Essays on Models for Liabilities of Banks in the United States

By

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A dissertation submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy
(Economics)

at the
UNIVERSITY OF WISCONSIN – MADISON
2022

Date of final oral examination: 11/29/2022

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Abstract

This dissertation consists of three chapters on models for liabilities of banks in the United States. Among other liabilities, banks mainly use deposits as a cheap funding source because the Federal Deposit Insurance Corporation (FDIC) guarantees the debt financing vehicle. One strategy banks can use to collect more deposits is simply offering a higher interest rate to depositors. However, banks need to compete in local markets by operating multiple branches, which is a distinctive feature compared to corporate or government debt markets. Therefore, the first two chapters covers questions associated with deposit market competition. On top of deposits, equity capital is an important part of liabilities due to government guarantees as well as regulatory policies. The last chapter of this dissertation studies how government bailouts could affect bank equity capital values.

Chapter 1 sheds a new light on the relationship between two liabilities of banks: *deposits and equity capital*. Using the logit and probit models with two-way fixed effects developed by Fernández-Val and Weidner (2016), we find that the cost of deposits is a quantitatively important factor to predict equity capital issuance of publicly listed bank holding companies in the U.S. banking sector. To explain the observation, we present evidence that the rising cost of deposits increases insolvency risk, so equity capital can be issued to protect the shareholder value of financial institutions. This impact can be amplified or reduced through a well-diversified deposit funding base. The empirical findings motivate us to develop a banking industry model to demonstrate how deposit market competition can affect equity capital issuance. The structural model is a variation of Egan, Hortacsu, and Matvos (2017) by incorporating multiple regional markets into deposit competition. We use the simulated method of moments to estimate two demand parameters which determine two supply parameters. From the benchmark model, we show that a bank is less likely to issue equity capital as the bank competes for deposits in more regional markets. With two simulation scenarios, we explain that a main advantage of having a well-diversified deposit funding base is the ability to control the cost of deposits. However, some of counterfactual simulations present a potential negative repercussion of having a well-diversified branch network under more restrictive capital requirements because intensity of deposit market competition soars, justifying the necessity of coordination between regulatory

and competition policies.

Chapter 2 is co-authored with Jangsu Yoon. We study determinants of the deposit market structure in the U.S. banking sector, focusing on *banks' entry and menu choice decisions*. The banks compete with deposit rates in local markets, simultaneously with entry decisions and decisions on which deposit products to sell by considering local market environments and competitors. We construct a novel data set describing county-level geographical features of deposit markets, allowing us to observe each bank's entry, menu choice, market share, and deposit rates across local markets. Our structural model with static games of strategic interactions incorporates the bank's entry and menu choice decisions into the traditional deposit rate competition framework. The estimation focusing on the competition among the top 5 banks demonstrates that strategic interactions play significant roles in joint entry decisions and deposit products menu compositions. Our work can suggest some implications for essential research topics in studies of the banking industry. For example, researchers can use the result that banks have an additional competitive strategy other than a deposit rate setting to understand the uniform deposit rate pricing pattern in the U.S. banking sector. Suppose some banks have a competitive advantage of providing more deposit products to gain market share. In that case, the uniform pricing is not necessarily inefficient, in contrast to retail sectors studied in DellaVigna and Gentzkow (2019). The implications from the benchmark model are stable and consistent with an extended model of the top 10 banks. We also simulate three counterfactual scenarios motivated by empirical observations after the financial crisis of 2008. The structural model-based prediction indicates that deposit competition models excluding the menu composition channel may derive a misleading implication.

Chapter 3 shows that the observed heterogeneity in bank stock returns during both a crisis period and a normal period can be explained by *the government bailouts* with a simple dynamic model extended from Gomes and Schmid (2010) by considering a banking-specific environment and incorporating a government bailout option. Our findings are consistent with Gandhi and Lustig (2015), showing that these institutions can enjoy the equity financing as a cheap source of funding due to the safety net provided by the government bailouts. The government bailouts can keep the stock returns of large commercial banks and bank holding companies from further plummeting during a crisis period. Furthermore, the stock returns of large financial institutions during a normal period are smaller in the model with the government bailouts, implying that these institutions can enjoy the equity financing as a cheap source of funding. Two parameters associated with the idiosyncratic shock in the model with the government bailouts are calibrated by using the simulated method of moments. The model is matched well not only with the targeted moments but also with other external moments. From counterfactual exercises, we show that equity holders of banks in a riskier environment can benefit more from the government bailouts during a crisis period.

Acknowledgements

I am grateful for everything from my advisors during this long journey to pursue a doctoral degree in economics. First, I would like to express my deep gratitude to my main advisor Dean Corbae for his great advice, constant support and encouragement. Thanks to him, I got a passion for studying the U.S. banking industry, and could develop my own research agenda on deposit market competition. I also learned a lot from his computational classes which equipped me for a career in banking and finance. The dissertation could never be completed without his excellent guidance and patience.

I am also indebted to my advisors Jean-François Houde and Kenneth West. They were always generous with their time. With Dean Corbae, Jean-François Houde organized IO-Finance Reading Group for graduate students in economics and finance, and I learned a tremendous amount of knowledge about banking topics from industrial organization perspectives. The reading group has been the most intellectually interesting time for me. Kenneth West always carefully and kindly listened to my research topics from beginning stages and encouraged me to enjoy my works more. His keen insight into economics helped me to understand my research questions in depth. I am also thankful to Ivan Shaliastovich for his time and serving as a committee member of the final oral examination. I was interested more in finance by attending Macro-Finance Asset Pricing Reading Group organized by him.

