and smaller banks before and after the policy change, I summarize the marginal effect of 1 p.p. increase in SBL/assets at the lower panel. Model (1)–(5) use all banks in my sample and model (6)–(8) focus on community and large banks only. Results are statistically significant with decent goodness-of-fit, confirming the hypothesis that the regulation relief plan for regional and community banks provided positive incentives for them to lend more to small businesses.

The overall financial incentives since Dodd-Frank Act remain significantly positive and become two times larger after the relief plan in 2015: for a 1 p.p. increase in SBL/assets, Tobin's Q ratio would increase 0.611 p.p. after 2015, up from 0.319 p.p. for entire 2010–2017 period, shown in model (1) and (4). This enhanced incentives are mainly driven by smaller banks, especially community banks as indicated in model (8) which compares community and large banks. For community banks, a 1 p.p. increase in SBL/assets is associated with an increase

Table 1.5: Pooled OLS Results

This table reports results of pooled OLS regression of Tobin's Q on ratio of SBL/assets and its interaction with dummy variables. Coefficients are estimated using annual BHC level data spanning 2010–2017. SBL is defined as business loans with original amount of $1 million or less. DFA2 is a dummy variable for the Relief Plan period and equals 1 from 2015 onward and 0 before 2015. LARGE is a dummy variable and equals 1 for large banks which were once labeled as systematically important bank and 0 otherwise. SIB is a dummy variable and equals 1 when a large bank is labeled SIB and under stress test. Bank controls include nonperforming loans, consumer loans, residential real estate loans, commercial real estate loans, ratio of liquid assets to total assets, ratio of non-interest income to revenue, and ratio of deposits to all funding. All loan variables are scaled by assets. Fundamental controls are weighted state-level 5-year GDP growth rate and weighted county-level Herfindahl-Hirschman index. All standard errors are clustered at individual BHC level. Joint effects are estimated by using heteroscedasticity consistent covariance.

	Tobin's Q Ratio in 2010–17							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
SBL/Assets	0.319**	0.324**	0.325**	0.224	0.178	0.447***	0.318**	0.349**
(a)	(0.147)	(0.15)	(0.15)	(0.148)	(0.149)	(0.164)	(0.161)	(0.161)
(SBL/Assets)*SIB		-3.076***						
(b)		(0.592)						
(SBL/Assets)*LARGE			-2.711***		-2.095***	-3.352***		-2.917***
(c)			(0.538)		(0.451)	(0.667)		(0.643)
(SBL/Assets)*DFA2				0.387***	0.399***		0.48***	0.46***
(d)				(0.123)	(0.127)		(0.152)	(0.146)
(SBL/Assets)*LARGE*DFA2					-1.336***			-1.308***
(e)					(0.319)			(0.296)
Bank Controls?	YES	YES	YES	YES	YES	YES	YES	YES
Year FE?	YES	YES	YES	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES	YES	YES	YES
RegionalB Removed?						YES	YES	YES
Obs.	2810	2810	2810	2810	2810	2137	2137	2137
Adj.R^2	0.425	0.454	0.456	0.43	0.464	0.457	0.423	0.468
	Marginal Effect of 1 p.p. Increase in SBL/Assets:							
SIBs		-2.516***						
(a+b)		(104.17)						
Large Banks			-2.387***			-2.905***		
(a+c)			(95.49)			(94.49)		
During Relief Plan				0.611***			0.798***	
(a+d)				(23.07)			(20.6)	
SIB before Relief Plan					-1.917***			-2.568***
(a+c)					(64.83)			(62.26)
Non-SIB during Relief Plan					0.577***			0.809***
(a+d)					(21.02)			(24.43)
SIB during Relief Plan					-2.854***			-3.416***
(a+c+d+e)					(65.78)			(68.88)

[1] Clustered standard errors in parenthesis under estimated coefficients; Chi-Square values in parenthesis under marginal effect.
[2] *** stands for p<0.01; ** stands for p<0.05; * stands for p<0.1.
[3] Data are collected from Call Reports, Y-9C Reports, WRDS Compustat, Summary of Deposit, and Bureau of Economic Analysis.

in Tobin's Q of 0.349 p.p. before 2015 and of 0.809 p.p. after 2015. This implies that the relief plan which targets community banks and some regional banks successfully convinced investors and shareholders that reduced regulatory burden would make SBL more profitable for smaller banks.

For SIBs in post-crisis era, the capital market keeps penalizing them for lending to small businesses both before and after the Relief Plan, but since 2015, SIBs have been imposed about 50% more penalty from the capital market for SBL. Model (5) and (8) show that, for a 1 p.p. increase in SBL/assets, SIBs' Tobin's Q ratio would decrease about 3 p.p. after 2015, down from a decline of about 2 p.p. during 2010–2014. This can be explained by the capital market's reassessment of large banks' competitiveness in lending to small businesses, since community banks would gain exclusive benefits from the regulatory relief plan and become more competitive in lending market. For the entire post-Act period, large banks were severely penalized and SIBs suffered only slightly more, since most large banks were labeled as SIBs and under stress tests.

After removing regional banks from the sample, model (7) and (8) magnify the effects for community and large banks. The coefficient for SBL/assets is not significant in model (4) and (5) but become larger and significant in (7) and (8), implying that capital market was not sensitive to regional banks' lending to small businesses during post-crisis era. This is reasonable because regional banks are neither under stress tests like SIBs nor provided much regulatory relief like community banks.

Therefore, the capital market has completely different evaluation of SBL for large banks and smaller banks, and the incentives changed dramatically responding to the regulatory policy change. On the one hand, large banks, were penalized by the capital market for SBL throughout the sample period 2001–2017. Large banks' financial performance would decrease by more than 2 p.p. for increasing 1 p.p. of SBL/assets after Dodd-Frank Act, and the disincentive worsened after 2015 when Federal Reserve announced a regulatory relief plan for smaller banks. On the other hand, community banks were encouraged for SBL throughout the sample period, with an average of 0.174 p.p. increase of Tobin's Q ratio caused by 1 p.p. increase of SBL/Assets. The Dood-Frank Act did not affect the financial incentives for SBL for smaller banks, but the relief plan convinced the capital market that SBL is a profitable asset for smaller banks, as their Tobin's Q ratio would increase 0.6–0.8 p.p. for a 1 p.p. increase in SBL/assets.

Interpretation

For the convenience of comparing effects of policy changes, I summarize the marginal effects for large and smaller banks during different periods from panel estimation results in Table 1.4, 1.5, and 1.F.1[37]. Banks are grouped by their consolidated asset size: community banks refer to banks with assets under \$10 billion and large banks refer to banks with assets above \$50 billion and *at any time* under heightened supervision standards and annual stress test.

The comparison of marginal effects before and after Dodd-Frank Act gives a rough impression that large banks were penalized for SBL by the capital market while smaller banks were encouraged for it, and Dodd-Frank regulations intensified the divergence. Then I further divide the sample into the pre-Act period of 2001–2009, pre-relief of 2010–2014, and post-relief period of 2015–2017.

For community banks, capital market incentives were slightly positive and steady during 2001–2014, as Tobin's Q ratio would increase around 0.2–0.3 p.p.

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[37]To complete the story, I conduct similar panel regressions for pre-Act period and results are summarized in Table 1.F.1

Table 1.6: Marginal Effects of 1 p.p. Increase in SBL/Assets on Bank Financial Performance in Subsample Periods

Size	Sample Period			
Community Banks	2001–2009		2010–2017	
	0.205*		**0.447*****	
	2001–2006	2007–2009	2010–2014	2015–2017
	0.212*	**0.191****	**0.349*****	**0.809*****
Large Banks	2001–2009		2010–2017	
	-0.411***		**-2.63*****	
	2001–2006	2007–2009	2010–2014	2015–2017
	0.355	**-2.207*****	**-1.917*****	**-2.854*****

[1] The marginal effect coefficients are summarized from Table 1.4, 1.5, and 1.F.1.
[2] Large banks are defined as banks with consolidated assets of more than $50 billion and labeled as SIB at any time in the sample; regional and community banks refer to those with assets under $50 billion.

for a 1 p.p. increase in SBL/assets. How to explain the persistent positive capital market incentives? One might speculate that smaller banks were not suffered from the regulatory burdens imposed by Dodd-Frank which was designed to target systemically important banks. But the revival since the relief plan for smaller banks in 2015 suggests another explanation. After 2015, smaller banks would enjoy a 0.8 p.p. increase in Tobin's Q ratio for a 1 p.p. increasing in their SBL/assets ratio, which is about two times larger than during pre-relief period. Shareholders believed that the relief plan will make SBL a more profitable opportunity for smaller banks, which implies that smaller banks were under constraints before the relief plan.

Next question: knowing that smaller banks were affected by Dodd-Frank regulations and hit by the financial crisis, why the capital market or shareholders still evaluate SBL as profitable assets for smaller banks? There are two main reasons. First, smaller banks, especially community banks, have a comparative advantage in lending to small business. They are usually specialized in relationship lending, which is efficient in gathering and monitoring soft information of local community and its small businesses. They are also more flexible and able to engage with small businesses, with better customer services and faster loan decisions. According to the FDIC Small Business Lending Survey (2018), community banks are ranked by other banks as top competitors for SBL. Second, smaller banks have to be more committed to SBL and keep a larger share of SBL in their portfolio compared to large banks. One explanation is that small banks with less capital are unable to lend large amounts, due to regulations that require banks not to lend to a single borrower more than 25% of bank's capital. Another reason is that small banks need to diversify their portfolios by making more loans of smaller amounts. Therefore, the financial incentives to smaller banks for SBL maintained significantly positive, even during the financial crisis and under Dodd-Frank Act before the relief plan.

For large banks, ever since the recent financial crisis, their Tobin's Q ratio would drop more than 2 p.p. for a 1 p.p. increase in SBL/assets. During the financial crisis, small businesses were more likely to bankrupt and thus SBL was riskier than other types of assets. This also explains why large banks had significant incentives to replace SBL with large business loans or non-business loans in 2008, as shown in results of repeated cross-sectional estimations. The disincentives during the crisis could be also explained by the threat of insolvency faced by large banks, as suggested by Chen, Hanson, and J. C. Stein (2017). During post-Act period, large banks continued to be discouraged for SBL, probably because shareholders expect that SBL will be under stricter risk assessment in stress test and thus not a profitable asset for large banks. After the relief plan for smaller banks, large banks still faced bad capital market incentives probably because shareholders re-assessed the comparative advantage of large banks for lending to small businesses, as Chen, Hanson, and J. C. Stein (2017) hypothesized, and believed that SBL will be even more profitable for smaller banks and less profitable for large banks.

1.5 Robustness Check

1.5.1 Dynamic Effects

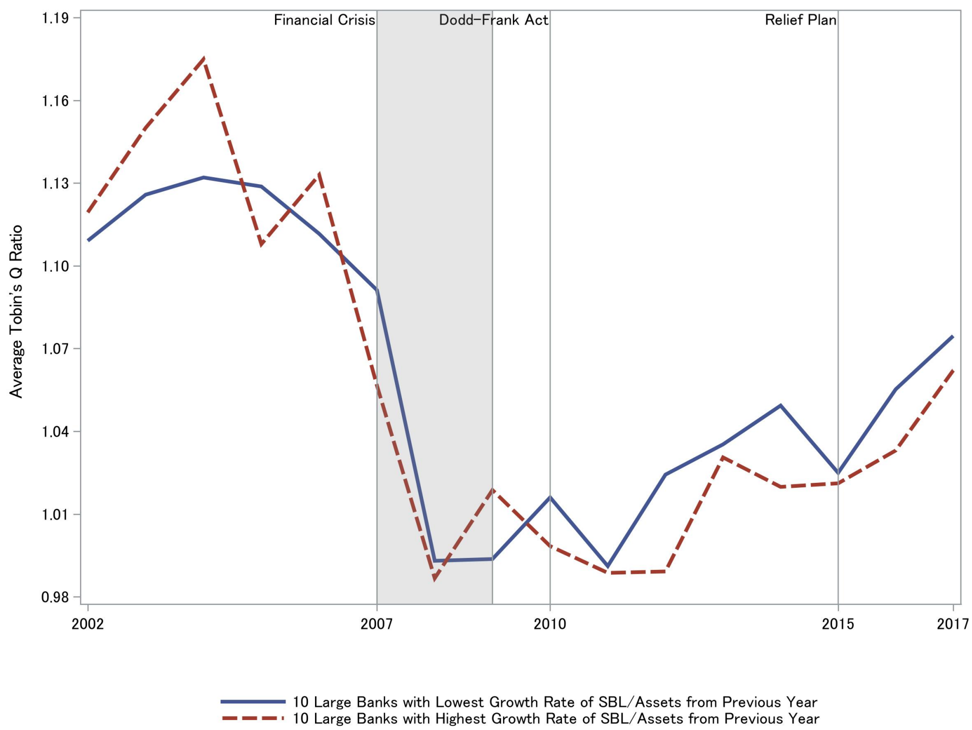
My data is year-end annual data, so shorter-period dynamics should be shown as instantaneous causality. To check the potential dynamic effect, I include a dummy variable *gSBL* which equals to 1 if the growth rate of SBL/assets of one BHC from previous year is positive, 0 otherwise. I interact it with size dummy and policy dummy and estimate in different periods during 2002–2017. Results are in Table 1.F.2 and consistent with previous findings.

Interestingly, the only significant dynamic variable is *gSBL*LARGE*DFA*, and the sum of *gSBL*LARGE*DFA* and *gSBL*LARGE* is also statistically significant. This implies that if a large bank increased its SBL/assets from previous year and it is under Dodd-Frank regulations, then this bank's Tobin's Q ratio is 0.026 p.p. lower than that of the large banks which did not increase SBL ratio from previous year, according to my estimation. But this effect did not exist in pre-crisis era.

To further illustrate it, I plot the annual average Tobin's Q ratio of 20 banks with highest/lowest growth rate of SBL/assets from previous year in Figure 1.9. Before Dodd-Frank Act, there is no obvious divergence, but since 2010, the bottom 10 banks with lowest growth rate of SBL/assets[38] has been outperforming the top 10 banks which increased SBL ratio most, in terms of financial performance.

[38] I exclude banks with zero SBL/assets growth. If including those, the divergence is more obvious.

Figure 1.9: Average Tobin's Q Ratio of Large Banks with Lowest/Highest Growth Rate of SBL/Assets from Previous Year during 2002–2017



Note: I extract 20 large banks (with assets more than \$50 billion) with highest or lowest growth rate of SBL/assets from the previous year, and this figure plots their average Tobin's Q ratio during 2002–2017. After Dodd-Frank Act of 2010, although financial performances of large banks have steadily recovered, large banks which increased SBL/assets most would underperform than those decreased SBL/assets most.

1.6 Discussion

The slow recovery of SBL following the recent financial crisis concerns many researchers and policymakers. This chapter looks at this issue in terms of how Dodd-Frank Act of 2010 and the Regulatory Relief Plan for Smaller Banks in 2015 altered the capital market incentives for large and community banks to lend to small businesses. The idea is that how shareholders evaluate changes in regulations would affect banks' lending strategy.

During 2001–2017, the capital market has been encouraging community banks to lend to small businesses, even during the recent financial crisis, while large banks have been penalized for SBL. Especially, when a large bank is labeled as a SIB and submit to heightened supervisions, the financial disincentive for its SBL triples. A possible explanation is that SBL is under higher risk assessment in stress tests and shareholders would believe that SIBs with increasing share of SBL are more likely to fail the test and lead to undesirable limitations on dividend and share buyback plan. Interestingly, although many bankers are complaining about the regulatory burden, my results imply that, during Dodd-Frank era, banks *overall* are encouraged by the capital market to lend to small businesses, which is mainly driven by smaller banks, especially after 2015. Ever since the regulatory relief plan of 2015, smaller banks' financial incentives have doubled, while SIBs have been subjected to worsen disincentives for SBL, possibly because the relief plan persuaded the capital market to reassess large banks' competitiveness in lending to small businesses.

Overall, this lack of financial incentives for SBL by large banks is not compensated by the surged incentives for community banks after 2015. Although as an unintended consequence, Dodd-Frank Act has contributed to the slow recovery of SBL by changing the capital market incentives for large banks' lending strategy. Large banks are important for the credit access of small businesses, because 70% of small businesses cited a large bank as their primary financial institution (Prager and Wolken, 2008) and the total amount of SBL by large banks is 1.2—1.4 times of that by smaller ones according to my estimation. While community banks are traditionally specialized in SBL through relationship lending, there are two advantages of large banks that are not replaceable by community banks. First, their SBL models use hard information and quantitative metrics, which are able to facilitate large volume of SBL. Second, SBL by large banks are relatively cheaper and more convenient compared to those made by community banks, due to the economies of scale. Although the credit gap has been gradually filled by smaller banks and fintech (Chen, Hanson, and J. C. Stein, 2017; Jagtiani and Lemieux, 2018), it takes time for adjustments and small businesses might face higher interest rates (Buchak et al., 2018).

Ironically, regulations are designed for financial stability, but when risk is lower, loans decrease too. Since the relief plan for smaller banks successfully improved their capital market incentives to lend to small businesses, we expect that the de-regulation law of 2018 for larger banks would also help alleviate the problem. Whether this round of deregulation would lead to a riskier financial market is an issue for future study. The preference of the public does not always agree with that of the regulators. One of the policy implications of this chapter is that regulators need to consider both when designing regulations.

Appendix

1.A Regulatory Relief for Smaller Banks and Heightened Standards for SIBs

Table 1.A.1: The Relief Rules for Smaller Banks

Effective Date	Affected Party	Rules
	CAPITAL	
1/30/2015	Savings and Loan holding companies **(< $500 million)** and meet requirements of Policy Statement	Exempted from minimum capital requirement (link)
5/15/2015	Savings and Loan holding companies **($500 million – $1 billion)**	Exempted from minimum capital requirement (link)
	FILING	
1/30/2015	Savings and Loan holding companies **(<$500 million)** and meet requirements of Policy Statement	Exempted from Schedule SC-R, Part I (Regulatory Capital Components and Ratios), of form FR Y-9SP (Parent Company Only Financial Statements for Small Holding Companies) (link)
5/15/2015	Savings and Loan holding companies **(<$1 billion)** and BHC **($500 million–$1 billion)**	Exempted from a number of filing and other provisions in Reguation Y and LL (link)
	POLICY STATEMENT	
5/15/2015	BHC **($500 million–$1 billion)**	Qualified for Policy Statement (which permits small BHCs to use higher levels of debt to finance acquisition of banks and exemption from capital guidelines) (link)
	EXAMINATION	
2/29/2016	Insured depository institutions **($500 million–$1 billion)**	Increase on-site examination cycle from 12 month to 18 month; previously, only institutions with assets below $ 500 million qualified (link)

Table 1.A.2: The Dodd-Frank and Basel III Rules for Large Banks

Regulation	Effective Date	Affected Party	Rules
Basel III	1/1/2014	BHCs **(> $50 Billion)**	Regulatory Capital, Implementation of Basel III, Capital Adequacy, Transition Provisions, Prompt Corrective Action, Standardized Approach for Risk-weighted Assets, Market Discipline and Disclosure Requirements, Advanced Approaches Risk-Based Capital Rule, and Market Risk Capital Rule (link)
Section 165 of Dodd-Frank Act	6/1/2014	BHCs **(> $50 Billion)** and some BHCs **($10 Billion–$50 Billion)**	Risk-based and leverage capital requirements, liquidity standards, risk management, stress-test requirements, 15-to-1 debt-to-equity limit (link)
Dodd-Frank Act: safety and soundness standards regulations	11/10/2014	Large insured national banks, insured Federal savings associations, and insured Federal branches of foreign banks **(> $50 Billion)**	Guidelines establishing heightened standards (link)
Basel III	1/1/2015	Large BHCs, certain savings and loan holding companies, and depository institutions **(> $250 Billion)** or meet other requirements	Quantitative minimum liquidity coverage ratio (link)
Section 165 of Dodd-Frank	12/1/2015	Global systemically important bank holding company	Risk-based capital surcharges (link)

1.B Systemically Important Banks

Table 1.B.1: The List of 19 SIBs in 2009 SCAP

SIBs	**2009***	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Ally Financial	Y	Y	Y	Y	Y	Y	Y	Y	Y	**N**
American Express	Y	Y	Y	Y	Y	Y	Y	Y	Y	**N**
Bank of America	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank of NY Mellon	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
BB&T	Y	Y	Y	Y	Y	Y	Y	Y	Y	**N**
Capital One	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Citigroup	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fifth Third	Y	Y	Y	Y	Y	Y	Y	Y	Y	**N**
Goldman Sachs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
JPMorgan Chase	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Keycorp	Y	Y	Y	Y	Y	Y	Y	Y	Y	**N**
MetLife*	Y	Y	Y	-	-	-	-	-	-	-
Morgan Stanley	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
PNC Financial	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Regions Financial	Y	Y	Y	Y	Y	Y	Y	Y	Y	**N**
State Street	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
SunTrust	Y	Y	Y	Y	Y	Y	Y	Y	Y	**N**
U.S. Bancorp	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Wells Fargo	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Number of Y	19	19	19	18	18	18	18	18	18	11

[1] The list contains 19 banks which participated in 2009 SCAP and most of them have remained under heightened regulations. There was no FDAST or CCAR in 2010. In 2011 and 2012, SIBs only participated in CCAR because the implementing rules for FDAST have not been developed yet. Since 2013, SIBs have been subject to both FDAST and CCAR.

[2] Y represents participating in Federal Reserve annual stress test and CCAR in that year. N represents not under stress test and the asset data is not available.

[3] MetLife failed the stress test in 2012 and sold the banking unit to GE Capital in the same year to avoid the heightened financial regulations. Although MetLife appeared in the list of stress test in 2012, the year-end bank data for MetLife in 2012 does not exist and I exclude this data point from my list of SIBs.

[4] In 2019, the asset threshold was increased from $50 billion to $100 billion and therefore several BHCs did not participate in the FDAST and CCAR in 2019.

Table 1.B.2: The List of SIBs Joined in 2014 or Later

SIBs	**2009***	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
BNP Paribas*	C	C	C	C	C	C	**Y**	**Y**	**Y**	N
BBVA Compass*	C	C	C	C	**Y**	**Y**	**Y**	**Y**	**Y**	N
BMO Financial*	C	C	C	C	**Y**	**Y**	**Y**	**Y**	**Y**	N
Barclays*	-	-	-	-	-	-	C	C	**Y**	**Y**
CIT Group	C	N	N	N	N	C	C	**Y**	C	N
Comerica	C	C	C	C	**Y**	**Y**	**Y**	**Y**	C	N
Credit Suisse*	-	-	-	-	-	-	C	C	**Y**	**Y**
Deutsche Bank*	C	C	C	C	C	**Y**	**Y**	**Y**	**Y**	**Y**
Discover	C	C	C	C	**Y**	**Y**	**Y**	**Y**	**Y**	N
HSBC*	C	C	C	C	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Huntington	C	C	C	C	**Y**	**Y**	**Y**	**Y**	**Y**	N
M&T	C	C	C	C	**Y**	**Y**	**Y**	**Y**	**Y**	N
Northern Trust	C	C	C	C	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Citizens	C	C	C	C	**Y**	**Y**	**Y**	**Y**	**Y**	N
RBC*	C	C	-	-	-	C	C	C	**Y**	N
Santander*	-	-	C	C	**Y**	**Y**	**Y**	**Y**	**Y**	N
TD Group	C	C	C	C	C	C	**Y**	**Y**	**Y**	**Y**
UBS*	-	-	-	-	-	-	C	C	**Y**	**Y**
MUFG*	C	C	C	C	**Y**	**Y**	**Y**	**Y**	**Y**	N
Zions	C	C	C	C	**Y**	**Y**	**Y**	**Y**	-	-
Number of Y	0	0	0	0	12	13	15	16	17	7

[1] The list contains 19 banks which participated in 2009 SCAP and most of them have remained under heightened regulations. There was no FDAST or CCAR in 2010. In 2011 and 2012, SIBs only participated in CCAR because the implementing rules for FDAST have not been developed yet. Since 2013, SIBs have been subject to both FDAST and CCAR.

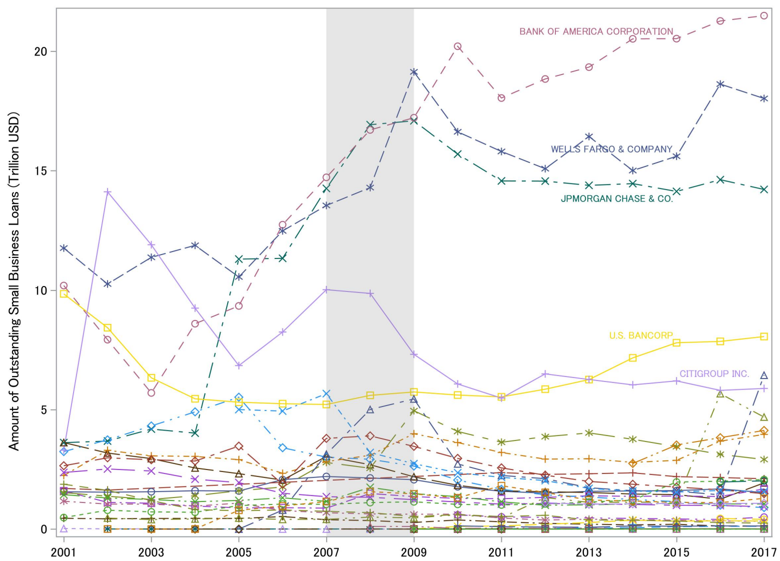
[2] Y represents participating in Federal Reserve annual stress test and CCAR in that year. N represents not under stress test and the asset data not available or less than the threshold. C represents not under stress test and with more than $50 billion in assets.

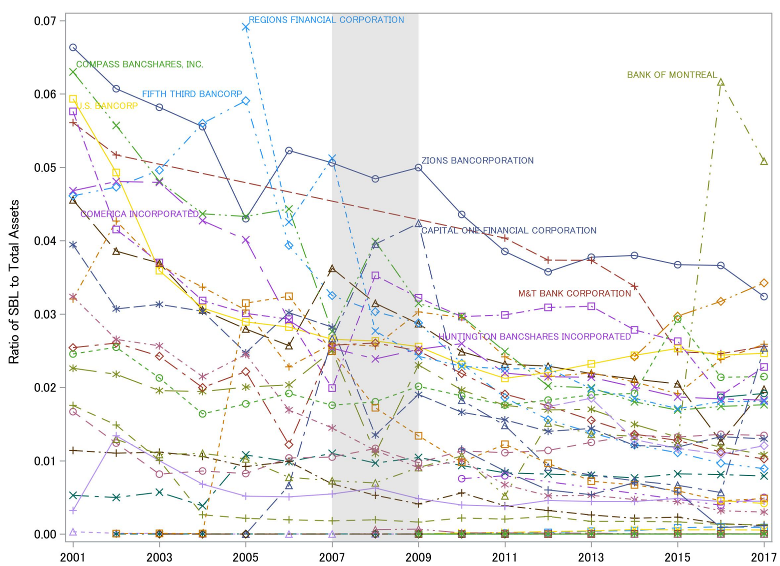
[3] In 2019, the asset threshold was increased from $50 billion to $100 billion and therefore several BHCs did not participate in the FDAST and CCAR in 2019.

[4] Banks with * are foreign banks operating in the U.S. and some of them did not file Y9C or Call reports for several years.

[5] Zions bank left the list after 2018 by shedding its BHC structure. CIT has also not been designated as a SIB since 2017 as it strategically sold its assets. Comerica also left the list in the same year.