My journey has been with many wonderful friends. Junhyong Kim advised me on choosing a doctoral program in economics, and I decided to come to the University of Wisconsin-Madison not only because of the excellent program but also because of his nice and pleasant personality. It has been always enjoyable to talk with him on academic as well as non-academic issues. Jangsu Yoon has been a great mentor during my doctoral study and we had a fantastic teamwork for the second chapter of my dissertation. He is living proof of right attitude and mindset as a exemplary researcher. I was fortunate and happy to have Yuteng Cheng and Marco Duarte as my long-time office mates. They are my blood brothers. Thanks to them, I really enjoyed my life in Wisconsin. I also thank Amelia Gibbons, Sahber Ahmadi-Renania, Shuhei Otani, Mizuhiro Suzuki, and Anson Zhou for our great friendship.

Among many different experiences I had during my doctoral study, one of the moments I enjoyed most was teaching economics. I was lucky to meet and serve many devotional educators in the Department of Economics. I would like to thank Elizabeth S. Kelly, Jack R. Porter, Xiaoxio Shi, and Marek Weretka for their commitment and dedication to students. Especially, I sincerely appreciate the Late Professor William H. Sandholm for giving me opportunities to work for his classes and textbooks, and realize the sheer joy of education. With a number of conversations with him, I became more confident in teaching, and I came to love teaching with my knowledge. It requires enormous amount of time and energy to be well prepared before teaching students, but the pleasure of witnessing their growth and success is precious. Furthermore, I would like to give special thanks to Julie Anderson, Becca George, and Kimberly Grocholski as administrative staff members for helping me to fulfill my teaching responsibility successfully.

As a student from the Republic of Korea on the other side of the Pacific Ocean, being far away from my family was tough. However, my parents and younger brother have constantly supported me to believe that I can do whatever I dream of, so I have been able to be on the right path. Finally, I want to show my love and gratitude to my wife, Nozomi Iwasaki. She was the reason why I could get over difficult situations to accomplish my goal. A French philosopher said “Life is C between B and D,” which means “Life is Choice between Birth and Death.” Getting married with her is the best choice I have ever made in my life. Everyday, she makes me feel that life is beautiful.

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Chapter 1

Deposit Market Competition and Equity Capital Issuance

1.1 Introduction

In the U.S. banking sector, deposits account for a major part of liabilities, so banks mainly rely on debt financing for their loan investment. However, unlike non-financial firms, banks do not pay the high cost of debt in order to take deposits since more than 50% of deposits are insured by the Federal Deposit Insurance Corporation (FDIC) as shown in Figure A-1.[1] In other words, banks are not normally faced with a high leverage risk due to the explicit government guarantee, which makes it difficult to apply the trade-off theory of capital structure to explain high deposit-to-asset ratios of financial institutions. Therefore, equity capital of banks has been discussed and studied in the context of regulatory policies without incorporating its relationship with deposits.[2]

In this paper, we shed a new light on a relationship between deposits and equity capital: *how deposit market competition can affect equity capital issuance*. Using the logit and probit models with two-way fixed effects, we show that the cost of deposits is a quantitatively important factor to predict equity capital issuance of publicly listed bank holding companies in the U.S. banking industry. Fixed effects estimators can be severely biased under the nonlinear panel data model due to the incidental parameter problem in Neyman and Scott (1948). To handle this issue, we use the analytic bias correction developed by Fernández-Val and Weidner (2016). The estimated outcomes from our full sample show that the average marginal effect for the cost of deposits is 1.20% increase in the likelihood of equity capital issuance, leading to a hypothesis that an increase in the cost of deposits can reduce retained earnings for given amount of deposits, which not

[1] In case of deposits saved in credit unions, the National Credit Union Administration (NCUA), created by the U.S. Congress in 1970, has been responsible for protecting the members who own credit unions, and chartering and regulating federal credit unions. Currently, both FDIC and NCUA insure deposits of up to $250,000.

[2] After the financial of 2008, a new regulatory framework, countercyclical capital buffer, has been discussed and will be implemented. This policy requires banks to add capital at times when credit is growing rapidly so that the buffer can be reduced when the financial cycle turns. Specifically, banks can use the additional capital buffers they have built up during the growth phase of the financial cycle to cover losses that may arise during periods of stress and to continue supplying credit.

only decreases the amount of shareholder equity but also increases insolvency risk. An implication of this hypothesis is that an incentive to raise additional funds through equity capital issuance can arise to protect the shareholder value by reducing insolvency risk.

To test the aforementioned hypothesis, we demonstrate that an increase of one unit in the cost of deposits is associated with 24.4% decrease in Z-score, as a proxy for insolvency risk, although bank holding companies can achieve higher deposit market share by spending more on the cost of deposits. This validate our hypothesis that the rising cost of deposits increases insolvency risk, so shareholders of bank holding companies are more likely to raise additional funds through equity capital issuance to protect the shareholder value of financial institutions. On top of that, we include independent variables capturing deposit market structure, deposit market share and a diversification index, into econometric models. The diversification index reflects a spatial feature on deposit allocation of a bank holding company over the United States, and ranges from 0 to 1. It shows a smaller value if a bank holding company has a well-diversified geographical distribution of deposits. A novel observation is that the impact of the cost of deposits on Z-score can be amplified or reduced through a well-diversified deposit funding base. For instance, our estimated models show that when the cost of deposits is 1%, 1% decrease in the diversification index, which is equivalent to a better-diversified deposit funding base, is associated with 0.084 % increase in Z-score. This shows a positive aspect of collecting deposits from a well-diversified deposit funding base. On the other hand, when the cost of deposits is 5%, 1% decrease in the diversification index is associated with -0.072 % change in Z-score. This implies a potential drawback of collecting deposits in more regions.

The empirical findings motivate us to develop a banking industry model to study how deposit market competition can affect equity capital issuance with a theoretical perspective. Our model is a variation of Egan, Hortacsu, and Matvos (2017) by incorporating multiple regional markets into deposit competition. If a bank in the model collects deposits in multiple regions, the bank competes for deposits by playing a deposit rate setting game with its competitors in each regional market. Therefore, the cost of deposits in the model is determined as a result of deposit market competition. Moreover, for given amount of deposits, the cost of deposits affects the market value of the bank, which leads bank shareholders endogenously choose whether to default or not in the model. If the market value of a distressed bank is high enough, shareholders of the bank can raise additional funds through equity capital issuance to finance its business even after a bad profit shock is realized. On the other hand, a distressed bank decides to default when its market value is lower than the amount of additional funds which shareholders of the bank should issue to support its business. We use the simulated method of moments to estimate two demand parameters from preference of depositors and these estimated parameters determine two supply parameters associated with profit shocks.

In the estimated model, a bank is less likely to issue equity capital as the bank competes for deposits in more regional markets. To understand a mechanism behind this outcome, we simulate two different scenarios from which it is found that that a main advantage of having a well-diversified deposit funding base is the ability to control the cost of deposits. This advantage is reconfirmed through a counterfactual exercise where we add more regions to a deposit funding base of a bank collecting deposits from multiple regional markets. Also, we change capital requirements in the model and present a potential negative repercussion of having a well-diversified deposit funding base under more restrictive capital requirements. When a mandatory capital ratio is high in the model, this results in a higher average return with lower volatility in loan investment. Therefore, a bank collecting deposits from multiple regional markets can encounter a number of competitors with good returns through its diversified funding base. Due to the soared deposit market competition, the bank ends up increasing deposit rates in all regional markets while losing its deposit market share, leading to the higher cost of deposits. This unintended consequence of a higher capital ratio gets worse through a well-diversified deposit funding base as the bank operates additional branches in more regional markets. This is consistent with our observation showing that the negative impact of the cost of deposits on Z-score can be amplified through a well-diversified deposit funding base when the cost of deposits is higher. In order to prevent unnecessarily intense competition, a rate cap rule, which imposes a ceiling on deposit rates, is introduced in the model. The rate cap rule can make a well-diversified deposit funding base work positively by decreasing the cost of deposits, justifying the necessity of coordination between regulatory and competition policies to achieve the safer banking system.

Literature Review

Our paper is relevant to several studies in banking literature. First of all, this paper is associated with rising literature on equity capital issuance of financial institutions. Among others, our work is closely related to Baron (2020) showing that large commercial banks in the U.S. banking sector raise and retain less common equity capital during credit expansions from 1980 to 2012 even though more equity capital might help banks to better absorb subsequent adverse shocks. This empirical pattern is labeled as countercyclical bank equity issuance, which is against what regulators have emphasized since the financial crisis of 2008. Baron (2020)

[3] To test this hypothesis, Baron (2020) uses a quasi-experimental setup where he can exploit the unanticipated removal of government guarantees to German Landesbanken creditors. There are three types of banks in Germany: private commercial banks, cooperative banks, and public banks. Public banks consist of Landesbanken and savings banks. Savings banks are each affiliated with a Landesbank, and each of the Landesbanken is associated with a German federal state or group of states. Common equity of the Landesbanken is held both by their member states and, to a considerable extent in the last two decades, by private investors, although shares are not publicly traded. Thus, they issue common equity to private investors and pay out dividends. One significant characteristic of the Landesbanken is that the main funding source is long-term bonds (not deposit-type debt), which were explicitly guaranteed by their affiliated states until 2001.

suggests that government guarantees to bank creditors are quantitatively important friction that leads banks to resist issuing equity capital during credit expansions since equity capital issuance is not compensated with a decrease in debt funding costs from creditors.[3] Also, Goetz, Laevan, and Levine (2021) evaluate the role of insider ownership in shaping equity capital issuance of banks in response to the financial crisis of 2008. They find that greater insider ownership leads to less equity capital issuance, supporting the view that bank insiders are reluctant to reduce their private benefits of control by diluting their ownership through equity capital issuance. Our paper can complement this literature by proposing deposit market competition as a mechanism to explain equity capital issuance.

Secondly, our approach to model the banking industry is pertinent to studies using industrial organization to understand deposit market competition.[4] Our model is a variation of Egan, Hortacsu, and Matvos (2017) that develop an empirical model of the U.S. banking sector to show how competition for uninsured deposits can lead to financial fragility. We add a branch network to deposit market competition, which is similar to Aguirregabiria, Clark, and Wang (2020). They use a model allowing deposit market competition and loan market competition to investigate how branch networks, market power, and scope of economies can prevent funding from flowing to high loan demand areas, leading to geographical imbalance of deposits and loans. However, their model dose not consider a default choice of banks so there is no explicit consideration on equity capital issuance. From our knowledge, our work is the first approach to study a relationship between deposit market competition and equity capital issuance with an industrial organization model.

Also, our simulation outcomes can complement the literature on capital requirements in quantitative models of banking by showing that more restrictive capital requirements can generate a negative repercussion on the stability of large financial institutions through their well-diversified deposit funding bases when deposit market competition is unnecessarily intense. Many of papers in this literature do not consider deposit market competition in order to concentrate on implications of capital requirements on the welfare cost (e.g. Van den Heuvel (2008)), bank policies (e.g. De Nicolo, Gamba, and Lucchetta (2014)), risk choices in loan investment (e.g. Begenau (2020)), and financial stability through loan market structure (Corbae and D'Erasmo (2021)).

Finally, our approach to equity capital of banks can shed a new light on the literature on bank capital structure. Most of works on the subject extrapolate an answer from capital structure theories of non-financial

[4] Some papers investigate monetary policy transmission through deposit competition. Drechsler, Savov, Schnabl (2017) present that when the federal funds rate rises, banks widen the spreads charged on deposits more and deposits flow our more in concentrated regional markets, which impacts bank lending. Xiao (2020) shows that monetary tightening could unintentionally increase financial fragility through the shadow banking sector since it can attract more deposits from a yield-sensitive clientele. Wang, Whited, Wu, and Xiao (2022) estimate a dynamic banking model to quantify the impact of bank market power on the transmission of monetary policy through banks to borrowers. All of these papers do not consider difference between large and small financial institutions in deposit market competition.

firms. However, Gorton and Pennacchi (1990) suggest that banks do not suffer the asymmetric information costs of equity capital issuance faced by non-financial firms, which is the key mechanism behind the pecking-order theory. The trade-off theory is also not perceived to be a candidate to explain bank capital structure since the cost of deposits does not reflect potential financial distress due to the deposit insurance. Therefore, some theoretical papers try to understand the determinants of bank capital structure by incorporating a liquidity-creation function (e.g. Diamond and Rajan (2000) and DeAngelo and Stulz (2015)) or bankruptcy costs (e.g. Allen, Carletti, and Marquez (2015)). A common assumption from these papers is that deposits can be collected from a centralized market such as corporate or government bond markets. However, deposit markets are geographically compartmentalized markets. Therefore, our work contributes to this literature by explicitly considering deposit market structure and competition to understand equity capital of banks.