Figure 1.B.1: Scattered Plot SBL by SIBs during 2001-2017



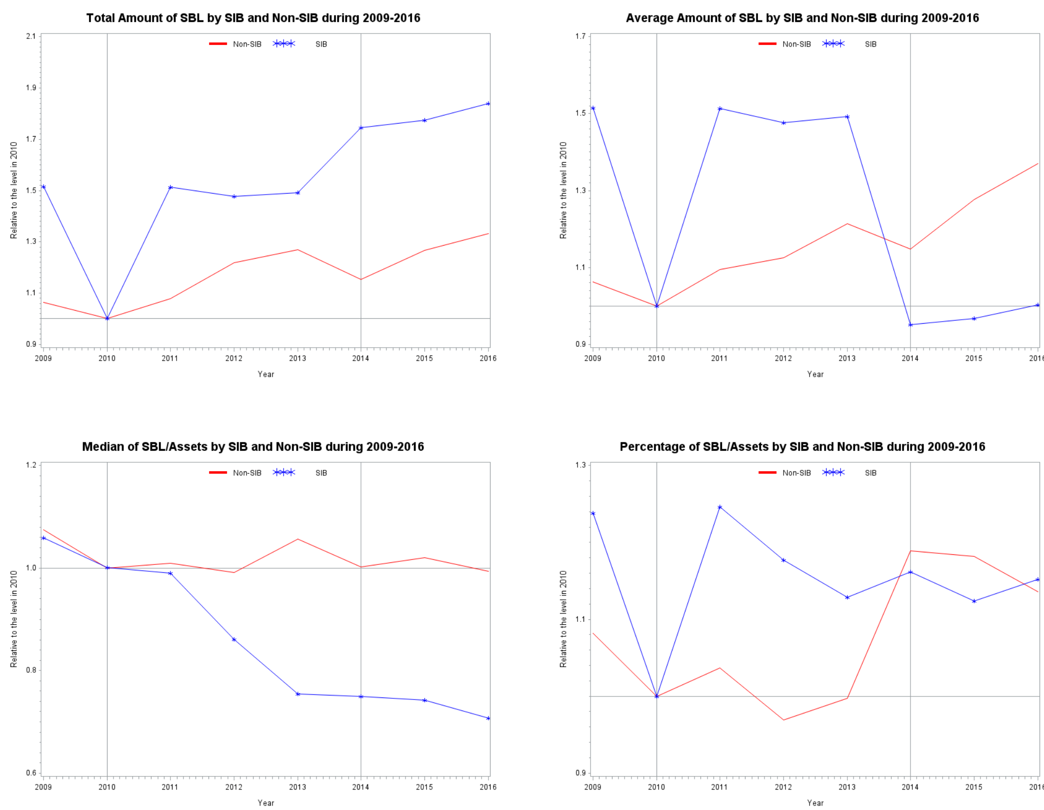


Source: Call Reports and U.S. Bureau of Labor Statistics.

Notes: SIB refers to the large bank which was labeled as systemically important and under Federal Reserves' stress test for at least once (including 12 foreign banks). The amount of SBL is adjusted by using the inflation level in 2001 as benchmark.

In Figure 1.B.2, I compare the SBL of SIBs and non-SIBs in 2009-2016, scaled by their levels in 2010 when Dodd-Frank Act was signed. Although the total amount of SBL from SIBs was larger and grew faster than that of non-SIBs, the average amount of SBL by SIBs dropped below its 2010 level after 2014. After scaled by assets, the total amount of SBL from SIBs has been declining since 2011, but non-SIBs started to steadily increase SBL from 2013. The median of ratio of SBL to assets, which can show how devoted a "typical" bank to SBL, has dramatically declined for SIBs since 2010, but non-SIBs have maintained a stable median value of the ratio.

Figure 1.B.2: SBL by SIBs and non-SIBs during 2009-2016



Source: The SBL data is from the CRA reports in 2009-2016, summed up to BHC level. Data is scaled by the level in 2010, when Dodd-Frank Act was implemented.

1.C Data Manual: The Construction of Bank Holding Company-Level Data

1.C.1 Overview

The purpose of this manual is to provide detailed information about how to construct BHC level data using raw regulatory data from the Federal Reserve System and other sources. The data construction process is very complex due to many reasons. First, the definitions of bank accounting variables are complicated and changing over time, so they should be defined and clarified carefully. Second, different types of banks report to Federal Reserve System, the Federal Deposit and Insurance Corporation (FDIC), the comptroller of the Currency, and the Federal Financial Institutions Examination Council (FFIEC) with responsibilities of Community Reinvestment Act (CRA), so the sample should be filtered according to certain criteria. Third, the bank-level data needs to be aggregated to BHC level data, because the banks under the same BHC will behave collectively. Lastly, some control variables, such as GDP and the Herfindahl-Hirschman index (HHI), need to be weighted by the bank deposit share in each state.

This manual combines BHC accounting data collected from Federal Reserve Y-9C reports,[39] market value data from Wharton Research Data Service (WRDS) Compustat, small business lending (SBL) data from the Consolidated Reports of Condition and Income (Call Reports),[40] branch-level bank deposit data from Summary of Deposits,[41] and GDP and income per capita data from Bureau of

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[39] Available from the Federal Reserve Bank of Chicago (`https://www.chicagofed.org/banking/financial-institution-reports/bhc-data`).

[40] Available from the FDIC (`https://cdr.ffiec.gov/public/`).

[41] Available from the FDIC (`https://www5.fdic.gov/sod/sodMarketBank.asp?barItem=2`).

Economic Analysis.[42] The time period of interest is 2001–2017, covering both before and after the financial crisis. Except for SBL and deposits data, other data is collected at the end of each year during 2001-2017. The methodology of this manual mainly follows Hughes et al. (2019).

1.C.2 Bank Accounting Data from Y-9C Reports

Federal Reserve Y-9C data are quarterly collected for all domestic holding companies with certain levels of consolidated assets. This manual only collects data in the fourth quarter during 2001-2017. The filtering criteria and accounting variable definitions in this section closely follow Hughes et al. (2019).

Bank data filtering criteria

There are approximately 5000 observations in each year's raw dataset, and several criteria are used to filter the data:

1. The observations with missing values or non-positive values for total assets are deleted (BHCK2170>0).
2. Keep BHCs (RSSD9331=28) and thrift holding company (RSSD9331=37), and exclude "not available" (RSSD9331=0).
3. The legal structure of the organization should be corporation (RSSD9047=1).
4. Keep holding company (RSSD9048=500) and securities broker or dealer (RSSD9048=700), and exclude insurance broker or company (RSSD9048=550), utility company (RSSD9048=710), and other non-depository institution

[42] Website of BEA: `https://www.bea.gov`

(RSSD9048=720). Notice that Goldman Sacks, Morgan Stanley, Ally, and American Express are kept, although they are not in the desired category.

5. Drop Grandfathered savings and loan holding company (RSSD9425=18).

6. Drop lower-tier holding companies whose higher-tier also files Y-9C (BHCK9802=2).

Note that I restrict the sample to banks that are holding company corporations with positive total assets. In the fourth criterion, I include four companies because they are systemically important, even though they are not in the desired category. In the sixth criterion, I cannot keep both lower-tier and higher-tier holding companies because I will combine the data to the higher-tier, which could lead to double counting.

The list of number of observations in each year and in total is provided in Table 1.C.1 Notice that during 2001-2005, there were approximately 2000 observations each year, but during 2006-2014, there were about 1000 observations and afterwards, there were only around 570 observations. This is because the asset-size threshold for filing the FR Y-9C increased from $150 million to $500 million in March 2006, and it increased further to $1 billion in March 2015. This respondent burden reduction is to reflect the influences of inflation, industry consolidation, and normal asset growth of BHCs.

Table 1.C.1: Number of Y-9C Observations in My Sample during 2001-2017

Year	**2001**	**2002**	**2003**	**2004**	**2005**				
N of Obs.	1791	1926	2073	2190	2202				
Year	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
N of Obs.	942	918	921	958	947	952	1003	1012	1005
Year	**2015**	**2016**	**2017**						
N of Obs.	576	566	564						

Definition of Accounting Variables

The bank accounting items[43] with corresponding codes from Y-9C reports and descriptions are listed in the Table 1.C.2. Below are some additional explanations for the accounting variables.

Book value and market value of assets Although BHCK2170 is usually used as total assets, I subtract goodwill (BHCK3163) from total assets and use it as the proxy of book value of assets. To calculate the Tobin's Q ratio, I use BHCK2948 as book value of liabilities, and then calculate the sum of the market value of bank equity and the book value of its liabilities as the proxy of market value of assets.

Loans The amount of total loans is calculated as the sum of BHCK2122 and BHCK2123, because BHCK2122 is the sum of different types of loans minus the unearned income on loans (BHCK2123). Total business loans, or Commercial & Industrial loans, include business loans both from domestic and foreign offices. Residential real estate loans include loans secured by residential properties and extended under lines of credit and other loans secured by residential properties as first liens or junior liens. Commercial real estate loans include construction loans, loans secured by farmland, 1-4 family and multi-family residential real estate loans, and other real estate loans. Consumer loans include credit cards, revolving credit plans, automobile loans, and other consumer loans such as student loans. Note that automobile loans (BHCKK137) and other consumer loans (BHCKK207) are not available until 2011.

[43]Note that all accounting amounts are in Thousand dollars.

Table 1.C.2: Accounting Variables in Y-9C Reports

Class	Variable	My Code	Code in Y-9C	Note
Identifier	Entity	ID	RSSD9001	
	Short Name	NAME	RSSD9010	
Liabilities	Book Value of Liabilities	TLIB	BHCK2948	
Assets	Book Value of Assets Net of Goodwill	BVA	BHCK2170 -BHCK3163	
	Total Assets	TOTA	BHCK2170	
	Liquid Assets	LQA	BHCK0081 +BHCK0295 +BHCK0397 +BHDMB987 +BHCK1754 +BHCK1773 +BHCKB989	
Revenue	Total Revenue	REVENUE	BHCK4079 +BHCK4107	
Loans	Total loans	LSUM	BHCK2122 +BHCK2123	
	Total Business Loans	LCIL	BHCK1763 +BHCK1764	
	Residential RE Loans	LRRE	BHDM1797 +BHDM5367 +BHDM5368	Before 1991/03: not exist
	Commercial RE Loans	LCRE	BHCK1410 -LRRE	
	Consumer Loans (including credit cards)	LIND	BHDM1975	
Equity	Tier 1 Capital	ECAP	BHCK3210	
	Tier 2 Capital	FCAP	BHCK3210 +BHCK4062 +BHCK3123	
Interest Rate	Interest on Loans	INT_LOANS	BHCK4435 +BHCK4436 +BHCKF821 +BHCK4059	2001/03 – 2007/12: BHCK4010
	Interest on Lease	INT_LEASES	BHCK4065	
	Total Interest Income	INTL	INT_LOANS +INT_LEASES	
	Contractual Rate	LTOTROA	INTL/LTOT	
Cost of Funding	Interest Expense	INTEXP	BHCK4073	
	Total Deposits	TDEP	BHDM6631 +BHDM6636 +BHFN6631 +BHFN6636	
	Other Borrowed Funds	OBMO	BHCK3190	
	Cost of Funding		INTEXP/(TDEP+OBMO)	
Nonperforming Loans	Past Due but Accruing		BHCK5525 +BHCK5524	
	Non-accruing		BHCK5526	
	Gross Charge-offs		BHCK4635	
	Nonperforming C&I	BNPL	BHCK1606 +BHCK1607 +BHCK1608	
	Total NPL	NPL	BHCK5525 +BHCK5524 +BHCK5526 +BHCK4635	
	Other Owned RE	ORO	BHCK2150	1990/09-2009/03: BHCK2744 +BHCK2745

Cost of Funding and Contractual Loan Interest Rate Cost of funding and contractual loan interest rate are very important for the analysis of credit access. Cost of funding is calculated as interest expense divided by the sum of total deposits and other borrowed funds. Contractual loan interest rate is calculated as the sum of interest and fees on loans and interest on lease divided by the total loan amount. Note that before 2008, the item of interest and fees on loans is available as BHCK4010 and afterwards it is calculated as the sum of BHCK4435, BHCK4436, BHCKF821, and BHCK4059. The spread is defined as the difference between cost of funding and contractual loan interest rate. The observations are deleted if either funding cost or loan rate is larger than 50%, or the spread is less than -10%.

Non-performing loans Nonperforming loan-to-total loan ratio is usually used to measure one bank's loan quality. Nonperforming loans (NPL) are calculated by summing up the delinquent loans and gross charge-offs. Charge-offs are uncollectible loans and leases whose amounts are charged off against the allowance for credit loss. Net charge-offs are calculated as gross charge-offs minus recoveries. Delinquent loans include those past due and still accruing interest and those not accrual. Because gross charge-offs are not included in the total loans, NPL ratio is defined as the amount of NPL divided by the sum of total loans and gross charge-offs. Although some literature included other real estate owned in calculation of NPL, which is foreclosed real estate which is nonaccrual but have not been sold for recoveries yet, I do not include this item. Outliers are eliminated by deleting the banks with the value of charge-offs more than four times of that of delinquent loans.[44]

[44] Although the magnitude of delinquent loans is usually more than three time of that of charge-offs (`https://www.federalreserve.gov/releases/chargeoff/delallnsa.htm`), I do not want to reduce much of the sample size. Further discussion are needed.

1.C.3 Bank Market Values from Compustat

The market values for banks are collected from WRDS Compustat. The market value of asset is proxied by the sum of the market value of equity and the book value of liability, and the market value of equity is calculated as the product of stock prices and outstanding shares by the end of each fourth quarter. Specifically, this manual uses the quarterly close market price (PRCCQ) and the quarterly shares outstanding number (CSHOQ) for the fourth quarter of each year during 2001-2017, instead of the monthly close market price (PRC) and the shares outstanding (SHROUT) on Center for Research in Securities Prices (CRSP), because CRSP data only contains one single class of stock. Note that the unit of CSHOQ is Million, so the unit of MVE should be adjusted to thousand to match that of Y9C accounting information.

To connect the unique bank identifier assigned by the Federal Reserve System (RSSD) with that used in CRSP (PERMCO), this manual uses the link created by the Federal Reserve Bank of New York.[45] However, since Compustat does not use PERMCO, this manual first connects RSSD with PERMCO, and then links PERMCO with CUSIP, which is used in Compustat.

1.C.4 Deposit Weighted HHI and GDP, and Holding Company-level Data

Summary of Deposit provides bank branch-level data on deposits for FDIC-insured banks in June. This data is used for three purposes. First, the Herfindahl-Hirschman index (HHI), as a measure of market concentration, is calculated by

[45] Available here: `https://www.newyorkfed.org/research/banking_research/datasets.html`

taking square of market share of each BHC's deposits in the market and then summing up to the state-level. The county-level HHI can be calculated using zip codes of branches.[46] Second, I calculate each BHC's share of deposits in each operating counties as weights to get weighted HHI. Similarly, using the state-level GDP data from the Bureau of Economic Analysis, I calculate the weighted average GDP growth rate for each holding company to control the economic fundamentals. Third, SOD contains the relationship structure of banks with their BHCs, which can be extracted and used to sum all the bank-level data can be summed up to top-tier holding company level.

There are approximately 90,000 observations in each year's raw dataset, and several criteria are used to filter or revise the data:

1. For banks without holding companies, use their bank identifier (RSSDID) as their holding company identifier (RSSDHCR), and drop banks without valid identifier.
2. Drop branches with no deposits (DEPSUMBR =0).
3. Drop branches in in U.S. territories (STNUMBR in (60 64 66 68 69 70 72 78)).
4. Drop holding companies with no domestic deposits (DEPDOM =0).
5. Create FIPS code[47] by combining state identifier (STNUMBR) and county identifier(CNTYNUMB), and note that if county identifier is not 3 digit then put 0 or 00 in front.

[46] According to FDIC Small Business Lending Survey (2018), banks usually view local banks of similar size as major competitors and local banks of other size as frequent competitors. Therefore, county-level HHI is a better proxy for market competition than state-level HHI.

[47] FIPS code, or "GEO.id2", is used by United States Census Bureau in American Community Survey to identify the state and the county.

The state-level GDP data can be downloaded from Bureau of Economic Analysis. I use the real GDP by state measured by chained 2009 dollars and unit is million dollars. Five-year average GDP growth rate is calculated. Since there is no county-level GDP data available, I use the county-level income per capita data from American Community Survey instead. Because this annual data is only available from 2005 to 2016,[48] I cannot calculate five-year average growth rate. I use the county-level income per capita divided by the nation-wide average level as the control for economic fundamental.

The HHI, as a measure of market concentration, is calculated by taking square of market share of each BHC in the market and then summing up to the state-level or county-level. The steps are:

1. Sum up all the bank deposits in each state.
2. Calculate each BHC's share of deposits out of total deposits in each state.
3. Calculate the sum of squares of deposit share in each state as the HHI of this state.
4. Sum up all the deposits for each BHC.
5. Calculate the share of its deposits in each operating state out of its total deposits as the weight for each BHC.
6. Calculate the weighted average HHI and GDP for each BHC.

This HHI value can be normalized by using the formula below, but since the difference between normalized and standard HHI is not large, I will use standard HHI in this manual.

[48]In 2005-2006, the data was simply estimated; in 2007-2008, the data was a three-year estimation; in 2009-2016, the data was a five-year estimation.

$$NormalizedHHI = \frac{HHI - \frac{1}{n}}{1 - \frac{1}{n}}$$

The county-level HHI can be calculated similarly by using FIPS codes of branches. The county-level HHI tends to be larger and maybe more accurate than the state-level one.

Because the bank code indicator (RSSDID) and its holding company code indicator (RSSDHCR) are both listed in Summary of Deposit, bank-level data can be summed up to top-tier holding company level according to the corresponding relationships. The same process is applied to SBL data and market values.

1.C.5 SBL from the Call Reports

The Call Report refers to the Consolidated Report of Condition and Income that U.S. banks are required to fill out quarterly. In Schedule RC-C Part II, the loans to small business and small farms are defined as the sum of (a) the outstanding commercial and industrial (C&I) loans with origination amount of $1 million or less, (b) the outstanding commercial real estate loans with origination amounts of $1 million or less, and (c) the agricultural production and farmland loans of $500 thousand or less. In most studies, SBL refers to small C&I loans captured in (a).

Specifically, banks are required to report the number and amount of outstanding of commercial and industrial loans to U.S. addresses with original amounts of $100,000 or less, more than $100,000 through $250,000, and more than $250,000 through $1,000,000 respectively. This manual uses the total amount of outstanding commercial and industrial loans with original amounts of less than one million dollars as the small business lending amount. In Schedule RC-C Part II, banks

Table 1.C.3: The Definitions of SBL in Call Reports

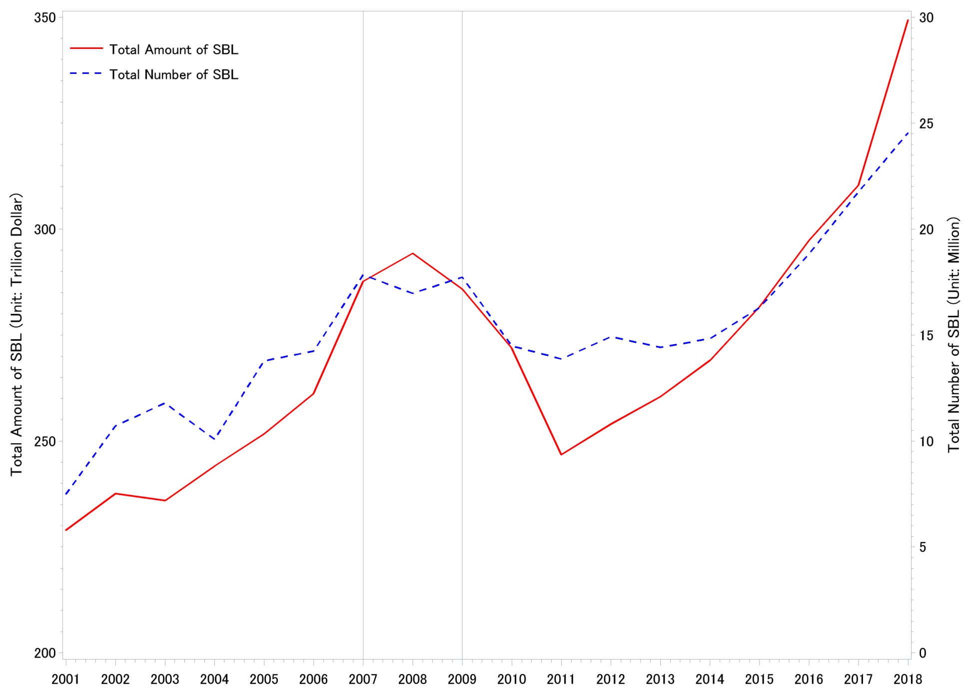
Variable	Code
Number of loans with origination amount less than $100,000	RCON5570
Outstanding balance for loans with origination amount less than $100,000	RCON5571
Number of loans with origination amount $100,000 - $250,000	RCON5572
Outstanding balance for loans with origination amount $100,000 - $250,000	RCON5573
Number of loans with origination amount $250,000 - $1,000,000	RCON5574
Outstanding balance for loans with origination amount $250,000 - $1,000,000	RCON5575
Total commercial and industrial loans	RCON1766
Whether all the commercial and industrial loans have origination amount less than $100,000:	RCON6999
SBL = RCON5571+ RCON5573+ RCON5575	if =False
or SBL= RCON1766	if =True

are also asked whether all commercial and industrial loans have original amounts of $100,000 or less. If the answer is yes, then the total amount of commercial and industrial loans is counted as small business lending. The definitions and details are summarized in Table 1.C.3. Because the SBL data was only collected in June reports before 2010, Call Report in June, instead of those in December, are used for each year. The total amount of SBL and the number of originations of SBL are plotted in Figure 1.C.1.

Note that FDIC Small Business Lending Survey (2018) criticized this SBL proxy from the Call Report because it failed to capture larger C&I loans with origination amounts of more than $1 million and loans secured by residential real estate that are also extended to small businesses. The limit of $1 million was set by the regulators in the early 1990s and was never adjusted for inflation. If adjusted by CPI, the limit would be over $1.6 million in 2015. Business loans secured by one-to-four-family residential properties in the Call Report are considered as home mortgages rather than business loans because they are recorded by their primary collateral rather than by purpose. According to FDIC's estimation, SBL in the U.S. was understated by at least 12% or $37 billion in 2015.

Nevertheless, C&I loans under $1 million in the Call Report is still the best

Figure 1.C.1: Total Amount and Number of SBL from Call Report during 2001–2017



Data Source: Call Reports in 2001–2017.

available measure of SBL in the U.S. First, loan size is highly correlated to business size, therefore the borrowers of small loans are usually businesses that are small. More importantly, all banks tract the size of loans but not all banks track the size of businesses. Many banks, particularly smaller ones, were unable to report loans by size of small businesses without substantial increase of staff resources.

1.C.6 SBL from CRA

Background

The Community Reinvestment Act of 1977 (CRA) was enacted to encourage federally insured commercial banks and savings banks and associations to meet the credit demand of local communities. A revision to the CRA in 1995 required commercial banks and savings banks associations with more than approximately $1 billion assets to report the data regarding their lending to small businesses to monitor their performance in reinvesting local community. These records are evaluated regularly and the CRA ratings record is taken into account in considering applications for deposit facilities, including mergers and acquisitions. The CRA has compiled annual county-level small business loans data since 1996.

This manual uses the branch-level *newly originated* SBL data in Disclosure Reports during 2001-2016. The SBL is defined as the loan amount of small business loans originated with loan amount at origination less than $1 million. The branch-level data is summed up to institution-level data by applying ID list in Transmittal Sheets of CRA. The institution-level data is summed up to the holding company level according to the link provided by the Summary of Deposit.

Comparison between the Call Report and CRA

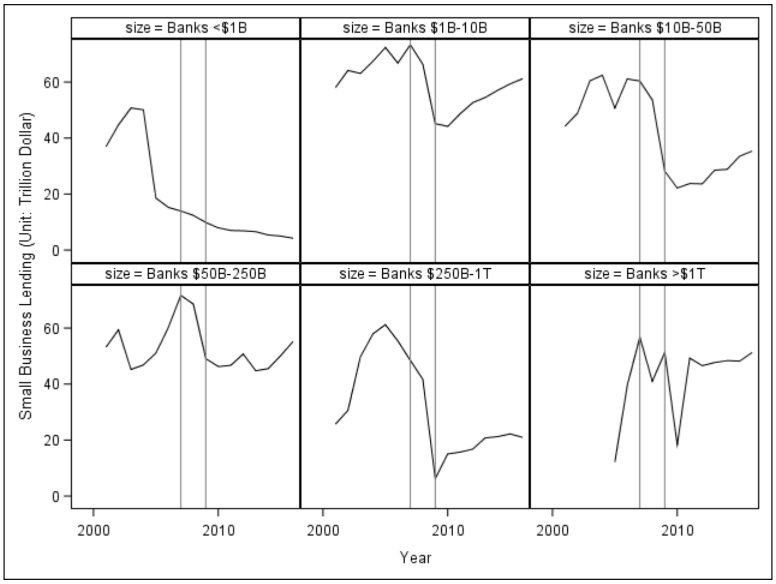
Comparing the SBL data in the Call Reports to that in CRA, I find that the trending patterns are obviously different in the two datasets, which might be due to several reasons. First, the definition of SBL is different. CRA defines SBL as loans with amount of $ 1 million or less, which can be commercial real estate loans or commercial and industrial loans, while Call Reports only consider small commercial and industrial loans with origination amount less than $1 million. Second, SBL data reported in CRA is loans newly originated or purchased, which are flow data, while SBL in Call Reports are outstanding balance, which are stock data. Third, not all banks report SBL data to CRA. CRA requires commercial banks and savings institutions with total assets of approximately more than $ 1 billion to collect and report SBL, while all FDIC-insured banks are required to file Call Reports. However, some banks with assets less than the mandatory reporting threshold also reported the SBL data either voluntarily or because they were elected to be evaluated as larger banks. For example, in 2016, there were 726 banks reported SBL data, within which 202 banks with assets below the threshold, and the SBL data in CRA "account for about 71 percent of small business loans outstanding by dollars".[49] Therefore, SBL reported in CRA data covers a large portion of that in Call Reports.

1.D The SBL Lending Behavior of Banks of Different Sizes

To check the performance of banks of different sizes, I categorize them by assets. The cut-off points are $1 billion, $10 billion, $50 billion, $250 billion, and $1 trillion. All banks have been slowly recovering their SBL since the recession,

[49]See `https://www.fdic.gov/news/news/press/2017/pr17088a.pdf`

Figure 1.D.1: The Amount of SBL by Banks in Different Sizes during 2001-2016



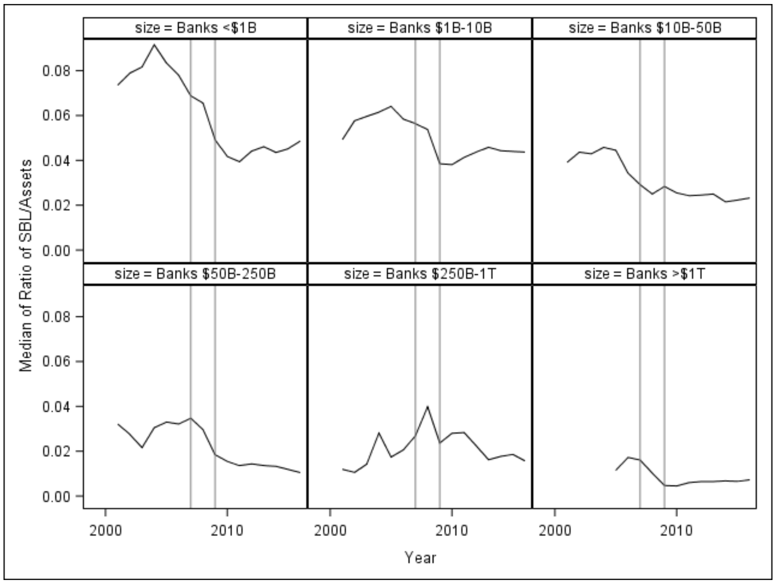
Source: the Community Reinvestment Act. SBL is defined as business loans with originated amounts less than $1 million. The total assets in CRA, which I use to calculate the ratio of SBL to assets, are the values of total assets in Call Reports of the previous year.

except for banks with assets of less than $1 billion, which have decreased 90% amount of SBL since 2005.

Graph 1.D.1 shows the total amount of SBL by banks in different sizes. However, this data is not adjusted by the change of number or the change of assets, so the information is vogue. Therefore, in 1.D.2, I plot the amount and the median share of SBL for banks in different sizes. During the post-crisis period, the median ratio of SBL/assets has remained at a level lower than pre-crisis. For banks with assets more than $50 billion, the median ratio of SBL/assets has been stable within 0.1-0.2 throughout the 16 years. For the smaller banks, the ratio has dropped dramatically. The smaller the bank size, the larger the drop of the ratio.

In Graph 1.D.3, I plot the number of banks in different sizes. Banks with assets less than $1 billion decreased 65% in 2005 and has been continuously decreasing since then, while the number of banks in larger size has not changed much. The

Figure 1.D.2: The Median of Ratio of SBL/Assets for Banks in Different Sizes during 2001-2016

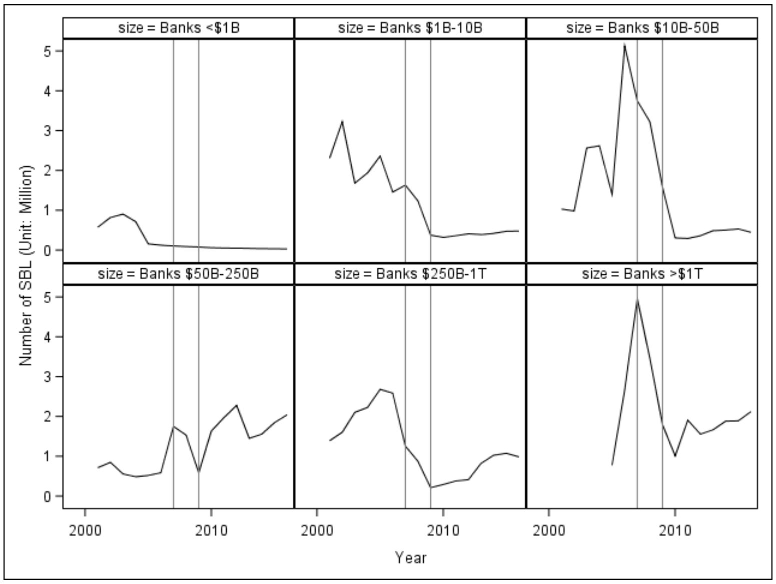


Source: the Community Reinvestment Act. SBL is defined as business loans with originated amounts less than $1 million. The total assets in CRA, which I use to calculate the ratio of SBL to assets, are the values of total assets in Call Reports of the previous year.

size of SBL is calculated as the amount of SBL divided by the number of SBL for banks in each size category.

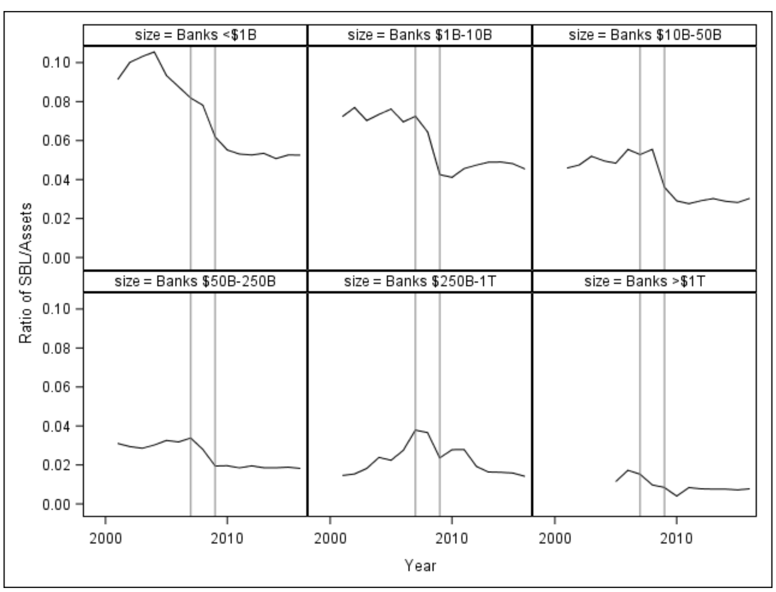
As in Graph 1.D.4, the average amount of loans has been growing steadily over time, not affected by the financial crisis. For banks with assets less than $250 billion, the size of SBL originated is within $150,000 - $200,000, while the largest banks offer average SBL of $25,000. For banks with assets between $250 billion and $1 trillion, the SBL size has been very volatile and increased dramatically after the recession.

Figure 1.D.3: The Number of SBL by Banks in Different Sizes during 2001-2016



Source: the Community Reinvestment Act. SBL is defined as business loans with originated amounts less than $1 million. The total assets in CRA, which I use to calculate the ratio of SBL to assets, are the values of total assets in Call Reports of the previous year.

Figure 1.D.4: The Ratio of Sum(SBL)/Sum(Assets) for Banks in Different Sizes during 2001-2016



Source: the Community Reinvestment Act. SBL is defined as business loans with originated amounts less than $1 million. The total assets in CRA, which I use to calculate the ratio of SBL to assets, are the values of total assets in Call Reports of the previous year.

1.E SBL Coefficients in Cross-sectional Baseline Models

Table 1.E.1: OLS Estimates of (SBL-Large Business Loans)/Assets in Cross-sectional Baseline Models
Dependent variable: Tobin's Q Ratio 2001-2017

The difference between coefficients of SBL/assets ratio and large business-loans/assets ratio in baseline models, as shown in Graph 1.7, represent financial incentives for banks to replace large business loans with SBL.

	All Banks				**Large&Regional**	**Banks**	(>$10Billion)	
Year	SBL/Assets	Std.Dev.	Adj. R^2	N	SBL/Assets	Std.Dev.	Adj. R^2	N
2001	0.191*	0.113	0.358	375	-1.287	1.115	0.484	39
2002	0.082	0.099	0.288	407	0.188	0.721	0.368	42
2003	0.045	0.12	0.217	440	0.949	0.773	0.519	42
2004	0.089	0.108	0.2	465	-0.205	0.651	0.478	45
2005	0.236*	0.093	0.287	456	-0.473	0.483	0.464	47
2006	0.328***	0.095	0.403	375	0.094	0.614	0.433	52
2007	0.076	0.082	0.376	355	-0.299	0.421	0.339	49
2008	0.097	0.115	0.325	345	-0.673*	0.368	0.592	50
2009	0.08	0.092	0.281	345	-0.087	0.295	0.571	55
2010	0.039	0.103	0.3	325	-0.84**	0.314	0.375	54
2011	0.242**	0.115	0.22	323	-0.454	0.313	0.322	54
2012	0.283***	0.099	0.201	329	-0.35	0.274	0.287	57
2013	0.2	0.125	0.22	331	-0.27	0.266	0.415	60
2014	0.182	0.122	0.198	326	-0.277	0.273	0.219	66
2015	0.08	0.106	0.205	281	-0.213	0.229	0.367	67
2016	0.537***	0.177	0.268	284	-0.304	0.303	0.387	76
2017	0.273*	0.151	0.384	264	-0.385	0.235	0.625	78
	Regional	**Banks**	($10-50Billion)		**Community**	**Banks**	(<$10Billion)	
Year	SBL/Assets	Std.Dev.	Adj. R^2	N	SBL/Assets	Std.Dev.	Adj. R^2	N
2001	-1.119	1.445	0.768	23	0.242**	0.106	0.269	336
2002	0.695	1.119	0.333	25	0.062	0.1	0.298	365
2003	0.526	1.243	0.395	25	0.025	0.122	0.198	398
2004	-0.41	1.003	0.444	27	0.095	0.113	0.211	420
2005	-1.071	0.854	0.478	28	0.226**	0.099	0.271	409
2006	-0.968	0.88	0.543	33	0.273***	0.097	0.384	323
2007	-0.986	0.621	0.193	29	0.097	0.088	0.36	306
2008	-1.283***	0.36	0.783	30	0.224*	0.117	0.427	295
2009	-0.256	0.37	0.512	31	0.08	0.102	0.296	290
2010	-0.693*	0.388	0.354	30	0.109	0.108	0.396	271
2011	-0.265	0.33	0.408	31	0.397***	0.122	0.338	269
2012	-0.307	0.278	0.35	36	0.443***	0.104	0.323	272
2013	-0.313	0.244	0.502	38	0.361***	0.127	0.38	271
2014	-0.523*	0.268	0.395	44	0.23*	0.127	0.368	260
2015	-0.339	0.257	0.421	44	0.129	0.116	0.317	214
2016	-0.807**	0.357	0.367	52	0.675***	0.193	0.448	208
2017	-0.797***	0.255	0.697	53	0.474***	0.179	0.408	186

[1] *** stands for $p<0.01$; ** stands for $p<0.05$; * stands for $p<0.1$.

Table 1.E.2: OLS Estimates of (SBL-OtherLoans)/Assets in Cross-sectional Baseline Models
Dependent variable: Tobin's Q Ratio 2001-2017

The difference of coefficients of SBL/assets ratio and non-business loans/assets ratio in baseline models, as shown in Graph 1.8, represent financial incentives for banks to replace non-business loans with SBL.

	All Banks				**Large&Regional**	**Banks**	(>$10Billion)	
Year	(SBL+C&I)/Assets	F-stat	Adj. R^2	N	(SBL+C&I)/Assets	F-stat	Adj. R^2	N
2001	-0.007	0.009	0.358	375	-1.836	2.764	0.484	39
2002	-0.058	0.826	0.288	407	-0.251	0.14	0.368	42
2003	-0.05	0.387	0.217	440	0.342	0.245	0.519	42
2004	0.004	0.003	0.2	465	-0.476	0.641	0.478	45
2005	0.192***	9.249	0.287	456	-0.615	1.901	0.464	47
2006	0.217***	9.358	0.403	375	-0.062	0.011	0.433	52
2007	0.086	1.904	0.376	355	-0.312	0.563	0.339	49
2008	-0.024	0.066	0.325	345	-0.72*	3.877	0.592	50
2009	-0.051	0.483	0.281	345	-0.247	0.774	0.571	55
2010	-0.039	0.23	0.3	325	-0.974***	10.52	0.375	54
2011	0.104	1.051	0.22	323	-0.629*	3.941	0.322	54
2012	0.12	1.84	0.201	329	-0.511*	3.32	0.287	57
2013	0.039	0.117	0.22	331	-0.368	1.852	0.415	60
2014	0.131	1.429	0.198	326	-0.319	1.322	0.219	66
2015	0.034	0.128	0.205	281	-0.239	1.12	0.367	67
2016	0.507***	10.251	0.268	284	-0.252	0.753	0.387	76
2017	0.316**	5.334	0.384	264	-0.303	1.808	0.625	78
	Regional	**Banks**	($10-50Billion)		**Community**	**Banks**	(<$10Billion)	
Year	(SBL+C&I)/Assets	F-stat	Adj. R^2	N	(SBL+C&I)/Assets	F-stat	Adj. R^2	N
2001	-1.869	2.284	0.768	23	0.039	0.33	0.269	336
2002	0.251	0.064	0.333	25	-0.057	0.895	0.298	365
2003	0.074	0.005	0.395	25	-0.036	0.215	0.198	398
2004	-0.593	0.508	0.444	27	0.015	0.044	0.211	420
2005	-1.001	1.797	0.478	28	0.201***	9.905	0.271	409
2006	-0.951	1.424	0.543	33	0.194***	8.002	0.384	323
2007	-0.715	1.676	0.193	29	0.114*	3.154	0.36	306
2008	-1.14***	9.464	0.783	30	0.07	0.596	0.427	295
2009	-0.298	0.874	0.512	31	-0.009	0.016	0.296	290
2010	-0.65*	3.993	0.354	30	0.042	0.273	0.396	271
2011	-0.517*	3.005	0.408	31	0.217**	4.571	0.338	269
2012	-0.425	2.518	0.35	36	0.201**	5.316	0.323	272
2013	-0.317	1.802	0.502	38	0.128	1.321	0.38	271
2014	-0.433	2.758	0.395	44	0.168	2.396	0.368	260
2015	-0.204	0.709	0.421	44	0.114	1.35	0.317	214
2016	-0.545	2.629	0.367	52	0.665***	15.857	0.448	208
2017	-0.647***	7.629	0.697	53	0.499***	10.015	0.408	186

[1] *** stands for p<0.01; ** stands for p<0.05; * stands for p<0.1.

Table 1.E.3: OLS Estimates of SBL/Assets in Cross-sectional Baseline Models

The coefficients of SBL/assets ratio in baseline models, as shown in Graph 1.6, represent financial incentives for banks to increase SBL/assets. Dependent variable is Tobin's Q Ratio 2001-2017.

	All Banks				**Large&Regional Banks**		(>$10Billion)	
Year	Sum/Assets	F-stat	Adj. R^2	N	Sum/Assets	F-stat	Adj. R^2	N
2001	0.179*	3.304	0.358	375	-1.5	2.015	0.484	39
2002	-0.077	0.608	0.288	407	0.029	0.14	0.368	42
2003	0.22*	2.84	0.217	440	0.763	1.212	0.519	42
2004	0.4***	9.195	0.2	465	-0.124	0.04	0.478	45
2005	0.587***	25.601	0.287	456	-0.369	0.674	0.464	47
2006	0.658***	29.694	0.403	375	0.284	0.185	0.433	52
2007	0.187**	4.948	0.376	355	0.063	0.019	0.339	49
2008	-0.033	0.066	0.325	345	-0.545	1.307	0.592	50
2009	-0.022	0.048	0.281	345	0.122	0.136	0.571	55
2010	0.1	0.873	0.3	325	-0.792**	6.662	0.375	54
2011	0.178	2.241	0.22	323	-0.596*	2.937	0.322	54
2012	0.2*	3.18	0.201	329	-0.544*	3.484	0.287	57
2013	0.213	2.165	0.22	331	-0.397	1.811	0.415	60
2014	0.275*	3.78	0.198	326	-0.285	0.842	0.219	66
2015	0.245*	3.471	0.205	281	-0.024	0.009	0.367	67
2016	0.941***	23.82	0.268	284	-0.184	0.32	0.387	76
2017	0.6***	11.94	0.384	264	-0.321	1.465	0.625	78
	Regional Banks		($10-50Billion)		**Community Banks**		(<$10Billion)	
Year	Sum/Assets	F-stat	Adj. R^2	N	Sum/Assets	F-stat	Adj. R^2	N
2001	-1.664	1.529	0.768	23	0.341***	9.926	0.269	336
2002	0.763	0.597	0.333	25	-0.437***	15.277	0.298	365
2003	0.574	0.319	0.395	25	0.091	0.221	0.198	398
2004	0.031	0.002	0.444	27	0.314*	2.861	0.211	420
2005	-0.402	0.371	0.478	28	0.385**	5.13	0.271	409
2006	-0.331	0.13	0.543	33	0.564***	10.103	0.384	323
2007	-0.376	0.293	0.193	29	0.081	0.683	0.36	306
2008	-1.556**	5.832	0.783	30	-0.269*	3.572	0.427	295
2009	-0.387	0.419	0.512	31	-0.215*	3.434	0.296	290
2010	-0.45	1.244	0.354	30	0.021	0.032	0.396	271
2011	-0.766**	4.411	0.408	31	0.131	1.189	0.338	269
2012	-0.529*	3.501	0.35	36	0.171	1.856	0.323	272
2013	-0.441	2.487	0.502	38	0.012	0.006	0.38	271
2014	-0.631*	3.592	0.395	44	0.089	0.311	0.368	260
2015	-0.436	1.917	0.421	44	-0.027	0.018	0.317	214
2016	-0.71*	2.979	0.367	52	1.091***	16.274	0.448	208
2017	-0.808**	4.993	0.697	53	0.793***	8.291	0.408	186

[1] *** stands for p<0.01; ** stands for p<0.05; * stands for p<0.1.

1.F Robustness Check

Table 1.F.1: Pooled OLS Results

This table reports results of pooled OLS regression of Tobin's Q on ratio of SBL/assets and its interaction with dummy variables. Coefficients are estimated using annual BHC level data spanning 2001–2009. SBL is defined as business loans with original amount of $1 million or less. FC is a dummy variable for the 2008 financial crisis period and equals 1 from 2007 to 2009 and 0 before 2007. SIB is a dummy variable and equals 1 for large banks which were once labeled as systematically important bank and 0 otherwise. Bank controls include nonperforming loans, consumer loans, residential real estate loans, commercial real estate loans, ratio of liquid assets to total assets, ratio of non-interest income to revenue, and ratio of deposits to all funding. All loan variables are scaled by assets. Fundamental controls are weighted state-level 5-year GDP growth rate and weighted county-level Herfindahl-Hirschman index. All standard errors are clustered at individual BHC level. Joint effects are estimated by using heteroscedasticity consistent covariance.

	Tobin's Q Ratio in 2001–09						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
SBL/Assets	0.155	0.156	0.205*	0.154	0.201*	0.159	0.212*
(a)	(0.103)	(0.104)	(0.113)	(0.105)	(0.112)	(0.105)	(0.113)
(SBL/Assets)*SIB		-0.596	-0.716			-0.514	-0.602
(b)		(0.377)	(0.532)			(0.385)	(0.542)
(SBL/Assets)*FC				0.002	-0.011	-0.006	-0.021
(c)				(0.063)	(0.064)	(0.062)	(0.063)
(SBL/Assets)*SIB*FC						-1.846***	-1.949***
(d)						(0.637)	(0.676)
Bank Controls?	YES	YES	YES	YES	YES	YES	YES
Year FE?	YES	YES	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES	YES	YES
Regional Banks Removed?			YES		YES		YES
Obs.	3657	3657	3385	3657	3385	3657	3385
Adj.R^2	0.469	0.471	0.457	0.469	0.455	0.472	0.459
	Marginal Effect of 1 p.p. Increase in SBL/Assets:						
Once Labeled as SIB		-0.44*	-0.511*				
(a+b)		(3.8)	(3.03)				
During Crisis				0.157*	0.19**		
(a+c)				(3.57)	(4.46)		
SIB in Pre-Crisis						-0.355	-0.39
(a+b)						(2.42)	(1.7)
Non-SIB during Crisis						0.153*	0.191**
(a+c)						(3.37)	(4.4)
SIB during Crisis						-2.207***	-2.36***
(a+b+c+d)						(14.93)	(15.82)

[1] Clustered standard errors in parenthesis under estimated coefficients; Chi-Square values in parenthesis under marginal effect.
[2] *** stands for p<0.01; ** stands for p<0.05; * stands for p<0.1.
[3] Data are collected from Call Reports, Y-9C Reports, WRDS Compustat, Summary of Deposit, and Bureau of Economic Analysis.

Table 1.F.2: OLS Estimates of the Interaction Effect of Regulation Change and Small Business Loans on Bank Financial Performance
Dependent variable: Tobin's Q Ratio 2002-2017

Coefficients are estimated using annual BHC level data spanning 2002-2017. SBL is defined as business loans with original amount of $1 million or less. LARGE is a dummy variable,which equals 1 for banks with assets more than $50 billion. DFA2 is a dummy variable with value of 1 during 2015-2017 and 0 during 2010-2014. DFA is a dummy variable with value of 1 during 2010-2017 and 0 during 2002-2009. gSBL is the growth rate of SBL/assets from the previous year. Other bank controls include nonperforming loans, consumer loans, residential real estate loans, commercial real estate loans, ratio of liquid assets to total assets, ratio of non-interest income to revenue, and ratio of deposits to all funding. All loan variables are scaled by assets. GDP is the sum of state-level GDP weighted by each BHC's deposit weight in operating state. HHI is the sum of county-level Herfindahl-Hirschman index weighted by each BHC's deposit weight in operating county. The F-test statistics are in parentheses.

	2002-2017	**2010-2017**	**2002-2009**
gSBL	0.001	0.002	0.001
	(0.001)	(0.002)	(0.002)
gSBL*LARGE	0.005	-0.018*	-0.012
	(0.009)	(0.01)	(0.01)
gSBL*LARGE*DFA	-0.032***		
	(0.011)		
gSBL*LARGE*DFA2		-0.004	
		(0.014)	
SBL/Assets	0.227***	0.134***	0.328***
	(0.033)	(0.051)	(0.043)
(SBL/Assets)*LARGE	-0.853***	-1.858***	-0.859***
	(0.204)	(0.273)	(0.224)
(SBL/Assets)*DFA	0.067		
	(0.045)		
(SBL/Assets)*LARGE*DFA	-1.298***		
	(0.302)		
(SBL/Assets)*DFA2		0.336***	
		(0.078)	
(SBL/Assets)*LARGE*DFA2		-0.677	
		(0.459)	
Bank Controls?	YES	YES	YES
Year Effect?	YES	YES	YES
Adj.R^2	0.497	0.454	0.489
N	5358	2340	3018
Marginal Effect of 1 p.p. Increase in SBL/Assets:			
Pre-DFA + non-LARGE	0.227***		0.328***
Post-DFA + non-LARGE	0.293***		
	(42.47)		
DFA1 + non-LARGE		0.134***	
DFA2 + non-LARGE		0.47***	
		(38.36)	
Pre-DFA + LARGE	-0.626***		-0.531
	(9.21)		(5.53)
Post-DFA + LARGE	-1.857***		
	(55.17)		
DFA1 + LARGE		-1.724***	
		(38.91)	
DFA2 + LARGE		-2.065***	
		(24.91)	

[1] Standard errors in parenthesis under estimated coefficients; F-test values in parenthesis under marginal effect.
[2] *** stands for p<0.01; ** stands for p<0.05; * stands for p<0.1.
[3] Data are collected from Call Reports, Y-9C Reports, WRDS Compustat, Summary of Deposit, and Bureau of Economic Analysis.

Chapter 2

Can the Greater Fool Theory Explain Bubbles? Evidence from China

2.1 Introduction

> "Insiders [who] destabilize by driving the price up and up, selling out at the top to the outsiders who buy at the top and sell out at the bottom...[T]he professional insiders initially destabilize by exaggerating the upswings and the falls, while the outsider amateurs who buy high and sell low are...the victim of euphoria, which infects them late in the day."
>
> — Charles Kindleberger (1978)[1]

Numerous studies have described a similar scenario in history: overheated asset markets attracted naïve and inexperienced investors, even though it was widely believed that the prices were far higher than the discounted future cash flows. These new investors bought overpriced assets in hope of selling them at higher prices to "greater fools," suggesting the Greater Fool theory of bubbles. Eventually, when all possible new investors have been drawn to the market or some exogenous shocks hit the market,[2] bubbles burst. Although the same story has repeated itself over centuries and has been widely discussed among investors, few studies empirically investigate the role of new investors in bubble formation.

[1]First cited by De Long, Shleifer, Summers, et al. (1990b)

[2]The government tried to control the bubble by increasing interest rates or implementing other restrictive measures, or smart and experienced investors sensed the limit and started to dump the assets.

Asset bubbles are broadly defined as asset prices persistently higher than the fundamental values for months or even years. One popular explanation of bubbles in behavioral finance is investors' irrational sentiments, such as animal spirits, overconfidence, and biases, which lead to herd behavior, momentum trading, trend chasing, and positive-feedback effects[3]. Due to institutional limits, such as short-sale constraints, a high cost to arbitrage, and lack of coordination, rational and sophisticated traders cannot easily arbitrage and eradicate bubbles[4]. Asset bubbles usually feature soaring trading volume, but the rational bubble theory fails to explain either the large trading volume or the existence of long-lasting asset prices deviating from fundamentals.

The dynamics of asset price and trading volume is explained by two key models. Building on Harrison and Kreps (1978), Scheinkman and Xiong (2003) and Hong, Scheinkman, and Xiong (2006) attributed trading volume to investors' heterogeneous beliefs on signals about fundamental values of risky assets. They developed a similar version of the Greater Fool Theory called the Resale Option Theory, stating that, with short sales constraint, risky assets are overpriced because optimists are willing to buy assets at prices higher than their optimistic belief of fundamentals, because they hope to resell the assets to even more optimistic investors in the future. Barberis, Greenwood, et al. (2018) argued that the past rapid growth of risky asset price attracts extrapolators, or positive-feedback investors, to buy overpriced assets from fundamental investors and then trade with other extrapolators to realize profits and to re-enter the market. Both models attribute large trading volume to disagreements, but disagreements are treated as exogenous shock in former model and as endogenous in extrapolation process.

[3]E.g., Shiller (1981), Lux (1995), De Long, Shleifer, Summers, et al. (1990b), De Long, Shleifer, Summers, et al. (1990a), Daniel, Hirshleifer, and Subrahmanyam (1998) and Odean (1998).

[4]E.g., Shleifer and Vishny (1990), Hong and J. Stein (2003), Hong and J. Stein (2007), Abreu and Brunnermeier (2003), and Ofek and Richardson (2003).

Therefore, the causality directions are different in two models. In the Resale Option Theory, exogenous disagreement shocks cause higher asset prices and trading volume at the same time, while in extrapolation, good news increase asset prices, which attracts extrapolators and then drives up trading volume. This chapter empirical tests the causality implications of these two models and measure the contribution of extrapolators (or optimists, or positive-feedback investors, or individual retail investors) to bubbles.

Moreover, most theories of bubbles assume that irrational or "noise" investors constitute a fixed percentage of the asset trading participants, but this is not a sound assumption because there is usually an indisputably large number of inexperienced individual investors entering the market during bubble expansion period. This phenomenon did not only happen in emerging markets (Xiong and Yu (2011)), but also existed in advanced countries[5], especially during the recent housing bubble in the U.S. (Bayer, Mangum, and Roberts (2016) and DeFusco, Nathanson, and Zwick (2017)). However, empirical studies often simply measure individual company returns or trading anomalies, which might be due to a lack of data. This chapter uses a unique data set of the aggregate number of newly opened brokerage account in China, which is not available in many advanced countries, and provides empirical evidence for the Greater Fool Theory in explaining asset bubbles.

The Greater Fool Theory has existed as a conventional wisdom for ages, and its implication of contagious irrational speculation and bubble riding behavior is similar to Shoeshine-boy Theory, Survivor Investing, and Keynesian Beauty Contest Principle. Xiong and Yu (2011) examined a bubble in China's warrants

[5] A blog article of Zerohedge (https://www.zerohedge.com/news/2017-04-22/last-time-happened-market-crashed) described that retail investors rushed to open new brokerage accounts during the Dotcom bubble. According to a survey of the Student Loan Report in 2018 (https://studentloans.net/financial-aid-funding-cryptocurrency-investments/), more than 20 percent of American college students have used student loans to buy cryptocurrencies.

market during 2005-2008, in which the out-of-money warrants were traded heavily at substantially high prices. They found that bubble size was positively correlated with trading volume and return volatility, and negatively correlated with asset float. Yet they were puzzled why this bubble lasted 3 years, because some experimental studies suggested that naïve investors would learn from experience and then the belief divergence would attenuate quickly (Dufwenberg, Lindqvist, and Moore (2005), Haruvy, Lahav, and Noussair (2007) and Hussam, Porter, and Smith (2008)). One possible explanation they suggested is that steady inflow of new investors sustain the bubble, despite the learning of previously arrived investors. This hypothesis was supported by a case study in China (Gong, Pan, and Shi (2016)), which found that the inflow of new capital to trade oneBaoGang call warrant was positively correlated with the price. They found that new investors initiated and sustained the bubble and it played a more important role than turnover, volatility, or market return[6]. An experimental paper, Xie and Zhang (2012) also confirmed the importance of inflow of new investors. This study contributes to the literature on bubbles by establishing the link between new investors and bubble formation in a bigger picture.

This study analyses the impact of the inflow of new investors in the Chinese stock market bubble, using a unique data set of aggregate newly opened brokerage accounts, which is not available in many advanced countries. It provides empirical evidence for the Greater Fool Theory in explaining asset bubbles. Using the Granger causality test, I find that increasing stock returns and trading volume

[6]However, they suggested that the inflow of new investors was an exogenous shock, that is, new investors were not attracted by the bubble. They provided two types of evidence: one is that investors started to rush into Baosteel warrant trading on the first day of its issuance; another is that when the bubble shrank, new investors were still flowing in. But, if looking at a bigger picture, during their sample period of August 2005 – August 2006, the Chinese stock market started to enter a huge stock bubble of 2006-07. The corresponding annual growth rate of SHCI was 43%, so, unsurprisingly, investors were eager to trade warrants even on its first issuance day. As for why new investors were not intimidated by the declining prices, it is possible that new investors were attracted by the previous high returns of the warrants or of whole asset market, and hoped to take advantage of the low prices.

Granger led to an increase of new accounts, not only during bubble period but also in other periods. This confirms the Greater Fool Theory that naïve investors were attracted to the frenzied speculation by the surging stock prices and intensive trading activities of other investors. The causality from past stock returns to new accounts disappeared during the run-ups and new investors were only driven by the trading volume, implying the psychological biases of individual investors or the contagion property of bubbles. By applying residual orthogonalization method, I am able to disentangle the instantaneous dynamics between stock price, trading volume, and new accounts. During the sample period, new investors contributed to the stock price by trading frequently, while during the run-ups, trading volume pushed up price by attracting new investors. Based on these data-driven structures, I build recursive structural models of errors, which explain 40-55% of Chinese stock return variations during 2003-2018.

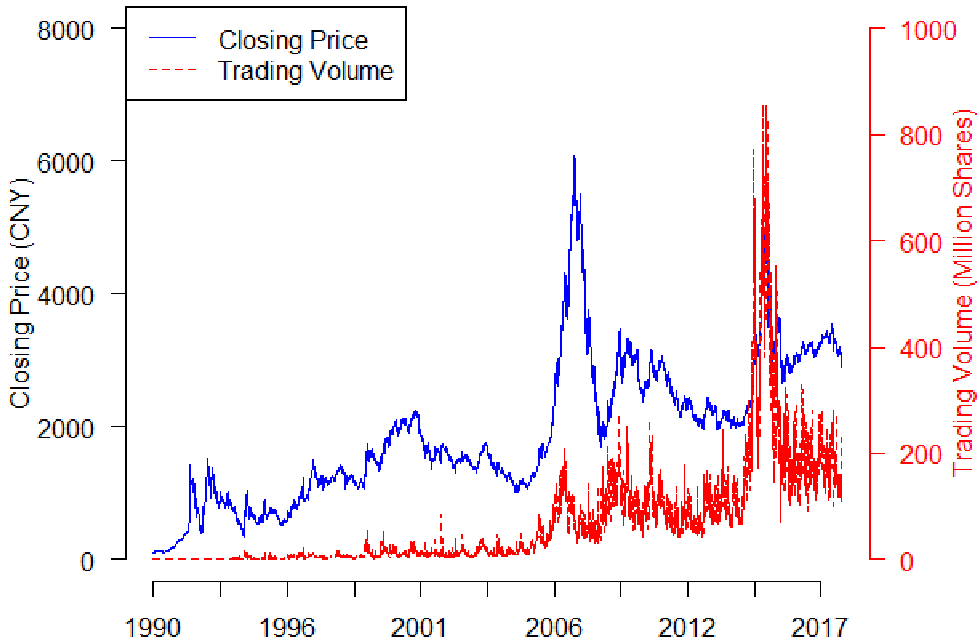
The remaining parts of this chapter are organized as follows. Section two briefly introduces the background of Chines stock market bubbles, and then describes the structure and composition of the new datasets. Section three explains the methodology of residual orthogonalization, and section four presents the empirical results and implications. Section five places this study in the context of literature on bubbles, and concludes.