1.2 Empirical Analysis

In this section, we present two novel observations showing a link between deposit market competition and equity capital issuance in the U.S. banking system. Using choice models with two-way fixed effects in Fernández-Val and Weidner (2016), our first empirical analysis finds that the cost of deposits is an important predictive factor to understand equity capital issuance. This result is further studied in the second empirical analysis, showing that a bank increases deposit market share by offering higher deposit rates, which reduces its Z-score, a proxy for bankruptcy chance, through the higher cost of deposits. Therefore, the bank can raise funds through equity capital issuance in order to protect the shareholder value, which is a potential explanation for the observation from our first empirical analysis. On top of that, we find that a bank with a well-diversified deposit funding base has a higher Z-score when the cost of deposits is relatively low, which implies that the bank is less likely to have an incentive to raise additional funds through equity capital issuance. These findings motivate us to build a structural model of deposit market competition with branch networks in Section 1.3.

1.2.1 Data Construction

For our empirical analysis, we combine three data sources of the U.S. banking sector from 2001:Q1 to 2014:Q4. For some cases, we divide the full sample into two sub-samples: before the financial crisis (from 2001:Q1 to 2007:Q4) and after the financial crisis (from 2008:Q1 to 2014:Q4). An entity in our sample is a

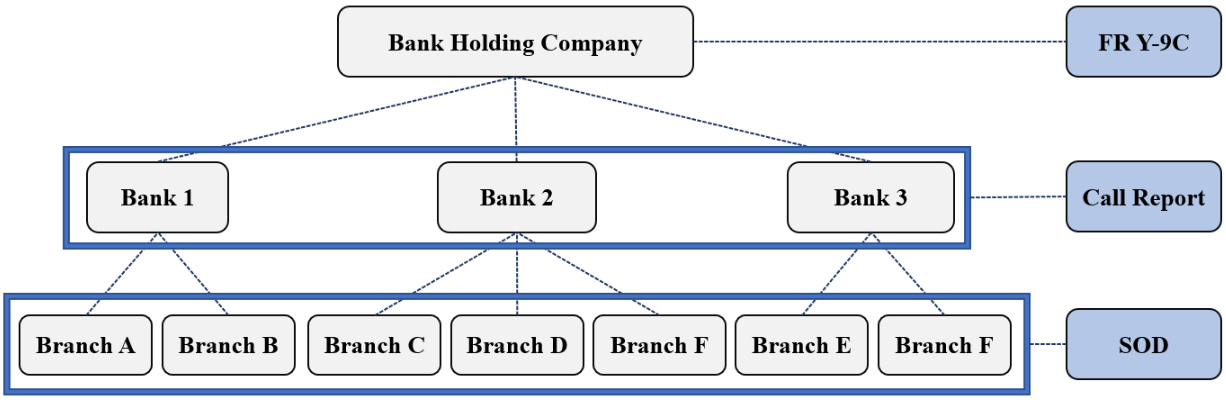


Figure 1-1: Organizational Structure of Bank Holding Companies and Data Sources

bank holding company. This holding company may have more than one commercial banks as its subsidiaries. Each commercial bank operates local branches to compete for deposits. Therefore, a deposit rate is a branch-level decision determining market share whereas equity capital issuance is a decision in a holding company level. Reflecting this. the data sources cover variables associated with different decisions within a bank holding company. Figure 1-1 shows an example of organizational structure within bank holding companies.

We collect equity capital issuance information from Consolidated Financial Statements for Holding Companies (FR Y-9C) quarterly provided by the Federal Reserve Board (FRB). We only consider institutions publicly listed in either the New York Stock Exchange or NASDAQ by using information from the Federal Reserve Bank of New York, which links regulatory identification numbers (RSSD ID) from the National Information Center to the permanent company number (PERMCO) used in the Center for Research in Security Prices. Therefore, we exclude a bank holding company whose RSSD ID is not linked to any PERMCO, which implies that the institution is not publicly traded in the stock exchanges.

Since a bank holding company can have multiple commercial banks as its subsidiaries, we should aggregate their balance sheets and income statements to define a representative variable for the bank holding company. For example, the total deposits of the bank holding company in Figure 1-1 is the sum of deposits from Bank 1, Bank 2, and Bank 3. We gather information on balance sheets and income statements of commercial banks from the Report of Condition and Income quarterly issued by FDIC, also known as Call Report. In Call Report, a commercial bank has a unique identification number, RSSD ID, assigned to its holding company, so we can combine information of commercial banks under the same holding company. In Appendix A, we show bank capital structure and deposit composition of bank holding companies in our sample.

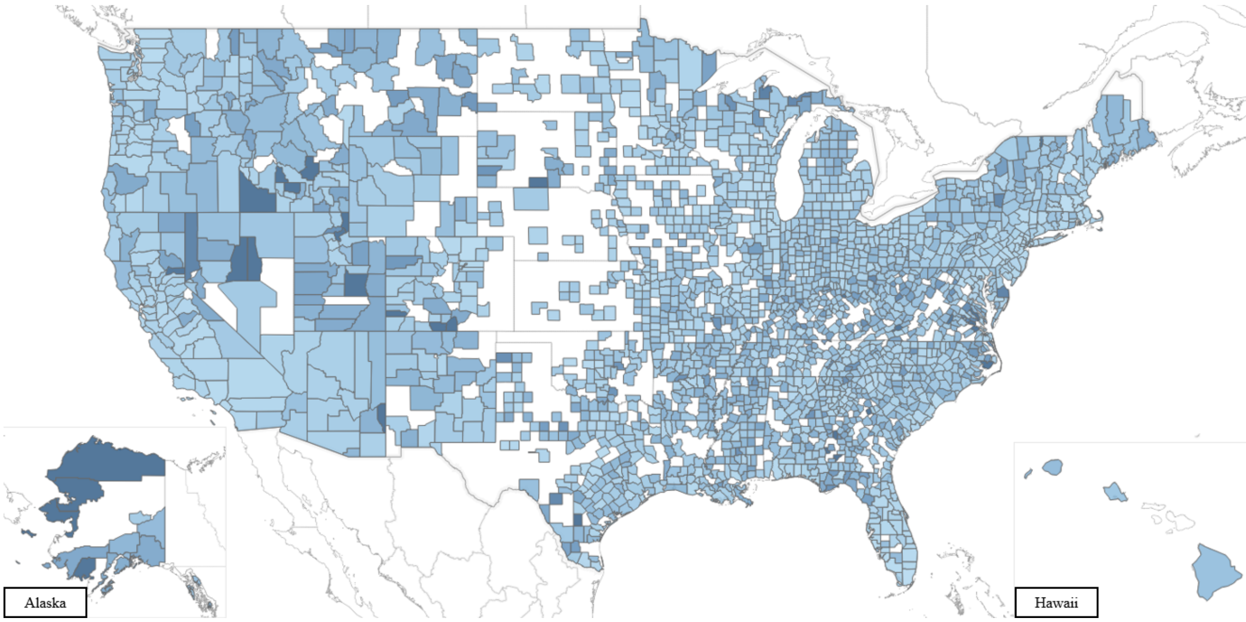


Figure 1-2: Deposit Market Concentrations of the U.S. in 2015

Branch-level deposits information is from SOD issued by FDIC. For calculating HHI in each county, we consider all financial institutions insured by FDIC including credit unions if their information is reported in SOD. A darker shade of blue means a more concentrated deposit market which has a higher level of HHI. Non-shaded areas are where there is no deposit-taking institution insured by FDIC. However, there may be an institution insured by the National Credit Union Administration.

A commercial bank operate branches to collect deposits in multiple markets. Geographical information on deposits is from the Summary of Deposits (SOD), the annual survey of FDIC. It is a well-documented fact that markets for deposits are geographically segmented.[5] In other words, each deposit market has a different characteristic from others. Illustratively, Figure 1-2 shows county-level deposit market concentrations of the U.S. in 2015, measured by the Herfindahl-Hirschman Index (HHI). A darker shade of blue means a more concentrated deposit market which has a higher level of HHI.

In addition, SOD allows us to trace a bank's history on establishing its branches. For example, Figure 1-3 shows how Wells Fargo has expanded its deposit funding base as well as county-level deposit market share of the bank over time. A darker shade of green means higher deposit market share for Wells Fargo in a county. From 1995 and 2005, the bank had established more branches across the country and acquired other

[5] Drechsler, Savov, and Schnabl (2017) use county-level information to show that a branch of banks in more concentrated deposit markets increases a rate less due to its regional market power after the federal funds rate rises. Aguirregabiria, Clark and Wang (2020) also use county-level deposit market information to investigate geographical imbalance between deposits and loans. These papers assume that depositors only consider deposit-taking institutions in their proximity because of transportation costs. This assumption is justified by Honka, Hortacsu, and Vitorino (2017) providing evidence that local branch presence is an important factor for the decision to open new bank accounts. More recently, Abrams (2019) shows that customers are quite attentive to which banks are situated in their regions.

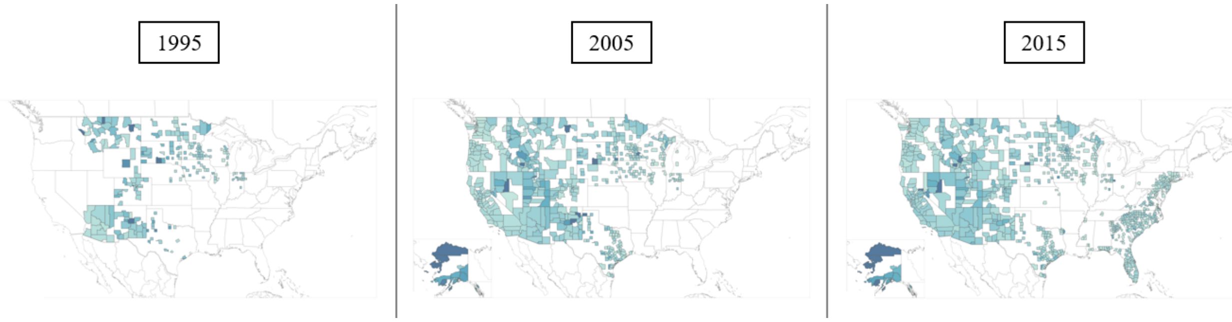


Figure 1-3: County-Level Deposit Market Share of Wells Fargo

A darker shade of green means higher deposit market share for Wells Fargo in a county. Wells Fargo has expanded its deposit funding base over time. From 1995 and 2005, the bank had established more branches across the country and acquired other financial institutions after the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994. After the financial crisis of 2008, Wells Fargo acquired Wachovia which had operated branches mainly in the Southeast.

financial institutions after the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994. A major reason behind the change in its deposit funding base from 2005 to 2015 is that Wells Fargo acquired Wachovia after the financial crisis of 2008. Since a unique institution reported in SOD is a subsidiary under a bank holding company, we aggregate information of institutions with the same RSSD ID to define a variable for the bank holding company. From this, we can define representative market share of the bank holding company in Figure 1-1 by using the weighted average market share over all of its branches.