2.2 Background and Data Description

2.2.1 Chinese Stock Market Bubbles in 2007 and 2015

On December 19, 1990, and July 3, 1991, respectively, the Shanghai Stock Exchange and Shenzhen Stock Exchange opened. Starting from the base of an index of 100, Shanghai Stock Exchange Composite Index (SHCI) reached its highest

Figure 2.1: SHCI Price and Trading Volume



Source: the Shanghai Stock Exchange. This graph shows the price and trading volume of Shanghai Stock Exchange Composite Index during December 19 1990 - May 2 2017. Stock price surged and dropped dramatically in 2006-07 and 2015.

point of 6092 on October 16, 2007. Although the stock index followed along bullish and bearish movements, it often displayed high levels of volatility as in many other emerging markets, partly because of frequent changes in government regulations and policies. Some of these actions may have contributed to the bubbles and subsequent busts. An overview of Chinese stock market is summarized in Appendix A.

Based on the peaks and troughs of the SHCI index prices (see Table 2.A.1 in Appendix A.1), the entire history of Chinese stock market can be divided into six periods, among which the bubble and bust in 2006-2007 and 2014-2015 are most striking. In the boom of 2006-07, the stock price soared to nearly 500%, with annualized growth rate of more than 100%. As a comparison, the annualized return of SP500 in 2006 was 15.8%. At the peak, the total market value for Shanghai and Shenzhen stock exchanges hit CNY 21000 billion, with a ratio of market value to GDP of more than 100%. The government took many actions to depress the bubble, but the market kept rising. Until November 2007 when the Political Bureau of the Communist Party of China Central committee made an announcement and many policies ensued, the SHCI declined from 6000 to 2000 and the sluggish decline lasted until 2014 (details in Appendix A.2).

In 2014, SHCI increased 53%, ranking first in the global financial market performance. Starting from 3300 in January 2015, the SHCI price soared to 5166 in five months and then collapsed to its original level in only two months. In the boom of 2014-15, the stock return was 160%, about one third of previous bubble, but the trading volume was more than 6 times of that in 2007 and its volatility was about 4 times larger. In 2015, the Chinese financial market seemed to have been on a roller coaster, and the instruments of leverage, such as margin trading and outside-of-the-stock-market margin financing, played a crucial part in the frenzy (details in Appendix A.3).

Whether these Chinese stock market maniacs can be counted as bubbles or were justified by fundamentals? In classical definitions of bubbles, asset prices exceed the fundamental valuation of future cash flows for months or even years, accompanied with massive trading volume and speculations. Chinese stock market booms and busts meet these criteria. More discussions and graphs are in Appendix A.4.

2.2.2 The New Brokerage Accounts

Data from China Clear (official)

The distinguishing feature of these booms was the large number of individual investors who moved their deposits from banks into the stock market, shown by the spike of newly opened brokerage account during the booms. In Figure 2.2, there is an obvious positive correlation between new accounts and stock prices.

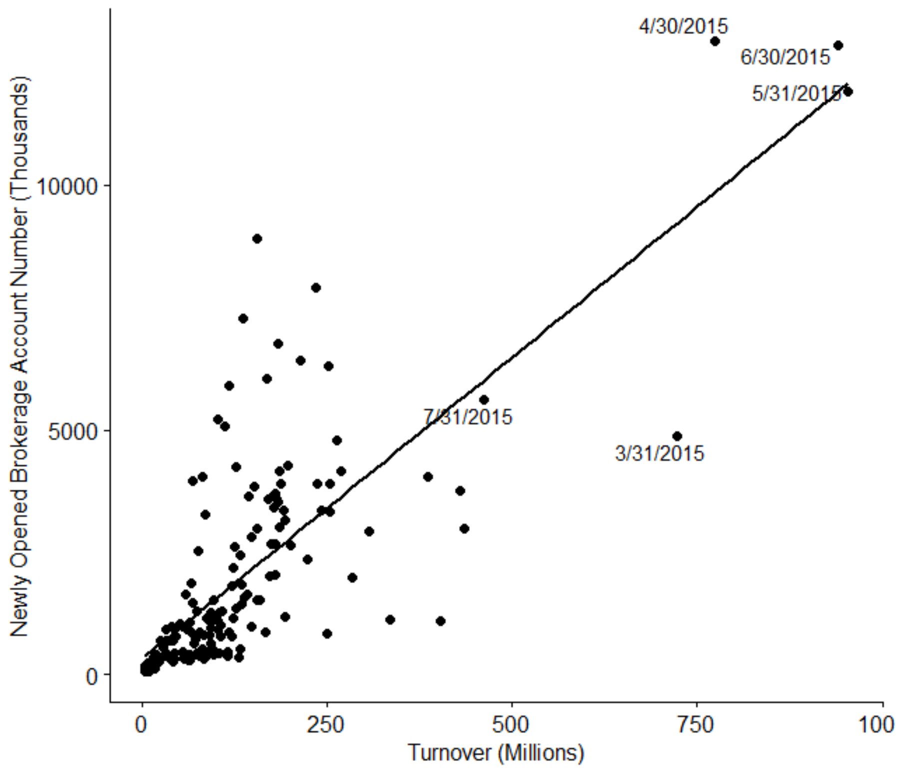
The official data on new accounts is released in the weekly and monthly reports of China Securities Depository and Clearing Corporation Limited (China Clear), whose shareholders are the Shanghai Stock Exchange and the Shenzhen Stock Exchange. China Clear started to release monthly reports beginning in January 2005. The total number of brokerage accounts is the sum of accounts for trading A shares, B shares, and closed mutual funds. They stopped reporting this data after June 2015, and started to release the monthly "Newly Increased Investor Number" starting in April 2015 and weekly in May 2015. It is called "Yimatong" accounts, which can trade A shares, B shares, and closed mutual funds. The overlapping three months of monthly new account number data enables me to splice them together (details in Appendix B.1).

Data from EastMoney database (unofficial)

There is another unofficial database EastMoney[7] which reports weekly new brokerage accounts from January 7, 2008 to May 29, 2015, then China Clear began to release weekly new investors starting on May 4 2015. Again the overlapping four weeks enables us to put together a full set of weekly data (details in Appendix

[7] *http://data.eastmoney.com/cjsj/yzgptj.html*

Figure 2.2: New Accounts and Index Price



* This graph shows the relationship between new accounts and Shanghai Stock Exchange Composite Index price, during December 2003 - March 2017. Both new accounts and index price increased and dropped dramatically during 2006-07 and 2015.

B.2, with a creditability check with monthly data). But due to the limited time period, this data only captures the latest surging number of new accounts during the 2014-15 stock boom. This weekly data is used for robustness check.

2.2.3 Composition of accounts

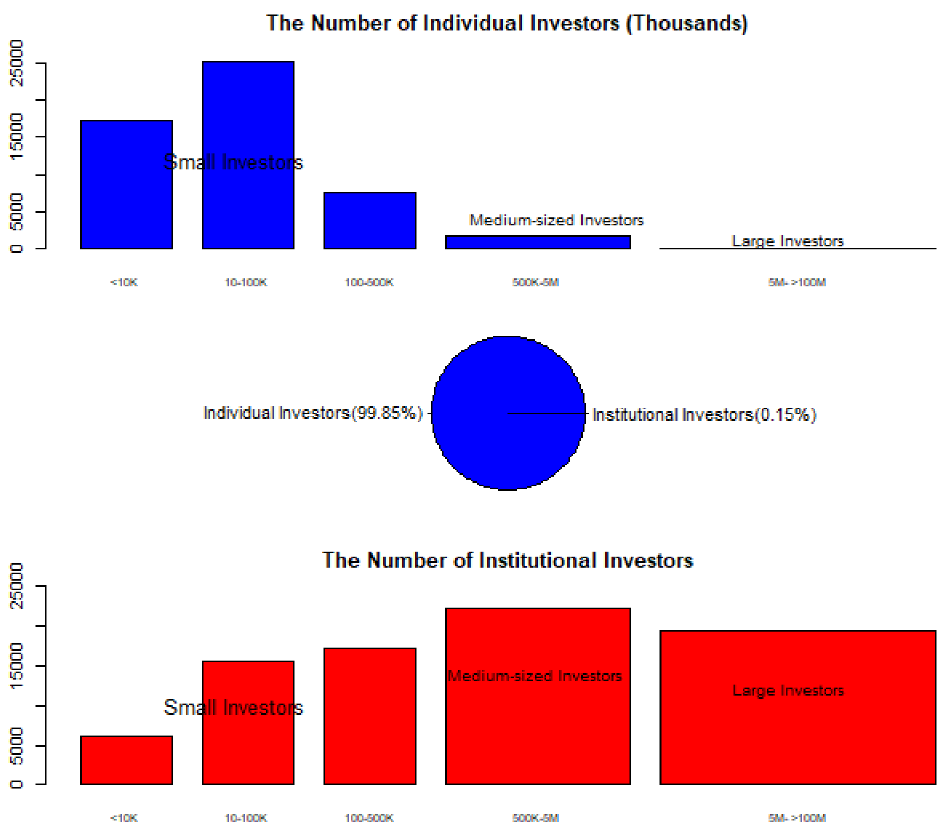
The composition for brokerage accounts reveals many interesting facts about Chinese stock market, although the data covers only short period of time.

Size

The data of accounts with different levels of size were released quarterly in 2009 and 2010, and then monthly from 2011[8]. We consider the brokerage accounts with balances less than CNY 500,000 (equivalent to about USD 73,000) as small investors, accounts with balances between CNY 500,000 and CNY 5,000,000 as medium-size investors, and accounts with balances above CNY 5,000,000 as large investors. The small investors constitutes about 96.5% of accounts, and the medium-size investors less than 3%. This proportion confirms the idea that the majority investors in Chinese stock market are individual retail investors. In Graph 2.4, the number of new median-size and large accounts closely followed the stock market movement, while the small account numbers appeared not to follow the trend and even increased when market started to collapse. This might reflect the fact that those small account holders are usually inexperienced and new investors who could not have full access to the new information or do not have the ability to analyze information, as the medium-size and large investors do. They are usually the "greater fools" who bought high priced stocks from

[8] Again since October 2014 they count Yimatong account, so our data is somewhat fragmented.

Figure 2.3: Share of Individual and Institutional Investors



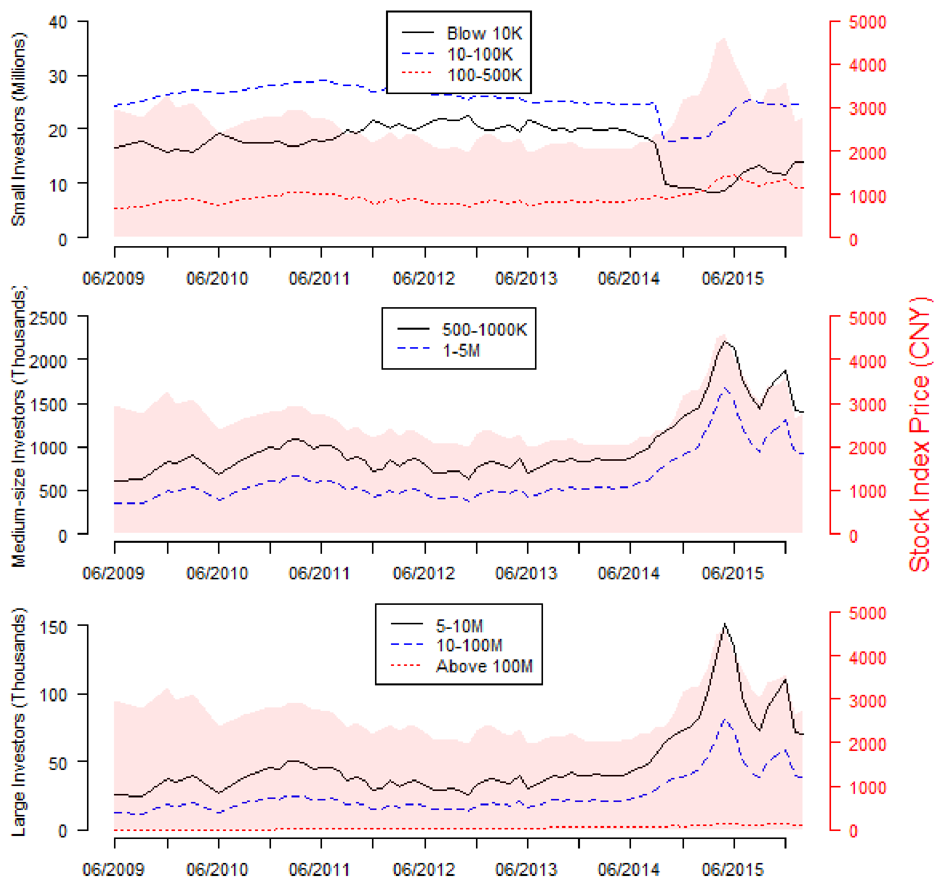
Source: China Clear. Individual investors account for more than 99.85% of total brokerage accounts.

smart investors and could not find buyers.

Age

China Clear reported the age composition of brokerage accounts every 6 month from June 2007 to December 2010. The age composition of investors in Chinese stock market is quite constant during the sample period. The average percentage of each group is calculated in Table 2.1. Compared with the age composition of 2009 National Population Census of China, investors between 30 and 50 years old more actively participated in investment.

Figure 2.4: Number of Individual Investors with Different Account Sizes



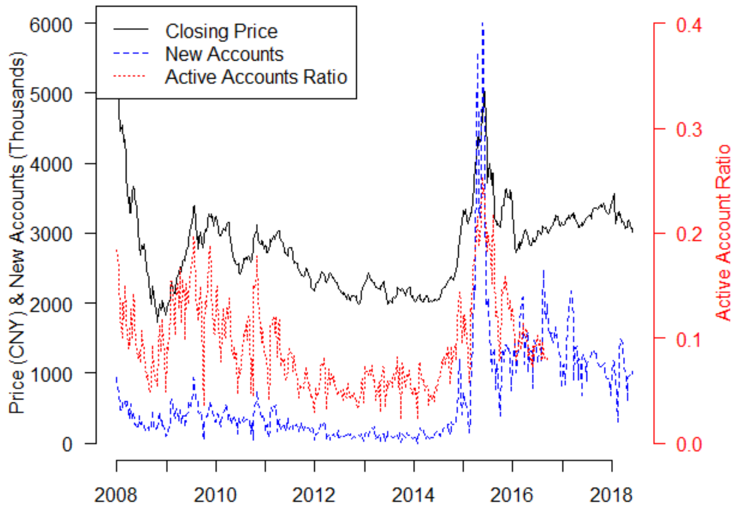
Source: China Clear. This graph show that the account number of individual investors with different sizes behaved differently with the movement of stock index. Notice that the unit of small investor accounts is million, while that of medium-sized and large accounts is thousand. Although small investors constitute more than 96.6% of total individual investor accounts, they did not follow the trend of stock prices as medium and large investors did.

Table 2.1: Age Distribution of Brokerage Accounts and National Consensus

	Under 20	20-30	30-40	40-50	50-60	above 60
Investors	0.42%	16.92%	30.38%	26.66%	15.73%	9.90%
Census	8.62%	16.84%	19.08%	21.14%	16.88%	17.44%

1 Source: Chinese Statistical Yearbook 2009.
2 I use the number of 15-19 years old to calculate "Under 20" for "Census".

Figure 2.5: Active Account Ratio with SHCI Price and New Accounts Number



Source: the Shanghai Stock Exchange; China Clear; EastMoney. This graph shows the ratio of the accounts which were active within recent one year or one month, compared with SHCI price trend. The sample period is June 2007 - June 2018, and the ratio of accounts which were active within recent one month is available during January 2011 - September 20186.

Active account number

China Clear also started to report the number of account which holds positive positions in A shares and trade A shares in the past year and month from June 2007 and January 2011. I calculate the ratio of active accounts over total accounts and plot in Graph 2.5. There is an obvious upward trend of active account number during the run-up in 2014-2015. Investors tended to trade more during market boom and trade less during bust, which confirms the Greater Fool Theory.

2.2.4 Description of Key Variables

I use the monthly data for the analyses in section four, and I use weekly data for robustness check in Appendix D.

The official monthly number of new accounts is collected from the reports of China Clear. The data is available from December 2003 to the present (June 2018). The corresponding SHCI price and its monthly average trading volume are collected from Shanghai Stock Exchange website. The monthly average turnover rate of SSE is from Qianzhan Database[9] and it is defined as trading volume divided by the number of outstanding shares. The basic statistical summary of data is shown in Table 2.2.

Table 2.2: Statistical Summary of Monthly Data

ENTIRE N=174	Index Price (CNY)	Turnover Rate (Thousand)	New Accounts (Thousand)
Min.	1061	4	69
Max.	5955	954	12947
Mean	2602	126	1874
Std.	931	144	2292
BUBBLES N=67	**Index Price (CNY)**	**Turnover Rate (Thousand)**	**New Accounts (Thousand)**
Min.	1081	5	70
Max.	5955	954	12947
Mean	2789	160	2410
Std.	1244	211	3069
RUN-UPS N=47	**Index Price (CNY)**	**Turnover Rate (Thousand)**	**New Accounts (Thousand)**
Min.	1081	5	70
Max.	5955	954	12947
Mean	2565	162	2441
Std.	1300	237	3553

* The entire period of monthly data is December 2003-June 2018. The bubble periods cover June 2005-November 2008, and January 2014-January 2016. The run-up periods include June 2005-October 2007 and January 2014-June 2015. The unit of Index Price is CNY. The unit of turnover rate and new accounts is thousand.

[9] *http://d.qianzhan.com/*

To see the relationships between the stock index price, trading volume (proxied by turnover rate), and new accounts, I first examine their correlations for entire period, bubble period, and run-up period. In the Table 2.3, the stock index price and trading volume are highly correlated with the number of new accounts, our indicator of the entry of "fools", with correlation around 70% to 80%, which is even higher than that between price and trading volume. Although the correlations increased in run-up, those in bubble periods slightly decreased.

Table 2.3: The Correlations between Variables

MONTHLY	Corr(P,T)	Corr(N,P)	Corr(T,N)
ENTIRE	0.58	0.74	0.77
BUBBLES	0.49	0.73	0.77
RUN-UPS	0.57	0.82	0.77

* P represents stock index price; T represents turnover; N represents the number of new accounts. The entire period of monthly data is December 2003-June 2018. The bubble periods cover June 2005-November 2008, and January 2014-January 2016. The run-up periods include June 2005-October 2007 and January 2014-June 2015.

2.3 Methodology

To test the Greater Fool Theory is equivalent to check whether the boom of asset market drew new investors into the speculative trading game and whether the entry of new investors also reinforced the frenzy. Specifically, I test the causality direction among stock price, trading volume, and new investors, by testing the Granger causality and instantaneous causality. I also use residual orthogonalization method to construct a data-driven structural model system, to measure to what extent the trading activities of new investors would contribute to the stock bubbles in China. Weekly data is checked for robustness.

2.3.1 Granger Causality

A simple Granger causality test can show the correlation between two variables in successive periods. Specifically, a bivariate linear autoregressive model of X and Y, which is conducted for pairwise analysis for stock price, trading volume, and new investors, is shown below. The maximum number of lagged observation is 12 [10], because many studies used 12-month past observations for prediction. A, B, C, and D are coefficients of lagged observations, or the contribution of past values to the predicted value of X or Y. ϵ_t is residual for each model. Whether Y Granger causes X can be checked by a F-test with the null hypothesis of $B = 0$.

$$X_t = \sum_{i=1}^{12} A_i X_{t-i} + \sum_{i=1}^{12} B_i Y_{t-i} + \epsilon_{1,t} \tag{2.1}$$

$$Y_t = \sum_{i=1}^{12} C_i X_{t-i} + \sum_{i=1}^{12} D_i Y_{t-i} + \epsilon_{2,t} \tag{2.2}$$

2.3.2 Residual Orthogonalization

To disentangle the instantaneous causality relationships between the variables of interest, I adopt the residual orthogonalization method from Swanson and Granger (1997) to build data-driven structural models of the errors in vector auto-regressions (VAR).

The first step is to construct a VAR model for variables (in log level) and obtain residuals [11]. Assume a 3-dimensional multiple time series x_t, is generated

[10] Other numbers of lags are also checked, the results are similar.

[11] The model selection criteria I use is AIC, but using other criterion yields similar results.

by a stationary VAR(p) process:

$$x_t = \sum_{j=1}^{p} A_j x_{t-j} + u_t \tag{2.3}$$

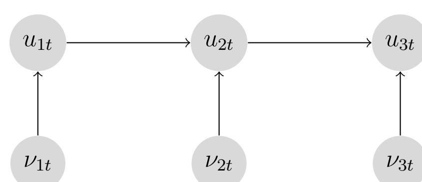
where $x_t = (x_{1t}, x_{2t}, x_{3t})'$, $u_t = (u_{1t}, u_{2t}, u_{3t})'$ and u_t is a continuous random vector satisfying zero mean, nonsingular covariance, and orthogonal.

The second step is to calculate partial correlations of two variable residuals conditioned on the other and test with the null hypothesis:

$$H_0 : \rho(u_{it}, u_{jt}|u_{kt}) = 0 \tag{2.4}$$

where (i,j,k) are any permutations of (1,2,3). If the null hypothesis cannot be rejected, then the zero partial correlation implies that the conditioned residual of variable cuts the causal link between the other two.

The third step is to specify the causality direction by considering economic senses. After checking all partial correlations and referring to economic theories, a linear causal link can be drawn as:



The last step is to build recursive structural models and estimate them. A set of structural models can be built from the above linear causal link:

$$u_{1t} = \nu_{1t},\ u_{2t} = \beta_{21}\nu_{1t} + \nu_{2t},$$
$$\text{and } u_{3t} = \beta_{31}\nu_{1t} + \beta_{32}\nu_{2t} + \nu_{3t}$$

where ν_t are orthogonal underlying shocks to each variable. The results can be estimated by ordinary least squares.

2.4 Results

The Granger causality analysis shows that new investors were attracted to Chinese stock market by both past returns and past trading volumes, which supports the Greater Fool theory and the positive-feedback effect (De Long, Shleifer, Summers, et al. (1990b)). However, stock price is irrelevant to past trading volume, or vice versa, contrary to the assumptions of many behavior finance studies (e.g., Barberis, Greenwood, et al. (2018)). According to the data-driven structural models, new investors pushed up stock price by trading intensively, contributing 40% to 55% of the bubbles.

2.4.1 Why new investors entering the market?

The Granger causality results on monthly and weekly data are summarized in Table 2.C.1 and 2.C.2 in Appendix C, and the implied causality directions are shown in Table 2.1. In the entire sample period, increasing stock returns and trading volume in the last periods were associated with an increase in new accounts, not the other way around. This confirms the idea that the good performance of stock market as well as the intensive trading activities of other investors attract new investors to participate the speculation. Interestingly, new investors were no longer sensitive to past returns during the run-ups, contrary to the positive-feedback effect. In the context of Chinese stock market, where more than 95% of investors are individual retail investors, it is understandable that inexperienced and naive investors can be easily affected by others' trading enthusiasm but might not be smart enough to analyze the price movement. Trading volume is a common proxy for investor sentiment, and my result confirms this assumption by connecting it to new investors.

Table 2.1: The Granger Causality Relationships

Entire Periods	$P \Rightarrow N \Leftarrow V$
Bubbles	$P \Rightarrow N \Leftarrow V$
Run-ups	$N \Leftarrow V$

* The entire period of monthly data is December 2003-June 2018. The bubble periods cover June 2005-November 2008, and January 2014-January 2016. The run-up periods include June 2005-October 2007 and January 2014-June 2015.

Most importantly, the fact that the causality direction runs from stock price or trading volume to the entry of new investors, not the other way around, supports the Greater Fool theory. The number of new investors is not closely related to future returns, implying that they are the "greater fools".

2.4.2 How did new investors drive up bubbles?

In Granger causality results, all variables have highly significant instantaneous causality relationship with each other, which deserves deeper investigation.

Following Swanson and Granger (1997), I fit VAR models of variables and then obtain residuals. All the possible partial correlations for corresponding residuals are calculated, and the values, test statistics, and corresponding p-values are listed in Table 2.2. N, P, and V are corresponding errors of new account number, stock index price, and trading volume (proxied by turnover rate). There are three partial correlations below 0.2 and one with value of 0.21. Inspection of the P-values also shows that five partial correlations are statistically no different than 0. As implied by a simple three-variable causal model, exactly one partial correlations should be zero, and there is one causal link for each case.

From the zero valued $\rho(N_t, P_t|V_t)$, I can decide that the causality is $N \Rightarrow T \Rightarrow$

Table 2.2: Partial correlations on Monthly Data

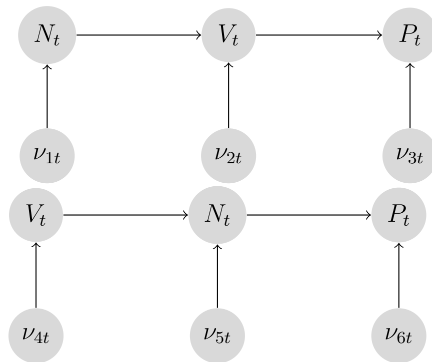
Entire Periods				
Partial correlations	Values	P-value	Test statistics	Decision
$\rho(N_t, P_t \vert V_t)$	0.19	0.01	2.60	**DNR**
$\rho(N_t, V_t \vert P_t)$	0.44	0.00	6.33	Reject
$\rho(P_t, V_t \vert N_t)$	0.56	0.00	8.90	Reject
Bubbles				
Partial correlations	Values	P-value	Test statistics	Decision
$\rho(N_t, P_t \vert V_t)$	0.16	0.19	1.32	**DNR**
$\rho(N_t, V_t \vert P_t)$	0.24	0.05	1.97	**DNR**
$\rho(P_t, V_t \vert N_t)$	0.58	0.00	5.63	Reject
Run-ups				
Partial correlations	Values	P-value	Test statistics	Decision
$\rho(N_t, P_t \vert V_t)$	0.70	0.00	6.52	Reject
$\rho(N_t, V_t \vert P_t)$	0.11	0.47	0.73	**DNR**
$\rho(P_t, V_t \vert N_t)$	0.21	0.16	1.42	**DNR**

* DNR refers to "Do Not Reject" the null hypothesis of zero partial correlation.

P, based on the common assumption in price-trading volume dynamics. For the case of the run-ups, $\rho(N_t, V_t|P_t)$ and $\rho(V_t, P_t|N_t)$ are both no different than zero, but for estimation purpose, I choose the causality direction of $V \Rightarrow N \Rightarrow P$. The causal directions are shown in Figure 2.1.

Intuitively, after new investors were attracted by soaring stock returns and others' trading enthusiasm as implied by Granger test results, new investors started to trade intensively (as a common characteristic of retail investors) and push up stock price further. Admittedly, the reverse direction is also possible theoretically. Yet, it is not plausible in an economic rationale. Many studies have provided evidences that stock prices can be pushed up by increased market liquidity, such as turnover rate, trading volume, and etc... Therefore, it is sensible to assert that the impact of new investors on stock prices is via trading volume, not the other way around.

Figure 2.1: Instantaneous Causality Directions and Structure



* This graph summarizes the causality relations implied by the Partial correlation results in Table 2.2. The first one presents the causality for entire period and bubble period. The second one represents the case of the run-ups.

During bubble formation period, the causality pattern changed and trading volume contributed to the bubble via attracting more new investors.

2.4.3 How much did new investors contribute to bubbles?

The estimation results are listed in Table 2.3. All the coefficients in the structural system of errors are positive and highly statistically significant and the R-squares are decently large. During the entire sample period and in bubble period, the shock to new accounts explains 12-15 % of trading volume variation, and new accounts together with trading volume account for 40% of variation in stock index return. During the run-ups, they explain more than 55% of stock return variation.

By iterating and plugging in the estimators, the structural system of errors can be written in reduced form, as summarized in Table 2.3. The impact of same amount of new investors on stock price during the run-ups is five times of that during other period, while the impact of trading volume on price during the run-ups reduces more than one-third. This might suggest that the number of

Table 2.3: The Estimation of Structural Model System

ENTIRE Model 1	ν_{1t}	ν_{2t}	ν_{3t}	R-squares
$N_t = \nu_{1t}$	-	-	-	-
$V_t = \alpha_1 + \beta_1\nu_{1t} + \nu_{2t}$	0.292***	-	-	12.18%
$P_t = \alpha_2 + \beta_2\nu_{1t} + \beta_3\nu_{2t} + \nu_{3t}$	0.067***	0.126***	-	40.01%
Reduced Form: $P_t = c_1 + 0.03N_t + 0.126V_t + \nu_{3t}$				
BUBBLES Model 2	ν_{4t}	ν_{5t}	ν_{6t}	R-squares
$N_t = \nu_{4t}$	-	-	-	-
$V_t = \alpha_3 + \beta_4\nu_{4t} + \nu_{5t}$	0.315***	-	-	15.71%
$P_t = \alpha_4 + \beta_5\nu_{4t} + \beta_6\nu_{5t} + \nu_{6t}$	0.071***	0.143***	-	40.88%
Reduced Form: $P_t = c_2 + 0.026N_t + 0.143V_t + \nu_{6t}$				
RUN-UPS Model 3	ν_{7t}	ν_{8t}	ν_{9t}	R-squares
$V_t = \nu_{7t}$	-	-	-	-
$N_t = \alpha_5 + \beta_7\nu_{7t} + \nu_{8t}$	0.762*	-	-	11.56%
$P_t = \alpha_6 + \beta_8\nu_{7t} + \beta_9\nu_{8t} + \nu_{9t}$	0.220***	0.181***	-	55.44%
Reduced Form: $P_t = c_3 + 0.181N_t + 0.082V_t + \nu_{9t}$				

[*] This table shows the results of estimation on structural models. Sample period is January 2004 - May 2018. N_t, V_t, and P_t represent the VAR errors of new account number, turnover rate and monthly Shanghai Stock Exchange Composite Index price. ν_t proxies exogenous shock to each variable.

[*] *** stands for p<0.01; ** stands for p<0.05; * stands for p<0.1.

new accounts could be a better proxy for investor sentiment than trading volume, especially during bubble formation.

2.5 Conclusion

In recent Chinese stock market bubbles in 2007 and 2015, the SHCI increased by more than 3000 within one year, with annualized returns of 114% and 96% respectively. Accompanying the surging stock prices was a tremendous inflow of new investors, rushing to open brokerage accounts and to actively speculate. New investors are attracted by the bubble, and buy assets at high prices in hope of selling at even higher prices to “greater fools”. This phenomenon, usually referred to as the greater fool theory, was widely discussed among investors, but seldom tested by researchers in empirical studies.

Using a unique data of aggregate number of new brokerage accounts, this study provides powerful evidence for the Greater Fool Theory that (a) inexperienced and new investors are attracted by soaring stock prices and the frenzied trading activities of other investors, and that (b) they are likely to be the “greater fools” who suffered in the following crash. One interesting find is that during the run-ups new investors were not sensitive to past stock returns but still were attracted by trading activities of others. This suggests investors’ contagions discussed in behavior studies, especially the housing bubbles (e.g., Bayer, Mangum, and Roberts (2016) and DeFusco, Nathanson, and Zwick (2017)). This ignorance of past returns’ changes during the bubble formation period helps explain the unusual phenomenon in Figure 2.4, in which small investors kept entering the market even after the market started to crash. Another evidence of “greater fools” is that past returns or trading volumes were associated with the number of new accounts but the accounts number could not be used to predict future returns, suggesting the cases in which new investors entered the market when bubble approaching the peak and thus they bought high and had to sell low.

This study also contributes to the literature on price-trading volume dynamics by introducing the role of new investors. Empirical studies identify the high trading volume or turnover as a phenomenon associated with asset bubble or speculations, and they use it as a proxy for investor sentiment (Baker and J. C. Stein (2004); Barberis, Shleifer, and Vishny (1998); Baker and Wurgler (2007); De Long and Shleifer (1991); Tetlock (2007)). This study further provides evidence that the force behind high trading volume and turnover might be naïve and new investors attracted by the asset bubbles. They drive up the bubble by trading frequently, which confirms this trading behavior of individual retail investors described by many studies (e.g., Kumar and C. M. Lee (2006)). Their participation can also be understand as showing "disagreement", which drives up both trading volume and price, confirming the hypothesis of disagreement model (Harrison and Kreps (1978); Scheinkman and Xiong (2003)). Lastly, my data-driven structural model system can explain 40% of Chinese stock price variation and during the run-ups its explanatory power increases to 55%.

The universality of the greater fool theory is undoubted, although I provide evidences from a market dominated by individual retail investors. The development of information technology enables individuals to participate in trading assets globally without barriers. The cryptocurrency boom and bust in 2017-2018 could be perfectly explained by the greater fool theory. The continuous and enormous inflow of new investors could be a good indicator to identify the asset bubble.

Appendix

2.A Chinese Stock Market Overview

2.A.1 The Business Cycle of Chinese Stock Market

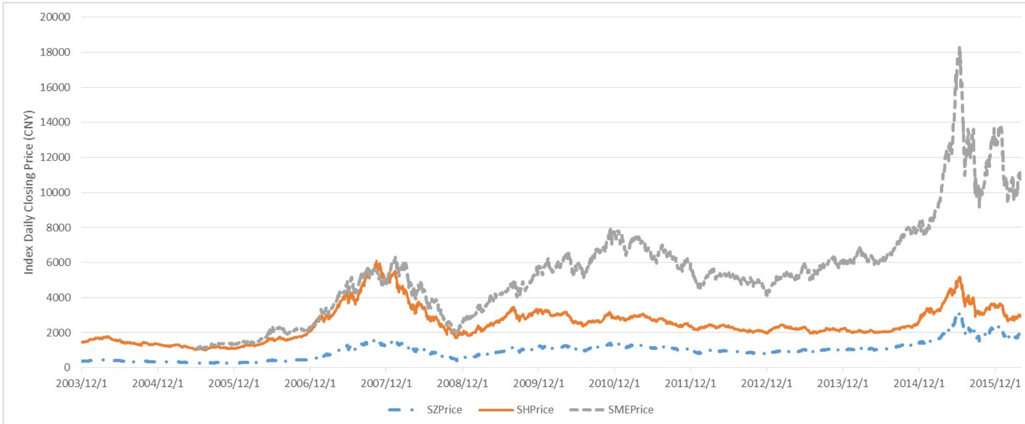
In the Table 2.A.1 below, I summarize the peaks and troughs of Chinese stock market, using SHCI as the proxy because it is the only index available from the beginning of Chinese stock market history, and also because the stocks listed in SHSE are mainly of large and established companies. Represented by the SZSE index, the small-and-medium companies' stocks were more volatile and had wilder swings. Nevertheless, the SHSE's index reals bubble-like movements (see Graph 2.A.1).

Table 2.A.1 shows the broad measures of the market by identifying the peaks and troughs of the SHCI index prices. Based on the information in Table 2.A.1, I divide the whole history into six periods as explained below.

- Beginning Years: 1991-1995

  In the 1990s, especially during the first half, the stock market demonstrated a high level of volatility and low trading volume, with modest variation as indicated by the standard deviation. In booms, the stock market grew 200-300%, and its standard deviation was as high as almost 300, however the index remained below 2000.

Figure 2.A.1: Composite Indices of SHSE, SZSE and SME



* This graph shows the prices of Shanghai Stock Exchange Composite Index, Shenzhen Stock Exchange Composite Index and Small-medium Enterprise Composite Index, during December 2003 - December 2015. SHCI was not as volatile as SME, but still demonstrated obvious bubbles in 2006-07 and 2015.

- Bull Market: 1996 – June 2001

  The index price increased from 500 to more than 2000 in five years, with an annualized growth rate of 31.2%.

- Bear Market: June 2001 – June 2005

  This bear market lasted four years and the SHCI declined 18%.

- Bubble and Bust: June 2005 – 2008

  In the boom of 2006-07, the SHCI hit 6000 and its growth rate was nearly 500% and its annualized growth rate was more than 100%. Although this might not be comparable with the previous boom, the volatility as measured by the standard deviations of both index price and trading volume was 6-10 times larger than before.

- Bear Market: 2009 – January 2014

  This bear market lasted around five years and the SHCI dropped 6%. But the volatility of index price and trading volume were about two times and five times higher than those of the bear market in early 2000s respectively.

- Bubble and Bust: January 2014 – present

  In the 2014- 2015 boom, the relative price change was not as dramatic as in 2007, and the volatility of prices was about 2/3 of the previous period, but the trading volume variation was more than four times of that in 2007.

Table 2.A.1: Bull Market, Bear Market, Bubbles and Crashes

Status	Date	SHCI	Price Change	Months	Std.P.	Std.V.
Beginning	12/19/1990	99.98	-	-	-	-
Peak	5/25/1992	1422	1322.28%	18	150.63	0.014
Trough	11/17/1992	394	-72.29%	6	260.88	0.035
Peak	2/15/1993	1537	290.1%	3	299.08	0.035
Trough	7/9/1994	333.9	-78.27%	17	248.03	0.795
Peak	9/13/1994	1033	209.36%	2	152.99	4.44
Trough	1/22/1996	516	-50.05%	16	81.94	1.998
Peak	5/12/1997	1500	190.7%	16	233.16	3.79
Trough	5/18/1999	1060	-29.33%	24	81.26	2.378
Peak	6/13/2001	2242	111.51%	25	264.65	8.16
Trough	6/7/2005	1031	-54.01%	48	210.63	7.671
Peak	10/16/2007	6092	490.88%	28	1319.54	43.997
Trough	11/4/2008	1707	-71.98%	13	1211.86	18.85
Peak	8/31/2009	2668	56.3%	10	472.09	40.074
Trough	1/20/2014	1911	-25.37%	53	365.1	35.309
Peak	6/12/2015	5166	159.47%	17	868.46	193.808
Trough	1/28/2016	2656	-48.59%	7	435.79	149.691

* I use SHCI closing price to calculate price change and price standard deviation. The trading volume standard deviation is calculated using the daily trading volume in Shanghai Stock Exchange.

Policies and regulations changes

Although the stock followed long bullish and bearish movements, it often displayed high levels of volatility because of frequent changes in government regulations and policies. Leading events and the corresponding index price changes are listed in the table 2 below, and will be discussed in detail in this section.

On January 19, 1992, former President Deng Xiaoping started his famous

Table 2.A.2: Key Events

Date	Key Regulatory Events	SHCI change/period
Dec. 19, 1990	Opening	-
May 21, 1992	SSE canceled Upward Circuit Breaker	+105%/one day
Aug. 10, 1992	"810 Incident"	-52%/three months
Jul. 30, 1994	"Three Policies"	+33%/one day
May 18, 1995	The suspension of bond futures trading	+31%/one day
Dec. 16, 1996	"12 Gold Plaques"	-31%/ten days
May 19, 1999	"519 Event"	+4.64%/one day
Oct. 22, 2001	"Reducing State Share" policy suspended	+9.86%/one day

southern tour of China, which was viewed by the public, as a reassertion of his "Open Up" reform policy following his retirement from office. His encouragement of stock markets in the speeches precipitated the first bull market in China in 1992. The Shanghai Stock Exchange canceled Upward Limit Circuit Breaker on May 21, 1992 [12] and SHCI surged to 1266 from 617 on the same day. Some stocks like the light industry machinery soared 470% in a day. It had become very popular to participate in the stock market.

In August 1992, 1.5 million investors rushed to Shenzhen, which had a resident population of only 0.6 million, to apply for IPO subscription lottery forms. At that time, to subscribe to IPO shares, you needed to buy an application form using your ID card to attend a lottery, where 10% of the subscribers won the rights to buy shares. The cost of one form was CNY 100 and one ID could buy a maximum of 10 forms. If you won the lottery, you could resell your right to buy in the secondary market and make CNY 10-20 thousand. By comparison, the monthly salary of a professor at a university in Shanghai was about CNY 400. Due to the limited number of the forms and corruption, the stock market fever finally

[12] In the beginning year of the stock market, the trading volume was extremely low because of the scarcity and the unavailability of stocks, so this regulation change was intended to encourage trading. See http://stock.hexun.com/2008-06-15/111113612.html

turned into a riot in August, the so called "810 Incident"[13], which directly led to the foundation of China Securities Regulatory Commission (CSRC) in October. These events led to the first bear market on both Shanghai and Shenzhen Stock Exchanges, with SHCI decreasing more than 50% within three months.

Hit by inflation, high interest rates, and the manipulation by large financial institutions, the stock market's performance was not very satisfactory between 1993 and 1995. On July 30, 1994, People's Daily, the most important official newspaper of Chinese Communist Party, announced the implementation of the CSRC's "Three Policies" to stabilize the stock market. These policies were: (1) a suspension of new IPOs; (2) controls on the watering of stock; and (3) encouragement of outside investors to enter the financial market. The market responded with a one-day 33% increase.

On May 18, 1995, the SHCI increased 31%, when trading in bond futures was suspended, which was not reopened until 2013 September. The suspension was to remedy the loss of faith in the bond futures market which was caused by a market crash in February. The huge amount of short-sell orders from Shanghai Wanguo Securities, which was the largest brokerage at that time, led to the market failure and later Shanghai Wanguo Securities' bankruptcy with a loss more than CNY 5.6 billion.

In 1996, inflation declined and interest rates fell, and the stock market revived. But the CSRC was worried about speculation and manipulation and announced 11 regulations to suppress the boom. However, the momentum was unstoppable, and by December, the SHCI reached 1240, more than doubled its level in March. Finally on December 16, the 12th regulation, a 10% Upper Circuit Breaker was

[13] See http://www.ftchinese.com/story/001042077?full=y

imposed again and People's Daily published an article entitled: "Correctly Recognize the Current Stock Market". The market then crashed with every stock, hitting the Lower Circuit Breaker for successive four days. The SHCI fell 31% from its peak in ten days. These 12 policies are known among Chinese investors as "12 Gold Plaques", which refers to a literary quotation about an ancient Chinese national hero Yue Fei.

In the first quarter of 1997, the SHCI again increased more than 50%. Several new regulations were imposed, including an increase from 3 mills to 5 mills of the Stamp Tax on Securities Trading. When the Asian financial crisis hit, the central bank lowered its policy interest rate four times in 1997 and 1998, leaving the SHCI was still around 1200.

Sluggish conditions prevailed until May 19, 1999, when the Shanghai stock market suddenly jumped by 4.64% and many internet and high-tech companies' stock price hit the upper circuit breaker. This dramatic and unexpected rise is called "519 Event". Some analysts argued that, this occurred because of the bullish international financial market, policies for industrial reform, for state-owned companies, and for promoting stock market development, which induced optimistic expectations and precipitated the "519 Event". The central bank lowered the interest rate on June 10 and officials from CSRC made optimistic comments, leading to 64% increase of the SHCI over the next 40 days. Yet, on July 1st, the day that began the official enforcement of Securities Law, the SHCI declined 7.61% and gradually dropped to 1345 by the end of 1999.

During 2000, the SHCI reached 2000 for the first time. The turning point appears to have been June 12, 2001, when the State Council announced the interim measures for the management of "Reducing Held State Shares and Raising Social Security Funds", the stock market started to tumble. The SHCI dropped

31.6%, then on October 22nd when the State Council suspended the policy[14], the stock index jumped 9.86% on the next day. However, this did not halt the bear market and the SHCI continued to decline, dropping to nearly 1000 by June 2005.

2.A.2 Bubble in 2006-07

At Late 2005 and early 2006, a bubble seems to have appeared. The SHCI reached 2000 again on November 20, 2006, rising 130% with trading volume up 333.24% in 2006. The distinguishing feature of this boom was the large number of individual investors who moved their deposits from banks into the stock market, with the growth rate of domestic saving deposits declining for the first time since June 2001[15].

On January 4, 2007, the trading volume in Shanghai Stock Exchange surged to more than CNY 120 million for the first time, and the ratio of total securities market value to GDP rose to more than 50%. In May, the SHCI reached 4000 and CSRC tried to emphasize that there was no state guarantee, by issuing a statement that "investors should be responsible for their own investment". Later in May, the central bank increased the interest rate and reserve requirement for banks, but the stock market kept rising. In the evening of May 29, Treasury Department suddenly announced an increase from 0.1% to 0.3% of stamp tax on securities trading. The SHCI then dropped 6.5% on May 30, and fell below 4000 with a 15.33% loss in four days. But the market recovered soon and the total market value for Shanghai and Shenzhen stock exchanges hit CNY 21000 billion, with a ratio of market value to GDP of more than 100%. The SHCI rose to 5000 on August 23 and then 6000 on October 15, the day of the 17th Communist Party

[14] Details see http://finance.sina.com.cn/focus/20ygyg/

[15] $http://jjckb.xinhuanet.com/caijing/2007-07/19/content_58590.htm$

of China National Congress, hitting a historical highest point of 6124.04 the next day.

At the same time, CPI increased rapidly, especially the number in October was 6.5%, the highest since 1996. On November 27, 2007, the Political Bureau of the Communist Party of China Central Committee announced an efforts to limit inflation and cool the overheating economy. A bear market then started. During the following winter, an unprecedented snow storm struck South China and on January 16, and the bank reserve requirement ratio was raised 0.5%, leading to a monthly decline of 17% of the SHCI. In the first quarter of 2008, rumors about several financial institutions trying to refinance hit the market, and the index dropped more than 40% when on April 22 Treasury Department again suddenly announced a decrease in the stamp tax on securities trading from 0.3% to 0.1%. On the next two trading days, SHCI increased 4.15% and 9.29% and the trading volume rose 191.19%. However, central bank suddenly and strangely announced an increase in the bank reserve requirement ratio by 1% to 17.5% on June 7th Saturday, and on the following trading day SHCI declined 7.73% and thousands of stocks hit the Lower Limit Circuit Breaker. The SHCI collapsed to 2000 in September, suffering a loss of 43.06%. On September 16, the central bank benchmark lending rate was decreased by 0.27% but the market continued to be pessimistic. On September 19, the stamp tax orders were changed to charge only sell-side and China Central Huijin, a government-owned investment company, started to purchase the stocks of the three biggest state-owned banks. Due to these policies, SHCI increased 9.45% and 7.77% on the following trading days and almost all the stock prices hit the Upper Circuit Breaker. Yet in October, the government failed to prevent the market dropping 25.63%.

The bearish market became an important factor of social instability, so the government announced many rescue policies, for example, the famous "4000 billion investment plan" which temporarily stimulated the stock market, but also accumulated considerable amount of debt and the "excess production capacity"[16]. The policies pushed the market up from October 2008 to August 2009, but then the market began a sluggish decline, lasting untill 2014.

Table 2.A.3: Summary of the Stamp Tax Rates

Date	Stock Exchange	Tax Rate	Which side
Jul. 1990	SZSE	0.6%	Sell-side
Nov. 1990	SZSE	0.6%	Both sides
Oct. 1991	SHSE	0.3%	Both sides
Oct. 1991	SZSE	0.3%	Both sides
May 1997	Both	0.5%	Both sides
Jun. 1998	Both	0.4%	Both sides
Jun. 1999	Both(B share only)	0.3%	Both sides
Nov. 2001	Both	0.2%	Both sides
Jan. 2005	Both	0.1%	Both sides
May 2007	Both	0.3%	Both sides
Apr. 2008	Both	0.1%	Both sides
Sep. 2008	Both	0.1%	Sell-side

2.A.3 Bubble in 2015

Starting from 3300 in January 2015, the SHCI price soared to 5166 in five months and then collapsed to its original level in only two months. In 2015, Chinese financial market seemed to have been on a roller coaster, and the instruments of leverage, such as margin trading and outside-of-the-stock-market margin financing, played a crucial part in the frenzy.

In 2014, SHCI increased 53%, ranking first in the global financial market performance. Fueling this growth was margin financing, which became very popular

[16] $http://finance.sina.com.cn/zl/china/2016-02-01/zl-ifxnzanm3927650.shtml$

among investors. In margin finance, investors borrow from financing companies based on the market value of their securities and pay interest. But if the market value drops to certain level, the financing company have the right to close the position of the borrowers, and the borrowers should absorb the loss. If they borrow from a brokerage or security company, it is called margin trading. If they borrow from outside, mainly from trust companies or "internet financial companies", it is relatively riskier because a brokerage or security company requires customer equity to be more than CNY 500,000 and the financing ratio to be less than 100%. The major risk comes from those so called "internet financial companies".

From late 2014 to May 2015, SHCI more than doubled its level and reached 5166 on June 12. Although during this period, the CSRC raised required customer equity for margin trading and prohibited the security company to sell umbrella trusts, which provides a form of margin financing. Yet, new money continued to rush in the market and pushed the prices even higher. On June 12, the CSRC finally started to take action to close some illegal margin financing accounts, which cut off more money and new entrants to the market. The high level of stock prices were not sustainable, and the collapse of stock prices led to huge mandatory liquidation, resulting in a further drop of margin accounts. One third of the stock market value was lost within one month and major aftershocks occurred around July 27th and August 24th "Black Monday".

The government tried to rescue the market, but the efforts were not effective. On July 6 2015, China Securities Finance Corporation Limited (CSF), which is a state-owned financial institution aiming to facilitate the margin transactions of securities companies in China[17] and a member of so called the "National Team", started to intervene the market with funding supported by the state-owned commercial banks. Goldman Sachs estimated that the funding used by CSF and

[17] http://www.csf.com.cn/publish/english/1071/1076/index.html

Huijin for market intervention from June to November was CNY 1,800 billion and owned 6% of the whole stock market in China[18]. At beginning, the "National Team" focused on buying the stocks of the commercial banks, securities companies, energy companies and other large companies, attempting to maintain the price stability. However, this strategy soon became ineffective because it was easily predicted by the public. Take Petro China for example, it was commonly viewed as a target company to be rescued by the "National Team", but when investors noticed that its stock price dropped substantially, they believed that the Chinese government had given up the rescue plan and was selling the stock. This change of belief directly led to a decline of 9.6% of price of Petro China and a drop of 8.5% of SHCI[19]. The rescue plan conducted by the Chinese government is very controversial, and many Chinese economists are against it. They argued that there were no evidence of systematic risk and direct market intervention would cause market distortion, corruption and other problems[20]. Soon, several senior government officials in CSRC were under investigation due to corruption and violation of disciplines.

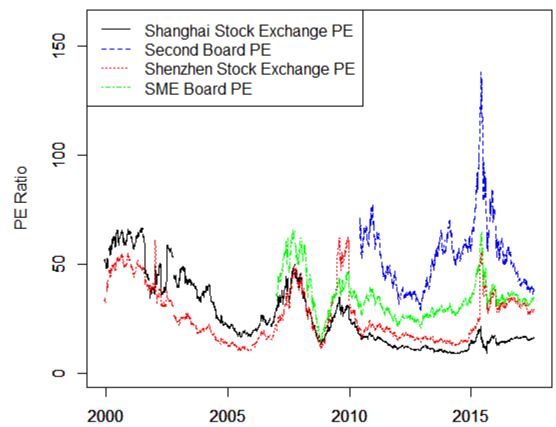
Along with the actions of "National Team", CSRC also investigated and closed illegal financing companies and strengthened regulations of the margin finance accounts and instruments. This effectively controlled the level of leverage in Chinese stock market, but some investors argued that margin trading is necessary in capital market and asked for supporting. Many questioned the ability of the Chinese government to keep balance of authority power and market freedom. By October 2016, SHCI still has not recovered to its level at the beginning of 2015.

[18] http://www.ft.com/intl/cms/s/0/7515f06c-939d-11e5-9e3e-eb48769cecab.html

[19] http://cn.wsj.com/big5/20160114/mkt111855.asp

[20] http://cn.nytimes.com/business/20150915/c15sino-stock/dual/

Figure 2.A.2: PE Ratio in different exchanges and boards



* This graph shows the P/E ratio in Shanghai Stock Exchange, Shenzhen Stock Exchange, Second Board, and Small-medium Enterprise Composite Index, during December 1999 - December 2017. Data source: Shanghai and Shenzhen Stock Exchange.

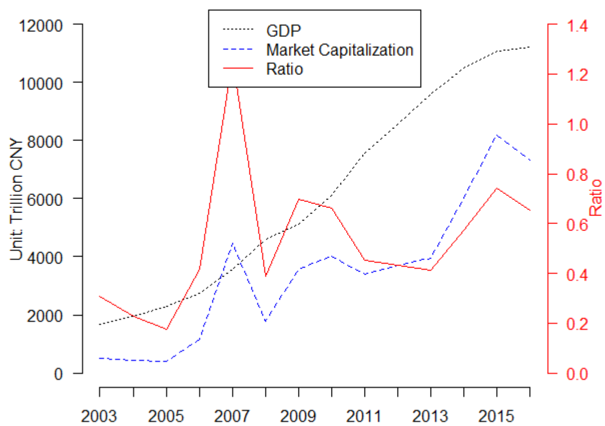
2.A.4 Bubbles v.s. Fundamentals

To justify the existence of bubbles, I compare the stock prices with the P/E ratio in different exchanges, the ratio of market capitalization over GDP, and the leverage ratio.

In Graph 2.A.2, Shanghai Stock Exchange Composite Index as benchmark, whose PE ratio reached a peak of 42 during 2007, but did not increase much during 2015. However, for Shenzhen Stock Exchange and its second board and SME board, prices and PE ratios are more volatile. Especially, the PE ratio of Second Board soared to 140 in 2015, which might imply the existence of stock market bubble in 2015. Yet, PE ratio may fluctuate with cyclical profit margins.

The ratio of market capitalization over GDP is a more reasonable measure for market valuation than the P/E ratio because it eliminates the variation of profit margins. Usually the ratio of total market capitalization over GDP should not

Figure 2.A.3: Ratio of Market Capitalization/GDP

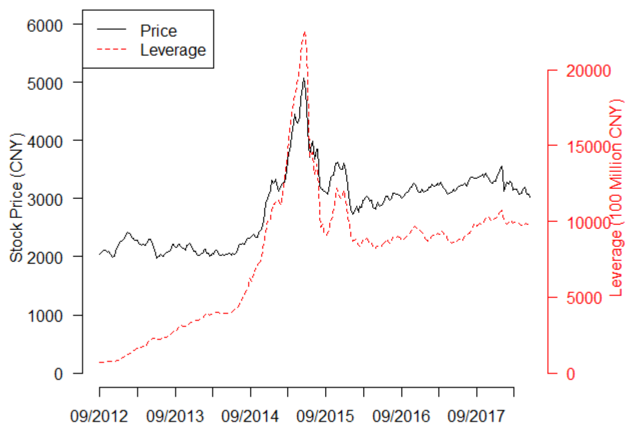


* This graph shows the ratio of market capitalization over GDP, along with GDP and market capitalization values, during 2003 - 2016. Data source: World Bank.

exceed 1, but it violated in 2007, implying a bubble in 2007 (See Graph 2.A.3).

In Graph 2.A.4, the stock market boom and bust in 2015 was closely associated with leverage, measured by the outstanding balance of margin trade in China. This implies that the participation of speculation fueled the stock market fever.

Figure 2.A.4: Stock Price v.s. Leverage



* This graph shows the prices of Shanghai Stock Exchange Composite Index and its outstanding balance of margin transaction, during September 2012 - June 2018. Data source: Shanghai Stock Exchange; Bloomberg.

2.B New Brokerage Account Data

2.B.1 Monthly data adjustment

China Clear started to release monthly reports beginning in January 2005. They ended reporting this data after June 2015, because of the security brokerage account reform in October 2014, promoting Yimatong accounts which combine investors' accounts for trading A shares, B shares, mutual funds and derivatives[21]. They started to release the monthly "Newly Increased Investor Number" starting in April 2015 and weekly in May 2015, which is the increased number of Yimatong accounts.

The overlapping three months of monthly new account number data enables me to splice them together. As shown in **??**, I calculate the ratio of account

[21] $http://finance.sina.com.cn/stock/stocklearnclass/20141008/165520483402.shtml$

number to investors number, which is around 2.7. This means that each investor has 2.7 trading accounts on average, so if this ratio is held constant, then I can estimate new accounts per month from July 2015 till the present. One thing tricky about the released data is that in June 2015 the Chinese stock market reached the highest point and started to crash, and in July ChinaClear stopped releasing new accounts. This break makes it difficult to compare the account numbers, but using the new investor number, there is still a dramatic drop in new accounts.