Using RSSD ID, we merge FR Y-9C, Call Report, and SOD. We drop observations with negative capital ratios. Also, we exclude observations with negative values of deposits. After this initial cleaning process, we remain bank holding companies with observations of at least three full calender years. As a result, our sample includes approximately 1,000 bank holding companies in each year on average during the sample period. Annually, these institution account for 70% of the total deposits reported in Call Report. Most of the bank holding companies in our sample are reliant on deposits for their debt financing. Only some mega banks, Globally Systematically Important Banks (GSIB) and Domestically Systematically Important Banks (DSIB), finance a small portion of their projects through subordinated debt, a type of non-deposit financing.[6]

1.2.2 Definition of Variables

With the constructed sample, we expound some key variables used in our main empirical analysis. Variables for robustness checks are defined in Appendix B. First of all, equity capital issuance is defined as a binary

[6] In the U.S. banking system, GSIB are JP Morgan Chase, Bank of America, Wells Fargo, Citi Group, State Street, and Bank of New York Mellon. These are designated by the Financial Stability Board. DSIB include financial institutions not being big enough for GSIB status, but still with high enough domestic importance making them subject to the Stress Test by FRB. DSIB in

variable

$$\text{Issuance} = \mathbb{1}\{\underbrace{\text{Sale of Common Stock}}_{\text{BHCK3579}} + \underbrace{\text{Conversion or Retirement of Common Stock}}_{\text{BHCK3580}} > 0\}.$$

Another binary variable is dividend payment

$$\text{Dividend} = \mathbb{1}\{\underbrace{\text{Cash Dividends Declared on Common Stock}}_{\text{BHCK4460}} > 0\}.$$

These two binary variables are from FR Y-9C.

Using Call Report, we measure variables associated with profitability and cost of banking business. The return on assets (ROA) is calculated as

$$\text{ROA} = \frac{\text{Net Income}}{\text{Total Assets}}.$$

If multiple commercial banks are under the same holding company, we sum net incomes (RIAD4340) and total assets (RCON2170) to define the return of assets. To calculate the cost of deposits, we use three categories of deposits from Call Report:

$$\begin{aligned}
\text{Time (CD)} &= \text{RCONA579} + \text{RCONA580} + \text{RCONA581} + \text{RCONA582} \\
&\quad \underbrace{+\text{RCONA584} + \text{RCONA585} + \text{RCONA586} + \text{RCONA587}}_{\text{during 2001:Q1-2009:Q4}} \\
&= \underbrace{\text{RCON6648} + \text{RCONJ473} + \text{RCONJ474}}_{\text{during 2010:Q1-2014:Q4}} \\
\text{Savings \& Money Market (MM)} &= \text{RCON6810} + \text{RCON0352} \\
\text{Checking} &= \text{RCON2385}.
\end{aligned}$$

From information on interest expense,

$$\begin{aligned}
\text{Expense of Time} &= \text{RIADA517} + \text{RIADA5108} \\
\text{Expense of Savings \& MM} &= \text{RIAD0093} \\
\text{Expense of Checking} &= \text{RIAD4508}.
\end{aligned}$$

our sample are Ally Financial, American Express, BB&T, Capital One, Comerica, Discover Financial Services, Fifth Third Bank, Huntington Bancshares, KeyCorp, M&T Bank, Northern Trust, PNC Bank, Regions Financial, Santander, SunTrust Banks, U.S. Bank, Unionbancal Corporation, and Zions Bancorporation.

As a result,

$$\text{Cost of Deposits} = \frac{\text{Expense of Time (CD)} + \text{Expense of Savings \& MM} + \text{Expense of Checking}}{\text{Time(CD)} + \text{Savings \& MM} + \text{Checking}}$$

which is conceptually the per unit cost of deposits. Like ROA, we define the cost of deposits for each bank holding company if there are multiple commercial banks as subsidiaries of the same holding company. For our empirical analysis, we annualize both ROA and the cost of deposits.

Finally, we utilize SOD to define variables reflecting how a bank holding company performs from deposit market competition. For a simple terminology, we call a bank holding company as a bank or a financial institution in the following explication. We consider a sample from SOD as an economy with K banks, indexed by $k \in \{1, ..., K\} = \mathcal{K}$, over time $t \in \{1, ..., T\} = \mathcal{T}$. Considering entry and exit behavior in the U.S. banking sector, not every bank $k \in \mathcal{K}$ stays in the economy for all $t \in \mathcal{T}$. We denote each county-level deposit market with $m \in \{1, ..., M\} = \mathcal{M}$. Therefore, $\mathcal{M}$ is the set of all counties in the United States. Let $q_{k,t}^m$ represent the amount of deposits collected by bank k in county m at time t. Then, we can define deposit market share of bank k in market m at time t as follows

$$\text{MS}_{k,t}^m = \frac{q_{k,t}^m}{\sum_{k \in \mathcal{K}_t^m} q_{k,t}^m}$$

where $\mathcal{K}_t^m \subset \mathcal{K}$ is a set of financial institutions observed in market m at time t from SOD. Therefore, in order to measure county-level deposit market share, we use all financial institutions in SOD, not the bank holding companies in our sample after the procedure described in Section 1.2.1.

If bank k competes for deposits in multiple counties, we can define a set of counties where branches of bank k gather deposits at time t, $\mathcal{M}_{k,t} \subset \mathcal{M}$. As a result, we compute a weighted-average of the county-level deposit market share for bank k at time t,

$$\text{MS}_{k,t} = \sum_{m \in \mathcal{M}_{k,t}} \underbrace{(q_{k,t}^m / D_{k,t})}_{w_{k,t}^m} \text{MS}_{k,t}^m \tag{1.1}$$

where $D_{k,t} = \sum_{m \in \mathcal{M}_{k,t}} q_{k,t}^m$ is the total deposits of bank k at time t, so $\sum_{m \in \mathcal{M}_{k,t}} w_{k,t}^m = 1$. This weight reflects importance of some counties from which a bank secures a major portion of its deposits. For instance, Figure 1-3 shows higher deposit market share of Wells Fargo from Alaska than California. However, Wells Fargo obtained much more deposits from California than Alaska because of its corporate headquarters located in San Francisco, California.