Table 2.B.1: Overlapping period of New Accounts and New Investors

	March	April	May	June	July
New Account	486.89	1294.73	1190.69	1285.54	-
New Investor	-	497.53	415.87	464.22	204.87
Account/Investor	-	2.602	2.863	2.745	-

2.B.2 Weekly data adjustment

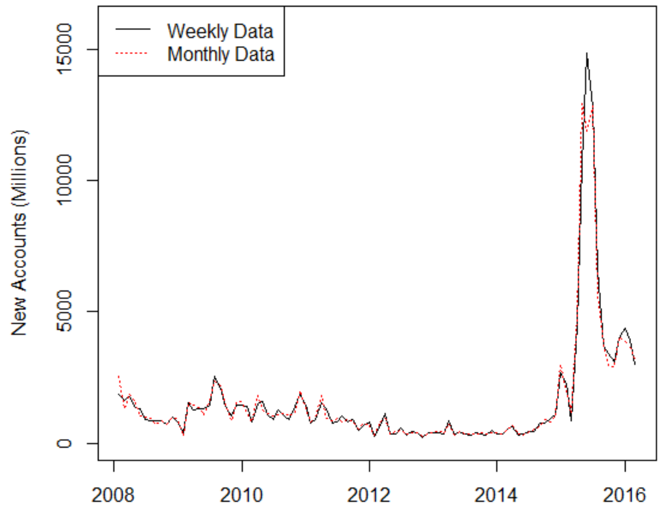
As shown in Table 2.B.2, the ratio of new accounts to new investors is relatively stable with an average of 2.9. So if I hold the ratio constant, I can create a weekly new account series from 2008 to the present. The dramatic drop on May 8 2015 maybe because of the data splicing shown in table 2.B.2, this is not for sure, nevertheless, the co-movement still exists in the following weeks.

Table 2.B.2: Overlapping period of New Accounts and New Investors

	5/1	5/8	5/15	5/22	5/29	6/5
New Account	295.42	245.38	238.71	263.07	443.53	-
New Investor	-	82.07	79.7	89.66	164.44	149.91
Account/Investor	-	2.99	2.99	2.93	2.70	-

To check the creditability of the unofficial weekly data, I sum up the weekly account number in every month to create a monthly data set, and then compare

Figure 2.B.1: Comparison of Weekly and Monthly Data



* This graph shows the comparison of weekly and monthly new accounts number during January 2008 - February 2016. There is not much difference between the data from two sources.

this with the official monthly data. It is clear in 2.B.1 that the two sets of data match well, except for the peak time in May 2015. The simple correlation between them is 98.25%.

2.B.3 Investor types and estimated investment size

Unfortunately, I do not know the inflows of investments by each of the size groups. As a rough approximation, the total balance of their accounts at the market peak are estimated as follows, using the mid-points of the range. For below CNY 10 thousand and above CNY 100 million, I use CNY 5 thousand and CNY 200 million for simplicity. 2015 May was the peak of last stock market boom, and the monthly average CNY/USD exchange rate was 6.2. To give an idea of account size, CNY 10,000 was about USD 1,613, and CNY 100 million was equivalent to

USD 16 million.

Table 2.B.3: Account Number and Value of Different Size Investors in 2015 May

	Small Investors			Medium Investors		Large Investors		
	Below 10K	10-100K	100-500K	500-1000K	1-5M	5-10M	10-100M	Above 100M
To. Acc.	8718	21374	11277	2224	1694	155	93	15
Pert.	19.14%	46.92%	24.76%	4.88%	3.72%	0.34%	0.20%	0.03%
Pert.Sum		**90.82%**			**8.6%**			**0.58%**
New Acc.	382	769	522	185	204	25	15	1.7
Pert.	18.15%	36.57%	24.80%	8.81%	9.70%	1.17%	0.73%	0.08%
Pert.Sum		**79.51%**			**18.5%**			**1.98%**
To.Value	43589	1175563	3383015	1668022	5081472	1165012	5135130	2995800
Pert.	0.21%	5.69%	16.38%	8.08%	24.61%	5.64%	24.87%	14.51%
Pert.Sum		**22.29%**			**32.69%**			**45.02%**
New Value	1908	42296	156470	138896	611865	184238	847165	341600
Pert.	0.08%	1.82%	6.73%	5.98%	26.32%	7.93%	36.45%	14.7%
Pert.Sum		**8.63%**			**32.3%**			**59.07%**

[1] To.Acc. refers to Total Accounts number for each size, and the unit is thousand. Pert. and Pert.Sum refer to the percentage share of each account size and each category of investors.
[2] New Acc. refers to the account number increased in 2015 May.
[3] To.Value refers to the total value of account balance, calculated by multiplying total account number to mid-point value of each account size. I use 5,000 and 200 million as the mid-point value of "below 10K" and "Above 100M".
[4] New Value calculates the total balance of the accounts newly opened in 2015 May.

As shown in Table 2.B.3, even though small investors' accounts were more than 90% of total accounts, at the market peak the number of median and large investors increased disproportionately. For total value at the peak, large investors owned almost half of it, medium investors 32% and small investors 22%. The newly entered money in the bubble peak month were disproportionately from large investors. If considering the possible downward bias that I use CNY 200 million as the average size of "above 100M" accounts, the contribution percentage of large investors would be even larger. When looking at each size, I find that accounts with balance more than CNY 1 million contributed to the bubble peak more aggressively than small investors.

2.C Granger Causality Tests

The Granger causality tests results are listed in Table 2.C.1 and Table 2.C.2.

Table 2.C.1: Granger Causality tests on Monthly Data

ALL	Null Hypotheses	P-value	Conclusion
	New Account doesn't Granger cause Index Return	0.38	DNR
	Index Return doesn't Granger cause New Account	0.00	**Reject**
	Index Return doesn't Granger cause Turnover Rate	0.06	DNR
	Turnover Rate doesn't Granger cause Index Return	0.80	DNR
	New Account doesn't Granger cause Turnover Rate	0.71	DNR
	Turnover Rate doesn't Granger cause New Account	0.00	**Reject**
BUBBLES	Null Hypotheses	P-value	Conclusion
	New Account doesn't Granger cause Index Return	0.14	DNR
	Index Return doesn't Granger cause New Account	0.00	**Reject**
	Index Return doesn't Granger cause Turnover Rate	0.79	DNR
	Turnover Rate doesn't Granger cause Index Return	0.84	DNR
	New Account doesn't Granger cause Turnover Rate	0.25	DNR
	Turnover Rate doesn't Granger cause New Account	0.00	**Reject**
RUN-UPS	Null Hypotheses	P-value	Conclusion
	New Account doesn't Granger cause Index Return	0.44	DNR
	Index Return doesn't Granger cause New Account	0.64	DNR
	Index Return doesn't Granger cause Turnover Rate	0.28	DNR
	Turnover Rate doesn't Granger cause Index Return	0.21	DNR
	New Account doesn't Granger cause Turnover Rate	0.97	DNR
	Turnover Rate doesn't Granger cause New Account	0.00	**Reject**

* DNR refers to "Do Not Reject".

Table 2.C.2: Granger Causality tests on Weekly Data

ALL	Null Hypotheses	P-value	Conclusion
	New Account doesn't Granger cause Index Return	0.58	DNR
	Index Return doesn't Granger cause New Account	0.00	**Reject**
	Index Return doesn't Granger cause Turnover Rate	0.81	DNR
	Turnover Rate doesn't Granger cause Index Return	0.00	**Reject**
	New Account doesn't Granger cause Turnover Rate	0.31	DNR
	Turnover Rate doesn't Granger cause New Account	0.00	**Reject**
BUBBLES	Null Hypotheses	P-value	Conclusion
	New Account doesn't Granger cause Index Return	0.90	DNR
	Index Return doesn't Granger cause New Account	0.14	DNR
	Index Return doesn't Granger cause Turnover Rate	0.95	DNR
	Turnover Rate doesn't Granger cause Index Return	0.00	**Reject**
	New Account doesn't Granger cause Turnover Rate	0.23	DNR
	Turnover Rate doesn't Granger cause New Account	0.00	**Reject**
RUN-UPS	Null Hypotheses	P-value	Conclusion
	New Account doesn't Granger cause Index Return	0.51	DNR
	Index Return doesn't Granger cause New Account	0.10	DNR
	Index Return doesn't Granger cause Turnover Rate	0.22	DNR
	Turnover Rate doesn't Granger cause Index Return	0.00	**Reject**
	New Account doesn't Granger cause Turnover Rate	0.19	DNR
	Turnover Rate doesn't Granger cause New Account	0.00	**Reject**

[*] DNR refers to "Do Not Reject".

2.D Robustness Check on Weekly Data

For weekly data analysis, I use the weekly number of new accounts and the ratio of active accounts over total accounts, from the database EastMoney and China Clear. The data is available from January 11, 2008 to the present (June 2018). The corresponding SHCI price and its turnover rate are from same source as monthly data. The basic statistical summary of data is shown in Table 2.D.1.

Table 2.D.1: Statistical Summary of Weekly Data

ENTIRE N=530	Index Price (CNY)	Turnover (Thousand)	New Accounts (Thousand)	Active Accounts (Percentage)
Min.	1730	23	16	2
Max.	5420	1233	4435	25
Mean	2804	167	501	9
Std.	613	156	569	4
BUBBLE N=105	Index Price (CNY)	Turnover (Thousand)	New Accounts (Thousand)	Active Accounts (Percentage)
Min.	2013	52	16	2
Max.	5074	1233	4435	25
Mean	2991	337	791	11
Std.	835	265	974	6
RUN-UP N=73	Index Price (CNY)	Turnover (Thousand)	New Accounts (Thousand)	Active Accounts (Percentage)
Min.	2013	52	16	2
Max.	5074	1233	4435	25
Mean	2741	299	693	10
Std.	845	287	1120	6

* The period of weekly data is January 11, 2008 - June 15, 2018. The bubble period covers January 2014-January 2016. The run-up period includes January 2014-June 2015. The unit of Index Price is CNY. The unit of turnover rate and new accounts is thousand. The active account ratio is shown in percentage.

For weekly data, all the correlations dramatically increased during bubble period, especially during run-up.

There are 530 observations for each variable. All variables are in log level. I

Table 2.D.2: The Correlations between Variables

WEEKLY	Corr(P,T)	Corr(N,P)	Corr(T,N)
ENTIRE	0.65	0.69	0.81
BUBBLE	0.90	0.85	0.88
RUN-UP	0.95	0.90	0.92

* P represents stock index price; T represents turnover; N represents the number of new accounts. The period of weekly data is January 11, 2008 - June 15, 2018. The bubble period covers January 2014-January 2016. The run-up period includes January 2014-June 2015.

Table 2.D.3: The Granger Causality Relationships

Entire Periods	$P \Rightarrow N \Leftarrow V \Rightarrow P$
Bubbles	$P \Leftarrow V \Rightarrow N$
Run-ups	$P \Leftarrow V \Rightarrow N$

* The period of weekly data is January 11, 2008 - June 15, 2018. The bubble period covers January 2014-January 2016. The run-up period includes January 2014-June 2015.

fit VAR model for each variable and then get corresponding residuals. N, P, and V are corresponding errors of new account number, stock index price, and trading volume (proxied by turnover rate). There are three partial correlations below 0.2 in Table 2.D.4. Inspection of the P-values also shows that four partial correlations are statistically no different than 0. As implied by a simple three-variable causal model, exactly one partial correlations should be zero, and there is one causal link for each case.

The causal directions are shown in Figure 2.D.1. The causality relationship in sample period and bubble period are the same as in the weekly data. During bubble formation period, the causality pattern changed and trading volume pushed up prices, which attracted more new investors. There is no implication on stock price probably because the data interval is too short.

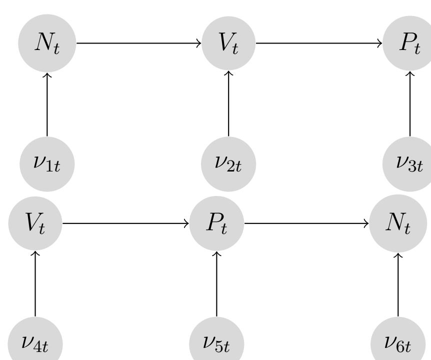
The estimation results are listed in Table 2.D.5. All the coefficients in the

Table 2.D.4: Partial correlations on Weekly Data

ENTIRE				
Partial correlations	Values	P-value	Test statistics	Decision
$\rho(N_t, P_t \mid V_t)$	0.07	0.12	1.55	**DNR**
$\rho(N_t, V_t \mid P_t)$	0.18	0.00	4.24	Reject
$\rho(P_t, V_t \mid N_t)$	0.39	0.00	9.73	Reject
BUBBLES				
Partial correlations	Values	P-value	Test statistics	Decision
$\rho(N_t, P_t \mid V_t)$	0.15	0.14	1.50	**DNR**
$\rho(N_t, V_t \mid P_t)$	0.18	0.06	1.87	**DNR**
$\rho(P_t, V_t \mid N_t)$	0.35	0.00	3.78	Reject
RUN-UPS				
Partial correlations	Values	P-value	Test statistics	Decision
$\rho(N_t, P_t \mid V_t)$	0.27	0.02	2.37	Reject
$\rho(N_t, V_t \mid P_t)$	-0.08	0.49	-0.70	**DNR**
$\rho(P_t, V_t \mid N_t)$	0.38	0.00	3.48	Reject

* DNR refers to "Do Not Reject" the null hypothesis of zero partial correlation.

Figure 2.D.1: Instantaneous Causality Directions and Structure



* This graph summarizes the causality relations implied by the Partial correlation results in Table 2.2. The first one presents the causality for entire period and bubble period. The second one represents the case of the run-ups.

structural system of errors are positive and highly statistically significant and the R-squares are not as large as in the monthly data case. During the entire sample period and in bubble period, the shock to new accounts explains 5% of trading volume variation, and new accounts together with trading volume account for about 16% of variation in stock index return. During the run-ups, trading volume alone explain 13% of stock price variation, and price and trading volume together explain 13% of new accounts. By iterating and plugging in the estimators, the structural system of errors can be written in reduced form, as summarized in Table 2.D.5.

Table 2.D.5: The Estimation of Structural Model System

ENTIRE	Model 1	ν_{1t}	ν_{2t}	ν_{3t}	R-squares
$N_t = \nu_{1t}$		-	-	-	-
$V_t = \alpha_1 + \beta_1 \nu_{1t} + \nu_{2t}$		0.179***	-	-	4.94%
$P_t = \alpha_2 + \beta_2 \nu_{1t} + \beta_3 \nu_{2t} + \nu_{3t}$		0.013***	0.041***	-	16.9%
Reduced Form: $P_t = c_1 + 0.006N_t + 0.041V_t + \nu_{3t}$					
BUBBLES	**Model 2**	ν_{4t}	ν_{5t}	ν_{6t}	**R-squares**
$N_t = \nu_{4t}$		-	-	-	-
$V_t = \alpha_3 + \beta_4 \nu_{4t} + \nu_{5t}$		0.175**	-	-	5.45%
$P_t = \alpha_4 + \beta_5 \nu_{4t} + \beta_6 \nu_{5t} + \nu_{6t}$		0.02*	0.043***	-	15.27%
Reduced Form: $P_t = c_2 + 0.012N_t + 0.043V_t + \nu_{6t}$					
RUN-UPS	**Model 3**	ν_{7t}	ν_{8t}	ν_{9t}	**R-squares**
$V_t = \nu_{7t}$		-	-	-	-
$P_t = \alpha_5 + \beta_7 \nu_{7t} + \nu_{8t}$		0.03***	-	-	13.02%
$N_t = \alpha_6 + \beta_8 \nu_{7t} + \beta_9 \nu_{8t} + \nu_{9t}$		0.037*	5.577**	-	13.67%
Reduced Form: $N_t = c_3 + 5.577P_t - 0.13V_t + \nu_{9t}$					

[*] This table shows the results of estimation on structural models. Sample period is January 2008 - May 2018. N_t, V_t, and P_t represent the VAR errors of new account number, turnover rate and monthly Shanghai Stock Exchange Composite Index price. ν_t proxies exogenous shock to each variable.
[*] *** stands for p<0.01; ** stands for p<0.05; * stands for p<0.1.

Chapter 3

How Does the Adoption of Mobile Payment Promote Financial Inclusion? Evidence from Rural China

3.1 Introduction

Mobile payments have become popular for making in-person or online payments and money transfer, which would contribute not only to lower transaction costs which boost business activities but also to extending financial services to underserved consumers and communities. Yet, few empirical studies have been done, especially from the perspective of economics, to answer basic but crucial questions such as: What determines the adoption of mobile payment? What is the relationship between mobile payment and bank services? How would mobile payment contribute to the financial inclusion and macroeconomic development?

Due to data limitation, most related research had to conduct small-scale online or phone surveys[1] with 200-400 responses on average which would encounter technical challenges.[2] This chapter aims to answer those questions by analyzing

[1]In several countries, such as, Kenya, India, Germany, Sweden, Finland, Vietnam, Qatar, and etc.

[2]Frist, the sample size of the survey is too small and the response rate is often too low, which puts the representativeness under question. Second, those surveys were conducted by phone or online which limits the length of questionnaires and therefore constraints the scope of studies. Third, the answers collected by phone or online might be vulnerable to errors and bias.

a large-scale survey on more than 4,000 representative households in rural China. The "Qian Ren Bai Cun[3]" survey[4] we use was well designed and conducted by about 1000 students and faculties from Renmin University of China in summer 2019, which covered 128 villages in 31 provinces. Although it was not originally designed for studying mobile payment, the survey questions cover various aspects of rural life and production. Most importantly, the novelty of this data is the information about the level of acceptance and perception of mobile payment, the access to bank services, and the number of smart phones. In contrast to the existing studies on the acceptance of mobile payment, we are able to analyze a full set of financial and demographic information of households, combined with macro-finance factors at aggregated levels, rather than only focusing on consumer behaviors.

This chapter provides four sets of major findings. First, we investigate the characteristics of households and analyze who are more likely to adopt and use mobile payment. Given abundant zeros in the responses to the question of mobile payment usage, we apply the hurdle model in Probit and OLS settings. In this two-part model, we first treat positive responses as 1, and examine what affects households' decisions on whether to adopt mobile payment. Then we focus on positive responses, that is, "cross the hurdle" and adopt mobile payment, and check what factors would contribute to how much they use it. We find that when the head of a household is younger or better educated, or if the household has higher income or more smart phones, the household is more likely to adopt mobile payment and use it to pay a larger portion of their expenditure. After complementing the analysis with information about income sources, we find that people with income from agricultural sector are less likely to adopt mobile payment and

[3]Meaning a thousand people and a hundred villages.

[4]`http://spap.ruc.edu.cn/freshman/public/index/index/course_cont/id/91.html`

would also use less. With other income sources, namely, income from manufacture, construction, transportation, hotels and restaurants, and working in urban areas, rural residents are more likely to adopt mobile payment than others. However, after controlling for household characteristics, especially income levels, this effect disappears. Although we hypothesize that people working in urban areas would contribute to higher acceptance and more usage of mobile payment in their families, our results do not support this hypothesis. Interestingly, consumers with income from the finance sector, only 12 in our sample, are more likely to adopt mobile payment but tend to use it less than others.

Second, we examine the relationship between mobile payment and bank services. To deal with the endogeneity issue between the adoption of mobile payment and the frequency of visiting banks which is a proxy for the access of bank services, we apply two instruments for the bank visit frequency. One is the distance to the nearest bank branch or ATM and the other is the village average of bank visit frequency (except for the household i). We find that the more frequently people visit banks, the more likely they would adopt mobile payment. One possible explanation is that being exposed to financial services and products would improve consumers' financial literacy and therefore they are more open to financial technologies. However, for those who have already adopted mobile payment, their usage would increase if they visit banks less frequently. This could be explained by a supplement effect: when people visit banks less frequently due to a long distance to banks (the average in our sample is 3 to 10 kilometers) or social reasons, they tend to switch to a more convenient way – using mobile payment to transfer money, pay bills, or buy groceries.

Third, we exploit a survey question about how people perceive the acceptance of mobile payment in the neighborhood and analyze the relationship between the perception and the usage of mobile payment. A growing number of studies on consumer behaviors have discussed this kind of peer-learning effect and social externality. We hypothesize that people who are more sensitive to their neighbor's usage of mobile payment would be more likely to accept mobile payment. We identify a group of "sensitive" people if their perception of surrounding acceptance rate is higher than the actual rate, and the results support our hypothesis on the positive relation. The "sensitive" group also shares the characteristics identified in the previous session, that is, they are younger, richer, better educated, having more phones than "insensitive" rural residents.

Lastly, we investigate the relationship between mobile payment acceptance and macroeconomic factors and FinTech services at an aggregated level. Comparing prefecture-level cities with top and bottom level of mobile payment adoption rate, we find that top cities enjoy higher level of GDP and better development in banking and FinTech services than bottom cities.

This chapter contributes to the literature from four aspects. First, this study contributes to the growing literature studying the effects of FinTech in financial inclusion, from the perspective of mobile payment. Most FinTech studies focus on FinTech loans and show that loans were extended to underserved consumers and penetrated in underserved areas (Buchak et al., 2018; Jagtiani and Lemieux, 2017; Havrylchyk et al., 2017). However, as far as we know, no research has investigated the effects of mobile payment in financial inclusion, and this study fills up this research gap by providing the empirical evidence in rural China. Additionally, we focus on rural residents' basic financial needs – payment and money transfer which are more fundamental than loans.

Second, while most research on the mobile phone technology-enabled money transfer (Beck et al., 2018; Jack and Suri, 2011; Jack and Suri, 2014) studied low-income countries, such as Kenya, this study investigates the case in the less developed areas in China, a middle-income country. Unlike those low-income countries which have a large portion of unbanked population, households in rural China enjoy a high rate of bank account ownership, yet their financial needs, especially payment and transfer, are underserved, partly due to geographic and cultural reasons. Our finding that mobile payment could fulfill consumers' underserved needs for financial payment provides implications for less developed areas in middle-income countries and even in advanced economies.

Third, this study contributes to the discussion about the relationship between FinTech and traditional banks. On one hand, since mobile payment is the basis of other FinTech products, our finding partially supports some studies[5] which found that FinTech filled the credit gap left by banks and therefore improved financial access. On the other hand, we find that access to banks could promote the adoption of mobile payment, providing new implications for policy makers and FinTech companies.

Lastly, when discussing the factors contributing to the mobile payment acceptance, most studies[6] focus on consumer behaviors and intentions, but this study conducts post hoc analysis and provides stylized facts not only on consumer's perceptions but also on socio-demographic factors. Most related research applied models, such as the unified theory of acceptance and use of technology (UTAUT), the technology acceptance model (TAM) (Davis, 1989), and Diffusion Theory (E. M. Rogers, 2010), which focus on user-related factors, such as personal innovativeness, related knowledge, and perceived risk and trust, and product-related factors, such as convenience, cost, compatibility, network externalities, and reachability. On one hand, our result regarding the perception of

[5]For example, Chen, Hanson, and J. C. Stein (2017), Jagtiani and Lemieux (2018), Ahmed et al. (2015), and Schweitzer and Barkley (2017)

[6]For example, Khalilzadeh, A. B. Ozturk, and Bilgihan (2017), C. Kim, Mirusmonov, and I. Lee (2010), and Schierz, Schilke, and Wirtz (2010)

neighborhood acceptance confirms some results of those studies, for example, the awareness of product would promote the acceptance. On the other hand, this study broadens the scope of similar studies and provides additional implications for FinTech industry.

The rest of the chapter is organized as follows. Session 2 introduces the development of mobile payment and the financial inclusion in China. Session 3 describes the data and identification strategy. Session 4 discusses results and session 5 concludes.

3.2 Background

3.2.1 The Fast Development of Mobile Payment in China

Mobile payment is a broad term for the smart phone enabled payment method which refers to consumers using mobile devices, such as smart phones, tablets, or laptops, to make in-person or online transactions. To make mobile payments, one needs to first set up a mobile wallet which is a smart device application with user's debit or credit card information stored securely. The common mobile wallets in developed economies are Apple Pay, Google Pay, and Samsung Pay, but in China, 92.53% of the market shares are owned by Wechat Pay and AliPay till the third quarter of 2018,[7] which leads to several key attributes in the definition of mobile payment in China.

First, the function of mobile payment in China is not limited to a method to

[7]Based on Alibaba and Taobao, AliPay is the pioneer in mobile payment in China. In 2014, Wechat launched the function of "red pocket" and quickly penetrated the market. In 2016, Apple Pay and Samsung Pay entered the Chinese market, and later Mi Pay and Huawei Pay also joined in the competition. But their market share is small.

pay. Wechat Pay and AliPay are like a combination of Apple/Samsung Pay, Paypal, Venmo/Zelle, and other FinTech apps. They can facilitate not only in-person purchases in supermarkets, restaurants, retail stores, public transportation,[8] and etc., but also person-to-person (P2P) transfers, online shopping, utility payment, ticket reservation,[9] money market fund, and other functions. Note that banking apps are not included in our definition of mobile payment in this chapter.

Second, Wechat Pay and AliPay are using a different technology to facilitate the payment. Apple Pay, Samsung Pay, and others mostly reply on near-field communication (NFC) or magnetic secure transmission (MST), facilitating contactless transactions when users bringing smart phones close to the point-of-sale devices (POS). But, Wechat Pay and AliPay use quick response (QR) code which requires consumers or merchants to scan counterparty's QR code to complete transactions, either online or in person.

China is the largest market for mobile payment with more than 890 million users till 2018. According to People's Bank of China (PBoC), financial institutions processed more than 27 billion transactions of mobile payment with a total amount of 86 trillion CNY in the third quarter of 2019.[10] According to a survey in *It's time for a consumer-centred metric: introducing 'return on experience.'* (2019), more than 86% of consumers in China have been using mobile payment in their daily consumption. This rapid growth is facilitated mainly by an increasing ownership of smart mobile phones, a decrease in the cost of mobile data plans, a fast development of related technologies, and an improved spending ability of consumers.

[8]Including subway, bus, parking lots, paying traffic violation tickets, and etc.

[9]Including flight tickets, train tickets, movie or show tickets, hotel room reservation, and etc.

[10]`http://www.gov.cn/xinwen/2019-11/25/content_5455100.htm`

3.2.2 The Financial Inclusion in Rural China

How to define financial inclusion? World Bank defines it as "*individuals and businesses have access to useful and affordable financial products and services that meet their needs – transactions, payments, savings, credit and insurance – delivered in a responsible and sustainable way*".[11] However, in the context of rural China, the major obstacle for the financial inclusion concentrates on the unfulfilled needs for payments and transactions which would also fundamentally influence the needs for credit and others (Bai et al., 2018).

On one hand, according to the 2017 Global Findex report,[12] about 85%[13] of households in rural China own at least one bank account,[14] which is higher than the average level of G20. On the other hand, 15%[15] of respondents who have bank accounts never deposit or withdraw in the previous year, which might be due to a lack of physical accessibility of bank branches, ATMs, or banking agencies in rural China. Although, at an aggregate level, China has about one million banking outlets[16] in remoted areas, ranking top in the world, the number of banking outlets *per capita* in China is smaller than that of many developing countries, such as Kenya, Peru, and Bangladesh. What is worse, banking agencies cannot provide certain services, such as opening an account. This issue is also

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[11] https://www.worldbank.org/en/topic/financialinclusion

[12] https://globalfindex.worldbank.org/

[13] The percentage of adults owning at least one bank account in rural China is 78%, and 32% of unbanked adults reported that their reason for not having an account is because family members have bank accounts. Therefore, it makes more sense to use a unit of household and we can calculate the percentage of households which have at least one bank account.

[14] For those who do not have any account, 60% claimed the reason of insufficient funds to deposit or transfer, which is more related to poverty than financial inclusion, although financial exclusion would also cause poverty.

[15] This percentage reported by the 2017 Global Findex is for urban and rural respondents in total, and the percentage for rural sample only should be even higher.

[16] According to PBoC by 2018.

reflected in our survey data: for rural residents, the medium frequency of visiting a bank is once a year and the average distance to a nearest banking outlet is 3 to 10 km.

Mobile payment could be an alternative solution. According to 2017 Global Findex, 64% of rural residents made or received digital payments in the previous year and 45% of rural bank account owners used mobile or internet to access accounts. First, 97% of Chinese respondents reported that their household has at least one smart phones, which is the highest among other countries, but only 52% claimed to have Wi-Fi coverage at home, according to the 2014 Gallup World Poll[17]. This implies that the widespread adoption of smart phones could overcome the obstacle of installing Wi-Fi in remote areas and allow consumers to connect with internet and use mobile payment easily. Second, the high ownership of bank account also enables rural residents to connect the account to Wechat Pay or AliPay in order to make payments or transfers via it.

The demand for credit or insurance is incredibly low in China. According to 2017 Global Findex[18], Chinese consumers' demand for borrowing, especially bank loans, is among the lowest, with only 8% of rural respondents claimed that they once borrowed from a regulated financial institution. The low demand for insurance is partly due to the fact that about 91% of rural residents are covered by social medical insurance system, according to the 2015 China Household Finance Survey. Therefore, this chapter emphasizes the function of payment and money transfer when discussing the financial inclusion.

The rural residents' lack of interests in applying for loans is also found in our data. In the survey, one question asked about loan application experience

[17] https://www.gallup.com/analytics/258293/world-bank-global-findex.aspx

[18] https://globalfindex.worldbank.org/

and about half of respondents did not answer it. Among the effective answers, 70.8% never considered applying for loans and 10.5% considered but never applied. Within 432 households which once applied for loans, 84.7% have successfully secured the loans, from either commercial banks and credit unions, or microfinance organizations. Surprisingly, no matter whether applied for loans or not, households share similar characteristics, except that those with loan application experience have slightly higher adoption rate for mobile payment. Similarly, no matter whether successfully secured a loan or not, household characteristics are not distinctly different, except for successful loan applicants having higher income, more mobile phones, and higher acceptance rate for mobile payment.

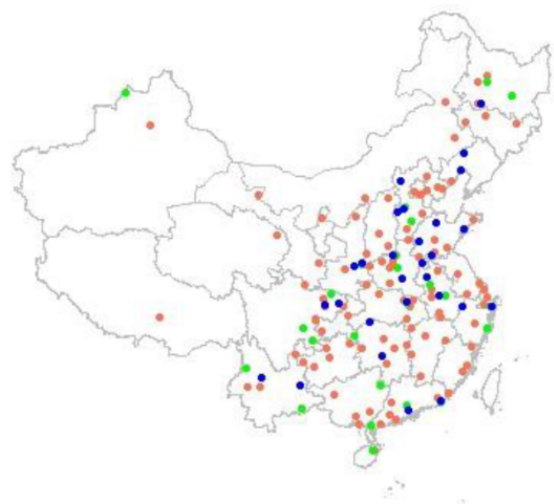
3.3 Data and Methodology

3.3.1 Data Sources

The "Qian Ren Bai Cun" survey has been conducted annually since 2012. In each summer, about 1000 students and faculties from Renmin University of China visited the sampled villages and collected information concerning agricultural production, land resources, education development, medical services, social organization, and household income and financing.

The survey sampling process is well designed to ensure that surveyed households are representative. First, counties were selected based on probability proportional to size (PPS) sampling method which uses demographic and economic information to cluster. Second, villages were randomly selected from the selected counties. Lastly, 3 or 4 students formed a group and selected certain households in a village by applying distance sampling or spot mapping.

Figure 3.1: The Surveyed Villages



Note: The 100 red dots are villages which were selected and actually surveyed; the 41 green dots represent villages which were selected but not surveyed; the 28 blue dots refer to villages which were not selected but actually surveyed.

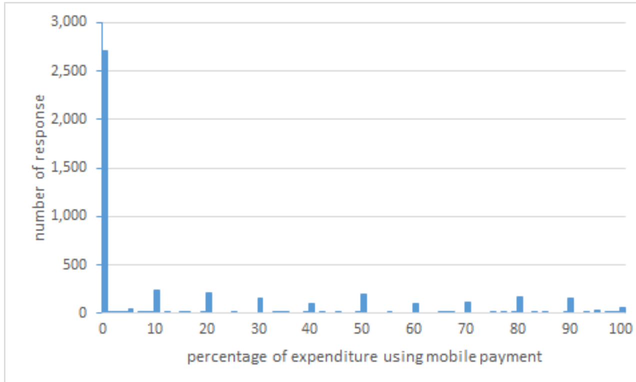
The survey we use is the one conducted in summer 2019,[19] which covered 128 villages in 31 provinces, showed in Figure 3.1. Although this survey was not originally designed for studying mobile payment, the questions covered various aspects of rural life and thus we can extract useful information to answer our research questions.

The aggregated data at the level of prefecture-level city[20] is from two sources. The set of FinTech Indices is published by the Institute of Digital Finance, Peking University. The GDP, percentage of GDP from different industries, outstanding balance of deposits and loans are provided by CSMAR database.

[19]We cannot construct panel data by adding more surveys from previous years, due to the changes in survey questions and the concern about the rapid growth in adoption of mobile payment in rural China.

[20]A prefectural-level municipality is an administrative division in China which ranks below a province and above a county in the administrative structure.

Figure 3.2: The Histogram of Percentage of Expenditure Using Mobile Payment



Note: this figure plots the number of each response to the question about what percentage of expenditure was paid by mobile payment recently. About 60% of responses in our sample are zeros.

Although, on average, residents in rural China use mobile payment for about 20% of their spending, about 60% of respondents did not use mobile payment at all,[21] as shown in Figure 3.2. The distribution of acceptance of mobile payment is similar in the east, middle, and west regions of China, the percentage of zeros in responses is 58%, 65%, and 61%, respectively. Therefore, this chapter uses a hurdle model to accommodate these zeros.

3.3.2 Hurdle Model

For data with a large portion of values at zero, so called "zero-inflated", common solutions are the Tobit model and its variation – the hurdle model (Cragg, 1971; Duan et al., 1983) which is a two-part model with one process for binary responses and another for positive responses. In the first part, all positive responses are fixed

[21]This percentage is similar to the survey results of World Bank. According to 2017 Global Findex, about 44% of rural respondents in China used online shopping and online bill payment services in the previous year.

at 1 and we use a Probit regression to study what factors influence a household's decision on whether to adopt mobile payment. The second part focuses on only positive responses, that is, "hurdle" being crossed, and studies what factors promote a household's usage of mobile payment. Although a typical distribution used in the second part is Poisson or Negative Binomial, we choose a truncated normal model[22] since the positive part is not over-dispersed. For comparison, a zero-inflated model is discussed in the robustness check session.

The hurdle model is

$$P(Y_{v,i} = y_{v,i}|x_{v,i}, z_{v,i}, \beta, \gamma) = \begin{cases} f_{zero}(0; z_{v,i}; \gamma), & if y_{v,i} = 0 \\ (1 - f_{zero}(0; z_{v,i}; \gamma)) \frac{f_{positive}(y_{v,i}; x_{v,i}; \delta)}{1 - f_{positive}(0; x_{v,i}; \delta)}, & if y_{v,i} > 0 \end{cases} \tag{3.1}$$

Where $y_{v,i}$ is the percentage of expenditure paid by mobile payment for household i at village v, $z_{v,i}$ is a vector of corresponding characteristics in the zero part, $x_{v,i}$ is a vector of corresponding characteristics in the hurdle part, γ is a vector of coefficients for z, and δ is a vector of coefficients for x. f_{zero} is a probability density function of a probit model and $f_{positive}$ is a probability density function of a OLS model. Note that, although hurdle models usually allow the two parts to have different variables (i.e., $x_{v,i}$ and $z_{v,i}$), we use the same set of variables, considering economic senses and the data limitation.

3.3.3 Instrumental Variables

The baseline specification for Probit and OLS regression is:

[22] The results from the lognormal model are very similar.

$$MobilePayment_{v,i} = \mu_v + \alpha X_{v,i} + \beta_f Frequency_{v,i} + \epsilon_{v,i} \tag{3.2}$$

Where the key variable $frequency_{v,i}$ is the frequency of household i in village v for visiting a bank branch or ATM, μ_v is the village fixed effect, $X_{v,i}$ is a set of household characteristics, including the education level and age of the head of family, total number of mobile phones, and household income. In the binary Probit model, the dependent variable is the inverse normal function of the probability for a household adopting mobile payment, while in the OLS model, the dependent variable is the percentage of expenditure paid by mobile payment. All the standard deviations are clustered at the village level.

One possible endogeneity problem for this specification is reverse causality, that is, how often a household visits banks could also be affected by how much this household uses mobile payment. For example, if one gets used to use smart phone to pay utility bills or make transactions, then he/she does not need to go withdrawing cash from ATM very often.

To generate sufficient exogenous variation in households' frequency of visiting banks, we use two instruments: one is the distance to the nearest bank branch or ATM, and the other is the average frequency of visiting banks in each village (except for household i). The distance to banks is irrelevant to mobile payment, but it affects how often people visiting banks. A village's average frequency of visiting banks can only contribute to one's acceptance of mobile payment through affecting one's habit of visiting banks. Therefore, we supplement the previous regression with the following first-stage regression:

$$Frequency_{v,i} = \upsilon_v + \pi X_{v,i} + \beta_d Distance_{v,i} + \beta_a Average_{v,i} + \omega_{v,i} \tag{3.3}$$

Where $Distance_{v,i}$ is the distance to a nearest banking outlet from household i in village v, and $Average_{v,i}$ is the average frequency of visiting banks in village v except for household i.

3.3.4 Summary of Statistics

The summary of statistics is listed in Table 3.1: full sample in panel A and the comparison between users and non-users in panel B. Except for the percentage of usage of mobile payment, total and per person number of mobile phones, and number of family member, all other variables are ordinal.

Out of total 4414 effective responses, 2705 households (about 61%) reported not using mobile payment. Compared with mobile payment users, these non-users, on average, are older and less educated, have one fewer smart phones, and earn about CNY 20,000 less. However, their financial access, proxied by the distance from home to a nearest bank and the frequency of visiting banks, is not obviously worsen than that of mobile payment users. Moreover, their perception of levels of accepting non-cash payment in the neighborhood is also not obviously lower than that of users.

Due to the possibility that the relationship between age and the acceptance of mobile payment might not be linear, we transform the age data into ordinal. The average age of the survey respondents is about 55, which reflects the widely discussed phenomenon that the majority of young people in rural regions have been working in urban regions. This fact could explain the abundant zeros in the response for the usage of mobile payment as old people are left home in rural areas (and respond to the survey) and they are naturally slow to adopt new technologies.

Table 3.1: Summary of Statistics

Panel A: Full Sample

Variable	Obs	Mean	Median	Std. Dev.	Min.	Max.	Survey Info
Percentage of Expenditure Paid by Mobile Payment	4,414	18.6	0	29.9	0	100	
Distance to Banks	4,414	1.8	2	0.9	1	5	1. 0-3km; 2. 3-10km; 3. 10-20km; 4. 20-30km; 5. More than 30km
Frequency of Visiting Banks*	4,414	2.6	2	1.6	1	5	1. almost never; 2. Once a year; 3. Twice a year; 4. Once a quarter; 5. Once a month
Total Number of Mobile	4,414	2.5	2	1.7	0	13	
Number of Mobile per person	4,414	0.8	0.7	0.7	0	9	
Number of Family Member	4,414	3.5	3	1.8	1	22	
Education	4,414	2.7	3	1.1	1	7	1. Illiterate; 2. Primary school; 3. Middle school; 4. High school; 5. Professional high school; 6. Three-year college; 7. Four-year college; 8. Graduate school
Age	4,414	3.3	3	0.7	1	5	1. under 20; 2. 20-40; 3. 40-60; 4. 60-80; 5. More than 80
Perception of Non-cash Payment in neighborhood*	4,159	2.8	3	0.8	1	4	1. totally not accepted; 2. Generally not accepted; 3. Generally accepted; 4. Totally accepted
Family Income	4,086	5.6	5	3.4	1	13	1. 0-5,000; 2. 5,000-10,000; 3. 10,000-20,000; 4. 20,000-30,000; 5. 30,000-40,000; 6.40,000-50,000; 7. 50,000-60,000; 8. 60,000-70,000; 9. 70,000-80,000; 10. 80,000-90,000; 11. 90,000-100,000; 12. 100,000-150,000; 13. More than 150,000

Panel B: Mobile Payment Users vs Non-users

	Mobile Payment Users						Mobile Payment Non-users					
Variable	Obs	Mean	Median	Std. Dev.	Min.	Max.	Obs	Mean	Median	Std. Dev.	Min.	Max.
Percentage of Expenditure Paid by Mobile Payment	1,709	47.9	50	30.0	1	100	2,705	0	0	0	0	0
Distance to Banks	1,709	1.7	2	0.9	1	5	2,705	1.9	2	0.9	1	5
Frequency of Visiting Banks*	1,709	3.0	2	1.6	1	5	2,705	2.4	2	1.5	1	5
Total Number of Mobile	1,709	3.1	3	1.3	1*	10	2,705	2.0	2	1.7	0	13
Number of Mobile per person	1,709	1.0	0.8	0.6	0.2	6	2,705	0.7	0.5	0.8	0	9
Number of Family Member	1,709	3.9	4	1.8	1	13	2,705	3.2	3	1.8	1	22
Education	1,709	3.2	3	1.2	1	7	2,705	2.4	2	0.9	1	7
Age	1,709	2.9	3	0.6	1	5	2,705	3.5	4	0.6	2	5
Perception of Non-cash Payment in neighborhood*	1,702	3.2	3	0.6	1	4	2,457	2.5	3	0.8	1	4
Family Income	1,608	7.0	6	3.4	1	13	2,4787 4.7	4	3.0	1	13	

*: the original direction of ordering in the frequency of visiting banks is reversed. We deleted 11 households who reported 0 smart phones but at the same time using mobile payment, probably due to misunderstanding the survey question.

3.4 Results

3.4.1 What Affects the Acceptance of Mobile Payment?

In Table 3.1, panel (a) presents results of the Probit model in the adoption part and shows how household characteristics affect a household's decision on whether to adopt mobile payment, while panel (b) presents results of the OLS model in the usage part and shows how household characteristics affect how much a household pay their spending via mobile payment.

A household is more likely to adopt mobile payment and use more, if the head of the household is better educated (column 1) or younger (column 2), or if the family income is higher (column 3), or if the family has more smart phones (column 4). The results are also robust in a multivariate setting (column7).

As discussed in many studies, the increasing ownership of smart phones in developing countries has provided poor households opportunities to access online financial services. Our finding also supports this idea that more smart phones a household has, more likely they adopt mobile payment and use more. This conclusion still holds after we divide the total number of phone into the number of phone per person (column 5) and the number of family members (column 6). The number of smart phone per person is a proxy for how much one person is exposed to online information and financing opportunities, while the number of family member represents an effect of learning within a household. The results are also robust in a multivariate setting (column8).

In Table 3.2, we complement the previous analysis with information about households' income source: agriculture, working in urban areas, manufacture,

Table 3.1: Household Characteristics

This table reports the estimated coefficients on household characteristics at the household level. In the adoption part, the specification is a Probit model and the dependent variable is an indicator which equals 1 if adopting mobile payment and 0 otherwise. In the usage part, the specification is a OLS model and the dependent variable is the percentage of expenditure in the previous month paid by mobile payment and it only includes positive numbers. The household characteristics include education level, age group, family income, total number of smart phones, number of smart phone per person, and number of family members. We control for village fixed effect and all standard deviations are clustered at the village level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

ADOPTION PART: PROBIT MODEL

	Dependent variable: whether accepting mobile payment							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Education	0.480***						0.294***	0.296***
	(17.07)						(8.606)	(8.693)
Age		-1.135***					-0.957***	-0.960***
		(-21.08)					(-16.34)	(-16.43)
Family Income			0.127***				0.0607***	0.0700***
			(12.80)				(5.909)	(6.857)
Total Mobile				0.259***			0.184***	
				(9.100)			(6.459)	
Mobile Per Ps					0.269***			0.287***
					(5.090)			(4.311)
Population						0.0986***		0.0936***
						(5.867)		(4.428)
Constant	-2.556***	2.745***	-1.902***	-1.724***	-1.501***	-1.582***	0.677***	0.528**
	(-33.68)	(14.56)	(-38.37)	(-37.09)	(-44.34)	(-36.30)	(2.919)	(2.112)
Village FE?	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	4,414	4,414	4,086	4,414	4,414	4,414	4,086	4,086

USAGE PART: OLS MODEL

	Dependent variable: percentage of expenditure paid by mobile							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Education	4.172***						2.434***	2.391***
	(6.920)						(3.461)	(3.397)
Age		-10.26***					-9.102***	-9.359***
		(-6.952)					(-5.822)	(-5.924)
Family Income			1.294***				0.705**	0.804***
			(4.441)				(2.397)	(2.785)
Total Mobile				2.864***			2.627***	
				(4.482)			(4.216)	
Mobile Per Ps					2.380*			6.448***
					(1.857)			(4.064)
Population						0.665		1.354**
						(1.463)		(2.517)
Constant	23.69***	68.04***	32.40***	30.09***	34.97***	35.26***	47.43***	44.30***
	(12.09)	(15.36)	(29.64)	(18.83)	(28.47)	(25.88)	(7.908)	(7.147)
Village FE?	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	1,709	1,709	1,608	1,709	1,709	1,709	1,608	1,608
R-Squared	0.282	0.294	0.281	0.271	0.261	0.260	0.330	0.329

construction, transportation, hotels and restaurants, real estate, finance, and others. Note that most families have more than one income source and majority of them rely on income from agricultural products and salary earned by family members working in urban areas. For people working in agriculture sector, they tend to not use mobile payment or use less than people in other sectors (row 1). This effect is highly significant even after controlling for household characteristics.

Generally, we would hypothesize that families with members working in cities or towns could be more likely to adopt mobile payment because the penetration rate of mobile payment is extremely high in urban areas and those who have learnt how to use it would like to teach their family members in rural areas, which is called the learning effect. However, our results in the adoption part (row 1) do not support this hypothesis. Although people working in manufacture, construction, transportation, hotels and restaurants, or urban areas seem to be more likely to accept mobile payment than those working in agriculture, real estate, and others (column 1), the effects are eliminated by controlling for household characteristics (column 3), which is mainly driven by the income level[23] (column 2). Working in those professions, people earn higher level of income than agricultural households, which increases their probability for adopting mobile payment.

In the usage part, professions also do not affect how much people using mobile payment, except for agriculture and finance sector. In an unreported Blinder-Oaxaca decomposition analysis, we find that the differences in household characteristics can explain about 40% of farmers' lower adoption rate for mobile payment, which is mainly driven by lower income and education level. But for the lower usage by farmers, the household characteristics can only explain 23% which

[23]We also try to add interaction terms of professions and household characteristics, but they are not statistically significant.

Table 3.2: Professions

This table reports the estimated coefficients on income sources at the household level. In the adoption part, the specification is a Probit model and the dependent variable is an indicator which equals 1 if adopting mobile payment and 0 otherwise. In the usage part, the specification is a OLS model and the dependent variable is the percentage of expenditure in the previous month paid by mobile payment and it only includes positive numbers. The percentage column shows the percentage of households having income from each industry. Note that most households have more than one income sources. We control for the household characteristics, including education level, age group, family income, and total number of smart phones. We also control for village fixed effect and all standard deviations are clustered at the village level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	ADOPTION PART: PROBIT MODEL Dependent variable: whether accepting mobile payment				USAGE PART: OLS MODEL percentage of expenditure paid by mobile		
	%	**(1)**	**(2)**	**(3)**	**%**	**(4)**	**(5)**
(1) Agriculture	63.75	-0.336***	-0.347***	-0.329***	55.00	-7.546***	-5.980***
		(-4.514)	(-4.417)	(-4.086)		(-3.671)	(-2.888)
(2) Work in urban	47.51	0.252***	0.122	0.0557	52.25	-0.853	-2.284
		(3.489)	(1.625)	(0.745)		(-0.446)	(-1.247)
(3) Finance	0.27	1.194***	0.955**	1.074**	0.59	-12.13**	-15.36***
		(2.674)	(2.439)	(2.091)		(-2.569)	(-3.785)
(4) Manufacture	2.24	0.379**	0.159	0.032	3.63	7.491*	5.073
		(2.130)	(0.812)	(0.154)		(1.777)	(1.104)
(5) Construction	2.29	0.375**	0.241	0.07	3.16	4.242	2.639
		(2.276)	(1.312)	(0.352)		(0.948)	(0.596)
(6) Transportation	2.06	0.583***	0.353	0.217	2.75	4.405	-1.170
		(2.897)	(1.572)	(0.967)		(0.891)	(-0.234)
(7) Hotels and restaurants	1.70	0.427**	0.218	0.151	2.87	0.502	-1.707
		(2.144)	(1.009)	(0.698)		(0.113)	(-0.402)
(8) Real estate	0.50	-0.051	-0.148	-0.416	0.53	9.388	1.778
		(-0.132)	(-0.474)	(-1.332)		(0.909)	(0.173)
(9) Others	17.54	-0.039	-0.075	-0.006	17.91	0.599	-1.428
		(-0.406)	(-0.732)	(-0.0530)		(0.292)	(-0.755)
(10) Education				0.294***			2.410***
				(8.567)			(3.289)
(11) Age				-0.953***			-8.596***
				(-16.23)			(-5.434)
(12) Family income			0.115***	0.0532***			0.662**
			(11.43)	(5.009)			(2.245)
(13) Total mobile				0.180***			2.704***
				(6.363)			(4.285)
Constant		-1.394***	-1.768***	0.800***		37.36***	49.18***
		(-17.88)	(-20.25)	(3.200)		(11.87)	(7.189)
Village FE?	YES	YES	YES	YES	YES	YES	YES
Obs.		4,414	4,086	4,086		1,709	1,608
R-squared						0.274	0.339

is solely driven by lower education level. Some latent factors related to agricultural households prevent them from adopting or using more of mobile payment, which requires further research in future.

The finance sector is a special case with only 12 households in the sample and 10 of them using mobile payment. Note that having income from finance sector does not necessarily mean working in a local bank or credit union. Actually only three of them have a college degree. Nevertheless, they are more likely to adopt mobile payment, probably because the exposure to financial products or services has increased their financial literacy and therefore they are more open to new financial technologies. Interestingly, this same group of people, after adopting the technology, are also less likely to use mobile payment than others. One hypothesis is that it is more convenient for them to use bank services and as a result they do not have incentives to use mobile payment to substitute those services. To confirm this hypothesis, we need to check the IV estimate of frequency of visiting banks, a proxy for the access to bank services.

3.4.2 Mobile Payment vs. Financial Literacy and Bank Services

A key hypothesis of this chapter is that the adoption of mobile payment is affected by the access to bank services proxied by the frequency of visiting banks. However, the possibility of reverse causality cannot be ruled out, for example, if one family gets used to using AliPay to pay utility bills then they do not need to visit a bank to pay bills.[24] To deal with this endogeneity issue, we use two instrumental variables: the distance to the nearest bank branch or ATM and the average

[24]Before adopting AliPay, a common way to pay utility bills is to visit a bank and pay through a bank service.

frequency of visiting banks in each village. A household may visit banks less frequently because of the long-distance to the nearest bank or some social norms in the village. Table 3.3 presents Probit/OLS and IV estimates for frequency to banks in adoption and usage parts. The two IVs perform very well as shown in various tests that IVs are exogenous, relevant, and valid.

Table 3.3: Probit, OLS, and 2SLS Estimates for Frequency to Banks

This table reports both estimated coefficients for probit/OLS and 2SLS on financial access which is proxied by the frequency of visiting banks. Two IVs are the distance from home to the nearest banking outlets and the village-level average frequency of visiting banks except for household i. In the adoption part, the specification is a probit model and the dependent variable is an indicator which equals 1 if adopting mobile payment and 0 otherwise. In the usage part, the specification is a OLS model and the dependent variable is the percentage of recent expenditure paid by mobile payment and it only includes positive numbers. We control for the household characteristics, including education level, age group, family income, total number of smart phones, number of smart phone per person, and number of family members. We also control for village fixed effect and all standard deviations are clustered at the village level. Asterisks denote significance levels (***=1%, **=5%, *=10%). The null hypothesis of Wald test for exogeneity is that IV is exogeneous. The null hypothesis of weak instrument test is that IV is irrelevant and coefficients of the endogenous regressors are jointly equal to zero. The null hypothesis of uner/weak identification test is that the endogenous regressor is unidentified. The null hypothesis of overidentifying test is that IVs are valid. The null hypothesis of DWH test is that IV and OLS/probit estimates are "close enough". The p-values are shown in the parentheses.

	ADOPTION PART: PROBIT MODEL Whether accepting mobile payment		USAGE PART: OLS MODEL Percentage of expenditure paid by mobile	
	(1) Probit	**(2) 2SLS**	**(3) OLS**	**(4) 2SLS**
Frequency to Banks	0.110***	0.113***	-1.910***	-1.873***
	(5.045)	(6.095)	(-3.473)	(-3.548)
Total Mobile	0.182***	0.182***	2.691***	2.689***
	(6.552)	(9.637)	(4.407)	(4.613)
Education	0.270***	0.269***	2.675***	2.670***
	(7.614)	(9.438)	(3.891)	(4.065)
Age	-0.963***	-0.963***	-9.063***	-9.064***
	(-16.12)	(-20.10)	(-5.844)	(-6.123)
Family Income	0.0547***	0.0545***	0.812***	0.810***
	(5.306)	(6.001)	(2.781)	(2.904)
Constant	0.489**	0.501	54.09***	53.97***
	(2.053)	(1.251)	(8.408)	(8.769)
Village Fe	YES	YES	YES	YES
Observations	4,086	4,086	1,608	1,608
Pseudo R-squared	0.391	0.391	0.337	0.337
Exogeneity	Wald test	0.94(0.33)		
Weak Instrument	Wald test	37.15(0.00)	Anderson-Rubin Wald test	19.03 (0.00)
Under/Weak Identification			Cragg-Donald	21760.94
Overidentifying	Amemiya-Lee-Newey	2.428(0.12)		
Consistency	Durbin-Wu-Hausman	297.95(0.00)	Durbin-Wu-Hausman	12.86 (0.00)

We find that the more often a household visit banks, the more likely they would adopt mobile payment (column 2). Interestingly, after adopting mobile payment, the less often they visit banks, the more they would use mobile payment (column 4). First, when deciding whether to accept mobile payment, visiting banks is a promoting factor. One explanation is that when visiting banks, consumers get exposed to financial services and products. Higher frequency of visiting banks leads to better financial literacy and more open to new financial technologies. Second, after adopting mobile payment, there is a supplement effect between bank services and mobile payment. The amount of usage seems to be determined by the level of convenience. When it is not convenient to visit a bank, due to either long distance or social norms, consumers turn to use smart phone to buy groceries, transfer money, or pay bills. Oppositely, for people having income from finance sector, as discussed in the previous session, they have to visit banks more frequently and therefore have more access to financial services, resulting in a less active usage of mobile payment.

3.4.3 Perception of Adoption of Mobile Payment in the Neighborhood

An interesting question in the survey is about the perception of acceptance of non-cash payment[25] in the neighborhood which asks respondent to rate whether his/her village "totally accepts", or "generally accepts", or "generally not accepts", or "totally not accepts" non-cash payment. Using this variable, we can construct a dummy variable to distinguish "sensitive" and "insensitive" groups. "Sensitive" individual is defined as those rated the overall acceptance higher than the actual level. For example, if a respondent rated the neighborhood "totally accepting" non-cash payment but actually his/her village only "generally accepts",

[25]Including mobile payment and payment via credit or debit card.

then this respondent is classified as “sensitive”. Similarly, “insensitive” individual is defined as those rated the overall acceptance lower than the actual level. Since there is no village 100% accept or reject non-cash payment, we define a village as generally accepting if more than 50% of respondents accepting non-cash payment, and define a village as generally not accepting if below 50%. The following results hold for grouping under different cutoff points.

Table 3.4 shows 462 “insensitive” and 2302 “sensitive” respondents and their group mean for the key variables. We calculate the differences and conduct t-test to compare them. The “sensitive” respondents who have more optimistic perception regarding the non-cash payment activities in the neighborhood are using mobile phones to pay larger portion of their expenditures, and they are younger, better educated, having higher income and more smart phones, and visit banks more often. These results support the idea in related studies in consumer behavior that the awareness of consumers matters in the acceptance of mobile payment. Our results further present the factors behind the perceptions or intentions by showing the correlation between them.

However, the distance from home to the nearest banks is not different in two groups, which implies that the physical location of financial institutions is less important than the frequency of visiting them, or the actual financial access, in affecting people’s perception about FinTech or financial literacy. It is worth arguing that the number of banking outlets in certain community might not be a proper proxy for financial availability which is commonly used in literature in finance.

Using a Blinder-Oaxaca decomposition which are not reported here, we analyze to what extent the household characteristics can explain the gap of adoption and usage of mobile payment by the two groups. The differences in all of the

Table 3.4: “Sensitive” vs “Insensitive” respondents

This table shows the comparison between “sensitive” and “insensitive” households. The definition of “sensitive” is that a respondent’s perception of non-cash payment acceptance is higher than the actual level, otherwise “insensitive”. Compared variables are the average percentage of expenditure paid by mobile payment, the average frequency of visiting banks, the average distance to banks, the average number of mobile phones in household, the average level of education, the average age group, and the average family income level. The difference between the two group averages is calculated and t-test is conducted to test the null hypothesis of zero differences. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Group	Obs	Usage of Mobile Payment	Frequency to banks	Distance to banks	No. of Mobile	Education	Age	Family Income
Insensitive	462	3.71	2.43	1.84	1.56	2.41	3.56	4.61
Sensitive	2302	22.87	2.67	1.75	2.66	2.73	3.21	5.87
Difference		-19.16***	-0.24***	0.08*	-1.10***	-0.32***	0.36***	-1.27***
T-test		t=-12.45	t=-2.98	t=1.95	t=13.54	t=-5.76	t=10.57	t=-7.15

* Except for usage of mobile payment and the number of mobile phones, all values are ordinal, not numeric.

listed household characteristics can explain about 60% of higher adoption rate of mobile payment by "sensitive" consumers. As to their higher usage of mobile payment than "insensitive" consumers, only 25% can be explained by household characteristics, mainly by the younger age of the "sensitive" group.