Although $\text{MS}_{k,t}$ simply gives us information on how well bank k is doing against its competitors across $m \in \mathcal{M}_{k,t}$, it dose not show any spatial feature on deposit allocation of bank k. Suppose that there are two banks: k_1 and k_2. Bank k_1 collects 50% of deposits from county m_1 and county m_2, respectively. It has 20% market share in county m_1 and 30% market share in county m_2. On the other hand, bank k_2 collects 80% of deposits from county m_1 and 20% from county m_2. It has 25% market share in both county m_1 and county m_2. Using equation (2.12) without the time subscript, we get

$$\begin{aligned} \text{MS}_{k_1} &= 0.50 \times 0.20 + 0.50 \times 0.30 = 0.25 \\ \text{MS}_{k_2} &= 0.80 \times 0.25 + 0.20 \times 0.25 = 0.25, \end{aligned}$$

which implies that $\text{MS}_{k,t}$ cannot show dependence of bank k_2 on county m_1 as a deposit funding source. Therefore, we define a diversification index as follows,

$$\text{DIV}_{k,t} = \sum_{m \in \mathcal{M}_{k,t}} \left(\frac{q^m_{k,t}}{D_{k,t}} \right)^2. \tag{1.2}$$

This diversification index ranges from 0 to 1 and it shows a smaller value if a bank has a well-allocated geographical distribution of deposits. Using this index to the previous example,

$$\begin{aligned} \text{DIV}_{k_1} &= (0.50)^2 + (0.50)^5 = 0.50 \\ \text{DIV}_{k_2} &= (0.80)^2 + (0.20)^2 = 0.68, \end{aligned}$$

which shows that bank k_1 has a well-diversified deposit funding base than bank k_2. Table 1-1 shows summary statistics of bank holding companies in our sample. We use total assets to define the bottom 30% banks as Small, the middle 40% banks as Medium, the top 30% banks excluding the top 1% banks as Large, and the top 1% banks as Mega. GSIB and DSIB are all included in Mega category. Although there is no evident relationship between size of banks and the average deposit market share, bigger bank holding companies tend to have more diversified allocation of deposits.

1.2.3 Regression Analysis I

Our sample is a standard unbalanced panel from which we observe a binary action, $\text{Issuance}_{k,t} \in \{0, 1\}$, for each quarter. $k \in \{1, ..., K\}$ identifies a bank holding company in our sample and $t \in \{1, ..., T\}$ signifies a quarter from 2001:Q1 to 2014:Q4.

Table 1-1: Sample Description on Bank Holding Companies

	Total Assets	**Total Deposits**	**Equity Issuance**	**Deposit Market Statistics**		
	Mean (Million)	Mean (Million)	Frequency	Avg Cost	Avg MS	Avg DIV
Bank Size						
Small BHC	$322.3	$266.4	35.20%	1.90%	17.28%	0.74
Medium BHC	$708.4	$575.1	43.12%	1.88%	14.79%	0.62
Large BHC	$8,056.9	$5,613.6	47.84%	1.71%	15.05%	0.45
Mega BHC	$492,533.5	$316,299.6	37.65%	1.26%	20.81%	0.20

Note: Our sample spans from 2001:Q1 to 2014:Q4 and only covers bank holding companies publicly listed in stock market. The first two columns show the average assets and deposits within a size group over the sample period. Balance sheet information is from Call Report. For each quarter over the sample period, we define the bottom 30% banks as Small, the middle 40% banks as Medium, the top 30% banks excluding the top 1% banks as Large, and the top 1% banks as Mega. GSIB and DSIB are all included in Mega category. The numbers are adjusted by the dollar value in 2011:Q1. The following two columns show on the average deposit market share computed in equation (2.12) and the average diversification index in equation (1.2). Variables associated with deposit market statistics are from SOD from FDIC.

Econometric Specification

We use the logit and probit models with two-way fixed effects to predict a probability that a bank holding company raises additional funds through common stock issuance. The econometric model is

$$\Pr\left(\text{Issuance}_{k,t} = 1 | \boldsymbol{X}_k^T, \boldsymbol{\gamma}, \boldsymbol{\theta}, \boldsymbol{\delta}\right) = F\left(X'_{k,t}\gamma + \theta_k + \delta_t\right) \tag{1.3}$$

where $F : \mathbb{R} \to [0,1]$ is a cumulative distribution function. This distribution is the standard logistic distribution in the logit model and the standard normal distribution in the probit model. The regressors $\boldsymbol{X}_k^T = (X_{k,1}, X_{k,2}, ..., X_{k,T})$ are

$$X'_{k,t} = \begin{bmatrix} \text{ROA}_{k,t} & \text{Cost of Deposits}_{k,t} & \log(\text{CR}_{k,t-1}) & \log(\text{DTA}_{k,t-1}) & \text{Dividend}_{k,t} \end{bmatrix}$$

where $\text{CR}_{k,t-1}$ is the total capital ratio in the percent value from BHCA7205 in FR Y-9C and $\text{DTA}_{k,t-1}$ is a deposit-to-asset ratio computed from Call Report

$$\text{DTA}_{k,t-1} = \left(\frac{\text{Time}_{k,t} + \text{Savings}_{k,t} + \text{Checking}_{k,t}}{\text{Total Assets}_{k,t}}\right) \times 100.$$

$\text{ROA}_{k,t}$ and Cost of $\text{Deposits}_{k,t}$ are flow variables simultaneously measured with $\text{Issuance}_{k,t}$. On the other hand, $\text{CR}_{k,t-1}$ and $\text{DTA}_{k,t-1}$ are stock variables and they are predetermined with respect to $\text{Issuance}_{k,t}$.

Finally, $\text{Dividend}_{k,t}$ is a binary variable observed with $\text{Issuance}_{k,t}$ over the same period.