3.4.4 Impacts at Aggregate Level

What are the relationships between the acceptance of mobile payment with macro-finance and FinTech development? Based on the fact that mobile payment is the infrastructure for other FinTech products, we assume that a higher level of adoption of mobile payment should promote the overall FinTech development and the financial industry, eventually contributing to macroeconomic growth. Our results show the positive correlations between them, though it is not a causal relationship.

We aggregate the adoption rate for mobile payment to the level of prefecture-level city, an administrative division in China ranking below a province and above a county, and then rank those cities based on the adoption rate. After grouping the top and bottom 30%[26] of prefecture-level cities (with each group of 34 cities), in Table 3.5, we compare their GDP, share of industries, and financial conditions (panel A), as well as their financial digitalization levels (panel B), by conducting both two sample t-test and Wilcoxon test.

Panel A shows that cities with higher adoption rate of mobile payment enjoy higher level of GDP and higher outstanding balance of loans, deposits, and residents' savings. Cities with lower adoption of mobile payment generally have higher ratio of agricultural production and lower ratio of manufactural production,

[26] We also use other cutoff points and find similar results.

Table 3.5: Comparison between Top and Bottom Cities of Adoption Rate for Mobile Payment

This table shows the comparison of prefecture-level city with top and bottom mobile payment adoption rate. We rank cities by their average mobile payment adoption rate and get the top 30% labeling “high adoption” and get bottom 30% labelling “low adoption”. We compare the group average for macro-finance factors in panel A and FinTech indices in panel B. Macro-finance factors include GDP level, percentage of agriculture, manufacture, and service industry, and the balance of loans, deposits, and savings in financial institutions. FinTech indices are for the overall service, AliPay, mobile insurance, mobile investment, small consumer and micro-finance loans, credit rating, and money market fund. The difference between the group average is calculated and both t-test and Wilcoxon test are conducted to test the null hypothesis of no difference between two groups. Asterisks denote significance levels (***=1%, **=5%, *=10%).

PANEL A: Macro-Finance

Group	Obs	GDP	% Agriculture	% Manufacture	%Service	Loans	Despoits	Savings
Low Adoption	34	1676.45	15.11	40.89	43.92	2136.43	3096.43	1571.25
High Adoption	34	3516.36	11.26	45.09	43.66	4813.54	6350.19	2755.85
Difference		-1839.91***	3.94**	-4.20**	0.26	-2677.11**	-3253.75*	-1184.59**
T-Test		t=-2.71	t=2.14	t=-2.12	t=0.13	t=-2.08	t=-1.95	t=-2.38
Wilcoxon		z=-3.19	z=1.89	z=-1.83	z=-0.26	z=-3.08	z=-2.29	z=-2.08

PANEL B: FinTech Products

Group	Obs	Index	Payment	Insurance	Investment	Loans	Credit Rating	Money Market Fund
Low Adoption	34	217.40	224.78	426.65	207.77	163.26	297.54	242.37
High Adoption	34	228.13	256.47	452.79	214.33	170.01	318.55	266.35
Difference		-10.74**	-31.70***	-26.15***	-6.57	-6.75***	-21.01**	-23.98***
T-Test		t=-2.46	t=-3.63	t=-2.70	t=-1.23	t=-3.15	t=-2.13	t=-3.22
Wilcoxon		z=-2.35	z=-3.01	z=-2.15	z=-1.01	z=-2.30	z=-2.48	z=-2.58

* The unit of GDP, Loans, Deposits, and savings is 100 million CNY.

which partially supports our previous finding that people working in agricultural sector are less likely to adopt and use mobile payment.

Panel B shows that cities with higher adoption of mobile payment generally enjoy higher level of FinTech development which is proxied by indices focusing on different types of FinTech services. Particularly, people in cities with higher adoption of mobile payment are using more FinTech services in insurance, consumer and micro-finance loans, credit rating, and money market fund. The overall index is less statistically significant as the investment via FinTech platform is not different in top and bottom cities.

3.4.5 Robustness Check

Considering the case when people did not report their usage of mobile payment accurately, we put their reposes in five intervals and the estimated results are similar with the ones we report.

Due to the dramatic demographic and economic difference between East, Middle, and West part[27] of China, we run regressions separately to explore the regional heterogeneity. Generally, East China enjoys more advanced economic development and higher level of financial digitalization, and accommodates both headquarters of Alibaba and Tencent. Yet, the basic results are almost the same as those in the aggregated model, except for some insignificant coefficients which might be due to smaller sample size and reduced variance.

[27] Our classification follows that of National Bureau of Statistics of China. East part includes Hebei, Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan, Shanghai, Beijing, and Tianjin. Middle part includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. West part includes Inner Mongolia, Guangxi, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, and Chongqing.

We also fit a zero-inflated ordered probit (ZIOP) model[28] for the robustness check. ZIOP model considers that zero responses come from two processes which in this chapter refers to people who have never used mobile payment and will never use and the ex-users. The zero inflation arises due to the former type of people and ZIOP model could provide insights about which factors contribute to the zero inflation. In unreported results, we find that no variable is significant in affecting zero inflation, except for age. On average, older people are about 11% less likely to be never-users of mobile payment than young people. Therefore, hurdle model is more suitable for this study.

Considering the possible correlation between consumers' decisions about whether to adopt mobile payment and how much to use, we utilize the exponential type II Tobit model, one version of Heckman selection model, or Heckit model. Although it is commonly used for missing data or data selection problem,[29] in this case we use it to obtain a flexible corner solution. However, the results show that such correlation is not statistically significantly different from zero after controlled for the covariates. Furthermore, some econometrics studies (for example, Manning, Duan, and W. H. Rogers, 1987), found that hurdle models could perform better than selection models in the absence of exclusion restrictions.

Some would concern about those households without any smart phone who are immediately excluded from adopting mobile payment, because the usage of mobile payment relies on owning a smart phone. Therefore, we exclude these household from our sample and compare the characteristics of these two groups.

[28]For detailed explanations and the comparison between the hurdle model and the zero-inflated model, see Hofstetter et al. (2016).

[29]Because the zeros in the responses are actual values, not censored or missing, our data does not suffer from sample selection. In a sample selection case, the outcome of the selection variable (whether to adopt mobile payment), does not restrict the outcome of response (how much expenditure paid by mobile payment), which does not hold in our data because not adopting mobile payment would rule out any usage of it.

Then we run the key regressions again, and find little change in our major results.

3.5 Concluding Remarks

Mobile payment is growing rapidly in both advanced and developing economies, but few empirical studies have been done in this field, especially from economic perspectives, partly due to data limitation. Using a large-scale survey data in China, this chapter investigates the acceptance of mobile payment and the relationship between mobile payment and financial inclusion. Our results provide important implications for policy makers, FinTech companies, and banks.

First, mobile payment plays an important role in promoting financial inclusion in rural China. Although Chinese rural residents enjoy a high rate of bank account ownership, their needs for financial payment and transfer are underserved. We find that mobile payment supplements some bank services. For mobile payment users, when they are not able to visit banks frequently due to long distance or social reasons, they use mobile payment to pay a larger portion of their expenditure. While most FinTech studies focus on FinTech loans, this chapter investigates mobile payment which is the fundamental of other FinTech products and concentrates on the basis of financial inclusion – payment and transfer. We also find that more often consumers visit banks, more likely they will adopt mobile payment, which contributes to the discussion on the relationship between FinTech and traditional banking.

Second, we find that younger, richer, better educated, more digitalized families are more likely to adopt and use more of mobile payment, governments should take care of those who are older, poorer, and less educated, especially the agricultural households, and ensure that they can also enjoy the convenience of FinTech. One way is to increase the ownership of smart phones. Another way is to provide financial education and advertisements to improve rural residents' awareness, because we find that the households which are more sensitive to the acceptance of mobile payment in the neighborhood are more likely to adopt and use mobile payment. This result agrees with those studies on consumer behaviors, but this study provides a broader scope in the topic of acceptance of mobile payment.

Lastly, this chapter shows that the regions with higher adoption of mobile payment also enjoy higher GDP and better development of bank and FinTech services. Since most research on economic development and smart phone-enabled payment technologies focus on low-income countries, especially African countries such as Kenya, this study provides policy implication for the less developed areas in middle-income countries or even advanced economies.

Appendix

3.A Survey Questions

Table 3.A.1: Survey Questions

Variable	Question	Options	Note
Percentage of Expenditure Paid by Mobile Payment	What is the percentage of your expenditure paid by mobile payment in the recent month?	%	
Distance to Banks	What is the distance from your home to the nearest bank branch/ATM?	1. 0-3km; 2. 3-10km; 3. 10-20km; 4. 20-30km; 5. More than 30km	
Frequency of Visiting Banks*	How frequent do you visit a bank/ATM?	1. almost never; 2. Once a year; 3. Twice a year; 4. Once a quarter; 5. Once a month	Reversed the original order in the survey
Total Number of Mobile	How many smart mobile phone in your family?		
Number of Family Member	How many people in your family?		
Education	Highest education level?	1. Illiterate; 2. Primary school; 3. Middle school; 4. High school; 5. Professional high school; 6. Three-year college; 7. Four-year college; 8. Graduate school	
Age	Age?	1. under 20; 2. 20-40; 3. 40-60; 4. 60-80; 5. More than 80	Grouped by authors
Perception of Non-cash Payment in neighborhood*	How much do your neighborhood accept non-cash payment methods?	1. totally not accepted; 2. Generally not accepted; 3. Generally accepted; 4. Totally accepted	Reversed the original order in the survey
Family Income	How much is your total household income in last year?	1. 0-5,000; 2. 5,000-10,000; 3. 10,000-20,000; 4. 20,000-30,000; 5. 30,000-40,000; 6.40,000-50,000; 7. 50,000-60,000; 8. 60,000-70,000; 9. 70,000-80,000; 10. 80,000-90,000; 11. 90,000-100,000; 12. 100,000-150,000; 13. More than 150,000	

Table 3.A.2: Summary of Statistics

Panel A: Whether applied for loans

	Not Considered or Considered But Not Applied						Applied					
Variable	Obs	Mean	Median	Std. Dev.	Min.	Max.	Obs	Mean	Median	Std. Dev.	Min.	Max.
Percentage of Expenditure Paid by Mobile Payment	1,854	14.66	0	26.53	0	100	429	16.86	0	29.03	0	100
Distance to Banks	1,854	1.84	2	0.80	1	5	429	1.82	2	0.82	1	5
Frequency of Visiting Banks*	1,854	2.58	2	1.49	1	5	429	2.54	2	1.56	1	5
Total Number of Mobile	1,854	2.32	2	1.60	0	10	429	2.71	3	1.43	0	8
Number of Mobile per person	1,854	0.77	0.67	0.67	0	6	429	0.83	0.67	0.61	0	5
Number of Family Member	1,854	3.46	3	1.74	1	12	429	3.90	4	1.92	1	12
Education	1,854	2.61	3	1.02	1	7	429	2.57	3	0.97	1	7
Age	1,854	3.30	3	0.63	2	5	429	3.10	3	0.61	2	5
Perception of Non-cash Payment in neighborhood*	1,758	2.75	3	0.82	1	4	405	2.86	3	0.71	1	4
Family Income	1,745	5.28	5	3.12	1	13	405	5.72	5	3.42	1	13

Panel B: Whether successfully secured loans

	Denied						Secured					
Variable	Obs	Mean	Median	Std. Dev.	Min.	Max.	Obs	Mean	Median	Std. Dev.	Min.	Max.
Percentage of Expenditure Paid by Mobile Payment	65	12.78	0	24.56	0	98	364	17.59	0	29.73	0	100
Distance to Banks	65	1.68	2	0.73	1	4	364	1.85	2	0.83	1	5
Frequency of Visiting Banks*	65	2.23	2	1.37	1	5	364	2.59	2	1.58	1	5
Total Number of Mobile	65	2.42	2	1.41	0	6	364	2.76	3	1.43	0	8
Number of Mobile per person	65	0.75	0.67	0.68	0	5	364	0.84	0.67	0.59	0	4
Number of Family Member	65	3.92	4	1.96	1	10	364	3.89	4	1.91	1	12
Education	65	2.65	3	0.74	1	4	364	2.56	3	1.00	1	7
Age	65	3.20	3	0.62	2	4	364	3.08	3	0.60	2	5
Perception of Non-cash Payment in neighborhood*	59	2.85	3	0.85	1	4	346	2.86	3	0.69	1	4
Family Income	62	4.23	4	2.68	1	13	343	5.99	5	3.47	1	13

*Note: the original direction of ordering in the frequency of visiting banks is reversed.

3.B Blinder-Oaxaca Decomposition Analysis

Table 3.B.1: Household Income Sources: Agriculture vs. Non-agriculture

This table reports the results of Blinder-Oaxaca decomposition on two groups of respondents: group 1 refers to households with income sources other than agriculture and group 2 refers to households having income from agricultural sector. In the adoption part, the dependent variable is an indicator which equals 1 if adopting mobile payment and 0 otherwise. In the usage part, the dependent variable is the percentage of expenditure in the previous month paid by mobile payment and it only includes positive numbers. All standard deviations are clustered at the village level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	ADOPTION PART				USAGE PART			
	coefficient	**std.dev.**	**z**	$P > z$	**coefficient**	**std.dev.**	**z**	$P > z$
Overall								
Group 1	0.50***	0.03	19.30	0.00	54.09***	1.79	30.20	0.00
Group 2	0.34***	0.02	19.02	0.00	42.19***	1.91	22.11	0.00
Difference	0.16***	0.03	6.19	0.00	11.89***	2.28	5.21	0.00
Endowments	0.07***	0.02	3.69	0.00	2.73***	0.88	3.11	0.00
Coefficients	0.10***	0.02	5.13	0.00	9.25***	2.18	4.24	0.00
Interaction	-0.01	0.01	-1.12	0.26	-0.08	0.72	-0.11	0.91
Endowments								
Mobile	0.01**	0.01	2.31	0.02	0.52	0.33	1.57	0.12
Education	0.03***	0.01	3.49	0.00	1.15**	0.55	2.11	0.04
Age	0.01	0.01	0.81	0.42	0.58	0.41	1.41	0.16
Income	0.02***	0.01	3.37	0.00	0.47	0.48	1.00	0.32
Coefficients								
Mobile	-0.02	0.03	-0.65	0.52	0.56	3.66	0.15	0.88
Education	-0.06	0.04	-1.52	0.13	-1.25	4.45	-0.28	0.78
Age	-0.21	0.09	-2.35	0.02	-4.17	8.43	-0.49	0.62
Income	0.00	0.03	-0.16	0.87	-0.25	3.29	-0.08	0.94
Interaction								
Mobile	0.00	0.00	-0.63	0.53	0.03	0.19	0.15	0.88
Education	-0.01	0.00	-1.42	0.16	-0.15	0.55	-0.28	0.78
Age	0.00	0.00	0.77	0.44	0.09	0.19	0.47	0.64
Income	0.00	0.01	-0.16	0.87	-0.05	0.60	-0.08	0.94
	Obs: 4097				Obs: 1619			
Group 1: Non-Agricultural	Group 1 Obs: 1481				Group 1 Obs: 741			
Group 2: Agricultural	Group 2 Obs: 2616				Group 2 Obs: 878			

Table 3.B.2: BO Decomposition: "Sensitive" vs. "Insensitive" Households

This table reports the results of Blinder-Oaxaca decomposition on two groups of respondents: group 1 refers to households not sensitive to the acceptance of mobile payment in the neighborhood and group 2 refers to the sensitive households. In the adoption part, the dependent variable is an indicator which equals 1 if adopting mobile payment and 0 otherwise. In the usage part, the dependent variable is the percentage of expenditure in the previous month paid by mobile payment and it only includes positive numbers. All standard deviations are clustered at the village level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	ADOPTION PART				USAGE PART			
	coefficient	**std.dev.**	**z**	$P > z$	**coefficient**	**std.dev.**	**z**	$P > z$
Overall								
Group 1	0.13***	0.02	5.51	0.00	29.61***	4.48	6.61	0.00
Group 2	0.46***	0.02	23.95	0.00	51.25***	1.64	31.21	0.00
Difference	-0.33***	0.03	-11.28	0.00	-21.63***	4.85	-4.46	0.00
Endowments	-0.19***	0.02	-10.30	0.00	-5.50***	1.35	-4.06	0.00
Coefficients	-0.22***	0.04	-5.19	0.00	-16.84***	5.56	-3.03	0.00
Interaction	0.08***	0.02	3.65	0.00	0.71	2.73	0.26	0.79
Endowments								
Mobile	-0.05***	0.01	-4.22	0.00	-1.63**	0.72	-2.26	0.02
Education	-0.03***	0.01	-3.75	0.00	-1.32**	0.59	-2.24	0.03
Age	-0.10***	0.01	-7.20	0.00	-2.20**	0.85	-2.58	0.01
Income	-0.02***	0.01	-3.42	0.00	-0.35	0.43	-0.82	0.41
Coefficients								
Mobile	0.00	0.04	0.06	0.95	1.16	11.71	0.10	0.92
Education	-0.18***	0.06	-3.10	0.00	-1.99	13.21	-0.15	0.88
Age	0.46***	0.11	4.21	0.00	10.16	19.02	0.53	0.59
Income	-0.03	0.04	-0.87	0.38	4.05	8.35	0.48	0.63
Interaction								
Mobile	0.00	0.02	-0.06	0.95	-0.19	1.92	-0.10	0.92
Education	0.02**	0.01	2.50	0.01	0.24	1.60	0.15	0.88
Age	0.05***	0.01	3.74	0.00	0.98	1.86	0.53	0.60
Income	0.01	0.01	0.86	0.39	-0.32	0.75	-0.43	0.67
	Obs: 2557				Obs: 1031			
Group 1: Insensitive	Group 1 Obs: 437				Group 1 Obs: 57			
Group 2: Sensitive	Group 2 Obs: 2120				Group 2 Obs: 974			

3.C Regional Heterogeneity

Due to the dramatic demographic and economic difference between East, Middle, and West part of China, we run regressions separately to explore the regional heterogeneity.

In panel A, the acceptance part is almost the same as that of the aggregated model. The fact that senior people are more reluctant or slower to adopt new financial technology is consistent through regions and highly significant in both parts of models (row 3). There is little regional difference in the acceptance part, except that the number of mobile phones is not very statistically significant in the West (column 6 row 2). Note that the instrument is not valid in the Middle and we cannot reject the null hypothesis of Durbin-Wu-Hausman test that the OLS model and 2SLS model are "close enough". Therefore, we can simply use the estimates from OLS model for the Middle part of China which provides similar results.

Education level is important in all regions for accepting mobile payment, but more education in the Middle and the West is not much related to more usage of mobile payment (row 3). Similarly, more household income is related to more acceptance but not related to more usage in all regions (row 5). The number of smart phone influences both acceptance and usage of mobile payment in the East but the results for the West and the Middle are mixing (row 2). This session raises more questions than answers and further studies need to be done.

Table 3.C.1: Regional Heterogeneity

PANEL A: ADOPTION PART (PROBIT MODEL)
Dependent Variable: Whether Accepting Mobile Payment

	OLS			2SLS		
	(1)EAST	**(2)MIDDLE**	**(3)WEST**	**(1)EAST**	**(2)MIDDLE**	**(3)WEST**
Frequency to Banks	0.105***	0.132***	0.0942**	0.105***	0.134***	0.0995***
	(2.762)	(3.863)	(2.481)	(3.304)	(3.967)	(3.170)
Total Mobile	0.226***	0.209***	0.0817*	0.226***	0.208***	0.0812**
	(4.247)	(5.093)	(1.801)	(6.661)	(6.440)	(2.564)
Education	0.269***	0.239***	0.279***	0.269***	0.237***	0.277***
	(4.355)	(4.402)	(4.128)	(5.601)	(4.898)	(5.371)
Age	-1.061***	-0.877***	-0.868***	-1.061***	-0.875***	-0.867***
	(-9.822)	(-9.175)	(-8.425)	(-12.81)	(-11.02)	(-10.09)
Family Income	0.061***	0.062***	0.048**	0.061***	0.061***	0.048***
	(3.423)	(3.636)	(2.455)	(3.769	(4.111)	(2.954)
Constant	0.698*	0.641*	1.108***	0.697	0.642	1.093***
	(1.662)	(1.699)	(2.888)	(1.396)	(1.538)	(2.689)
Village Fe	YES	YES	YES	YES	YES	YES
Obs.	1,530	1,383	1,184	1,530	1,383	1,184
Pseudo R-squared	0.478	0.340	0.318	0.478	0.340	0.318
Exogeneity		Wald test		0.00(0.962)	0.09(0.768)	0.67(0.414)
Weak Instrument		Wald test		10.19(0.001)	15.74(0.001)	10.05(0.002)
Overidentifying		Amemiya-Lee-Newey		0.126(0.723)	5.947(0.015)	0.15(0.699)
Consistency		Durbin-Wu-Hausman		92.31(0.00)	0.28(0.595)	22.33(0.00)

PANEL B: USAGE PART (OLS MODEL)
Dependent Variable: Percentage Of Expenditure Paid By Mobile

	OLS			2SLS		
	(1)EAST	**(2)MIDDLE**	**(3)WEST**	**(1)EAST**	**(2)MIDDLE**	**(3)WEST**
Frequency to Banks	-1.414	-2.410**	-1.843*	-1.128	-2.479***	-2.006**
	(-1.637)	(-2.444)	(-1.787)	(-1.373)	(-2.666)	(-2.053)
Total Mobile	3.487***	1.687	3.098***	3.501***	1.694	3.112***
	(4.072)	(1.418)	(2.799)	(4.347)	(1.521)	(2.999)
Education	2.648**	3.317**	1.891	2.641***	3.333**	1.923
	(2.684)	(2.374)	(1.424)	(2.811)	(2.537)	(1.539)
Age	-10.35***	-7.358***	-9.826***	-10.37***	-7.357***	-9.843***
	(-4.089)	(-2.856)	(-3.395)	(-4.315)	(-3.042)	(-3.608)
Family Income	0.751*	0.884	0.840	0.736*	0.888*	0.851
	(1.803)	(1.638)	(1.394)	(1.855)	(1.758)	(1.492)
Constant	54.174***	23.018*	27.641**	53.052***	45.724***	56.091***
	(5.062)	(2.011)	(2.673)	(5.155)	(4.079)	(5.968)
Village Fe	YES	YES	YES	YES	YES	YES
Obs.	652	500	467	652	500	467
Pseudo R-squared	0.357	0.329	0.299	0.357	0.329	0.299
Exogeneity		Wald test		13.09(0.001)	20.77(0.000)	27.39(0.000)
Weak Instrument		Cragg-Donald		9553.427	7274.805	5739.444
Consistency		Durbin-Wu-Hausman		112.64(0.000)	44.17(0.000)	68.37(0.000)

3.D Other Models and Sample

Table 3.D.1: Exponential Type II Tobit Model

	ADOPTION PART	USAGE PART
	Probit	Exponential Type II Tobit (log of positive usage)
Education	0.325***	0.084***
	(0.033)	(0.021)
Age	-0.826***	-0.261***
	(0.057)	(0.049)
Family Income	0.067***	0.018*
	(0.011)	(0.008)
Total Mobile	0.197***	0.085***
	(0.027)	(0.018)
Constant	0.586***	3.708***
	(0.224)	(0.195)
Clustered At Village Level	YES	YES
Obs	4086	1608
Log Pseudolikelihood	-3859.24	
Wald Chi-Sq	114.06***	
Wald Test Of Independent Equations (Rho=0)	0.01	
Rho	0.004	
Sigma	0.787	
Lambda	0.003	

Table 3.D.2: Lognormal Hurdle Model

Dependent Variable: Positive Percentage Of Household Expenditure Paid By Mobile Payment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Education	0.101***						0.052***	0.05***		0.051***
	(6.309)						(2.799)	(2.714)		(2.641)
Age		-0.284***					-0.259***	-0.270***		-0.248***
		(-7.054)					(-6.013)	(-6.241)		(-5.727)
Income			0.037***				0.022***	0.025***		0.021**
			(4.455)				(2.717)	(3.061)		(2.537)
Total Mobile				0.075***			0.066***			0.067***
				(4.118)			(3.696)			(3.732)
Mobile Per Person					0.075**			0.175***		
					(2.132)			(3.881)		
Population						0.0140		0.031**		
						(1.110)		(2.046)		
Agriculture									-0.180***	-0.137**
									(-3.188)	(-2.365)
Manufacture									0.184*	0.114
									(1.802)	(1.037)
Architecture									0.092	0.045
									(0.763)	(0.378)
Transportation									0.126	-0.0270
									(1.147)	(-0.236)
Hotel And Restraurant									0.105	0.0432
									(0.848)	(0.377)
Finance									-0.224	-0.305***
									(-1.586)	(-2.632)
Real Estate									0.226	0.020
									(0.891)	(0.078)
Work In Urban									0.0001	-0.038
									(0.00325)	(-0.76)
Others									0.028	-0.023
									(0.479)	(-0.432)
Constant	3.160***	4.340***	3.350***	3.301***	3.417***	3.447***	3.850***	3.781***	3.470***	3.888***
	(60.62)	(35.96)	(107.5)	(72.39)	(101.6)	(91.15)	(23.33)	(21.95)	(45.89)	(20.34)
Village FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	1,709	1,709	1,608	1,709	1,709	1,709	1,608	1,608	1,709	1,608
R-Squared	0.278	0.296	0.282	0.272	0.263	0.261	0.327	0.327	0.273	0.333

3.E Excluding the Household without Smart Phones

Table 3.E.1: Summary of Statistics for Households with or without Smart Phones

	Household without smart phone						Households having at least one smart phones					
Variable	Obs	Mean	Median	Std. Dev.	Min.	Max.	Obs	Mean	Median	Std. Dev.	Min.	Max.
Percentage of Expenditure Paid by Mobile Payment	614	99.27	100	5.40	10	100	3,800	74.81	100	33.59	0	100
Distance to Banks	614	0.00	0	0.00	0	0	3,800	21.55	0	31.22	0	100
Frequency of Visiting Banks*	614	1.89	2	0.89	1	5	3,800	1.79	2	0.86	1	5
Total Number of Mobile	614	2.38	2	1.52	1	5	3,800	2.68	2	1.56	1	5
Number of Mobile per person	614	0.00	0	0.00	0	0	3,800	2.85	3	1.43	1	13
Number of Family Member	614	0.00	0	0.00	0	0	3,800	0.94	0.8	0.68	0.09	9
Education	614	2.42	2	1.61	1	22	3,800	3.65	3	1.81	1	16
Age	614	2.15	2	0.86	1	7	3,800	2.78	3	1.12	1	7
Perception of Non-cash Payment in neighborhood*	614	3.83	4	0.52	2	5	3,800	3.19	3	0.64	1	5
Family Income	526	2.16	2	0.85	1	4	3,633	2.90	3	0.77	1	4

*Note: the original direction of ordering in the frequency of visiting banks is reversed.

Table 3.E.2: The Adoption of Mobile Payment: Sample without Households Having 0 Smart Phone

Dependent Variable: Whether Accepting Mobile Payment

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Education	0.434***						0.286***	0.288***	0.282***	
	(14.78)						(8.206)	(8.279)	(8.067)	
Age		-1.037***					-0.911***	-0.903***		-0.905***
		(-18.43)					(-14.92)	(-14.56)		(-14.75)
Income			0.102***				0.0607***	0.0668***		0.0537***
			(9.786)				(5.693)	(6.348)		(4.915)
Total Mobile				0.143***			0.108***			0.104***
				(5.616)			(3.962)			(3.852)
Mobile Per Person					0.0396			0.124**		
					(0.989)			(2.044)		
Population						0.0702***		0.0626***		
						(4.235)		(2.869)		
Agriculture									-0.400***	-0.349***
									(-5.074)	(-4.354)
Manufacture									0.399**	0.107
									(2.217)	(0.475)
Architecture									0.320*	0.0963
									(1.824)	(0.478)
Transportation									0.472**	0.211
									(2.363)	(0.945)
Hotel And Restraurant									0.315	0.132
									(1.586)	(0.612)
Finance									1.219**	1.195**
									(2.123)	(1.976)
Real Estate									-0.0992	-0.378
									(-0.256)	(-1.108)
Work In Urban									0.0725	0.0112
									(0.966)	(0.145)
Others									0.0559	0.0191
									(0.522)	(0.167)
Constant	-2.172***	2.592***	-1.486***	-1.315***	-1.055***	-1.211***	0.798***	0.698***	-1.003***	0.945***
	(-26.83)	(13.59)	(-28.52)	(-24.79)	(-29.48)	(-26.21)	(3.391)	(2.792)	(-11.97)	(3.729)
Village FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	3,800	3,800	3,516	3,800	3,800	3,800	3,516	3,516	3,800	3,516

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