$\boldsymbol{\gamma}$ is a vector of unknown model coefficient of the same dimension as $X_{k,t}$. The model has individual specific effects $\boldsymbol{\theta} = (\theta_1, ..., \theta_K)$ and time specific effects $\boldsymbol{\delta} = (\delta_1, ..., \delta_T)$ to capture unobserved heterogeneity. For the observation $\left(\text{Issuance}_{k,t}, X'_{k,t}\right)$, the conditional log-likelihood function is

$$\begin{aligned} l_{k,t}\left(\boldsymbol{\gamma}, \theta_k, \delta_t\right) := {} & \text{Issuance}_{k,t} \times \log\left(F\left(X'_{k,t}\boldsymbol{\gamma} + \theta_k + \delta_t\right)\right) \\ & + \left(1 - \text{Issuance}_{k,t}\right) \times \left(1 - \log\left(F\left(X'_{k,t}\boldsymbol{\gamma} + \theta_k + \delta_t\right)\right)\right) \end{aligned}$$

and the fixed effects estimators for $\boldsymbol{\gamma}, \boldsymbol{\theta}$, and $\boldsymbol{\delta}$ are obtained by maximizing the log-likelihood function of the sample

$$\left(\hat{\boldsymbol{\gamma}}, \hat{\boldsymbol{\theta}}, \hat{\boldsymbol{\delta}}\right) \in \text{argmax}_{(\boldsymbol{\gamma},\boldsymbol{\theta},\boldsymbol{\delta})\in\mathbb{R}^{\dim(\boldsymbol{\gamma})+K+T}} \sum_{k=1}^{K}\sum_{t=1}^{T} l_{k,t}\left(\boldsymbol{\gamma}, \theta_k, \delta_t\right). \tag{1.4}$$

This is a smooth concave maximization problem. We normalize $\theta_1 = 0$ since the log-likelihood function is invariant to the transformation $\theta_k \mapsto \theta_k + c$ and $\delta_k \mapsto \delta_k - c$ for any $c \in \mathbb{R}$.

However, the fixed effects estimators $\hat{\gamma}$ can be severely biased under the nonlinear panel data model in equation (1.3) due to the incidental parameter problem in Neyman and Scott (1948). These estimators are asymptotically inconsistent when T is fixed and $K \to \infty$ when the model has bank specific individual effects. They are also asymptotically inconsistent when K is fixed and $T \to \infty$ when the model has time effects. This problem arises from the fact that there are limited observations to estimate each unobserved effect. The nonlinear nature of the model aggravate the problem by transmitting the inconsistency in the estimation of the individual and time effects to $\hat{\gamma}$. To handle this problem, we use the analytic bias correction developed by Fernández-Val and Weidner (2016).

Results

Table 1-2 shows estimated outcomes in equation (1.3) with the analytic bias correction from Fernández-Val and Weidner (2016). Column (3) and (4) are our major results which use the logit and probit models, respectively, over the full sample periods. Column (5) and (6) are estimated outcomes from the sub-sample from 2001:Q1 to 2007:Q4, whereas Column (7) and (8) are from the sub-sample from 2008:Q1 to 2014:Q4. From Column (3) to (8), we set the trimming parameter in Cruz-Gonzalez, Fernández-Val, and Weidner (2017) as one to estimate spectral expectations since the econometric model in equation (1.3) has the predetermined variables, CR_{t-1} and DTA_{t-1}, with respect to the dependent variable.

Table 1-2: Prediction Models of Equity Capital Issuance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Issuance_t	Issuance_t	Issuance_t	Issuance_t	Issuance_t	Issuance_t	Issuance_t	Issuance_t
					(Before)	(Before)	(After)	(After)
ROA_t	0.039^{***}	0.020^{***}	0.039^{***}	0.020^{***}	0.052^{*}	0.030^{*}	-0.006	-0.002
	(0.010)	(0.006)	(0.010)	(0.006)	(0.027)	(0.016)	(0.015)	(0.008)
Cost of Deposits_t	0.121^{***}	0.067^{**}	0.125^{***}	0.069^{***}	0.152^{**}	0.075^{**}	0.201^{*}	0.116^{*}
	(0.047)	(0.027)	(0.047)	(0.027)	(0.065)	(0.035)	(0.112)	(0.063)
$\log(\text{CR}_{t-1})$	-0.035	-0.047	-0.024	-0.040	-0.798^{***}	-0.438^{***}	-0.166	-0.100
	(0.086)	(0.050)	(0.086)	(0.050)	(0.179)	(0.095)	(0.155)	(0.088)
$\log(\text{DTA}_{t-1})$	-1.291^{***}	-0.682^{***}	-1.303^{***}	-0.689^{***}	-1.611^{***}	-0.870^{***}	-1.440^{***}	-0.740^{***}
	(0.255)	(0.147)	(0.255)	(0.147)	(0.445)	(0.254)	(0.481)	(0.276)
Dividend_t	0.365^{***}	0.202^{***}	0.367^{***}	0.203^{***}	0.359^{***}	0.197^{***}	0.332^{***}	0.182^{***}
	(0.048)	(0.027)	(0.048)	(0.027)	(0.075)	(0.042)	(0.086)	(0.049)
Model	Logit	Probit	Logit	Probit	Logit	Probit	Logit	Probit
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Error Correction	Two-Way	Two-Way	Two-Way	Two-Way	Two-Way	Two-Way	Two-Way	Two-Way
Trimming	0	0	1	1	1	1	1	1
Pseudo R-Squared	0.374	0.373	0.374	0.373	0.346	0.345	0.384	0.384
Observations	36,770	36,770	36,770	36,770	19,102	19,102	12,115	12,115

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, and standard errors are in parentheses.

Note: Column (3) and (4) are our major results which use the logit and probit models, respectively, over the full sample periods. Column (5) and (6) are estimated outcomes from the sub-sample from 2001:Q1 to 2007:Q4, whereas Column (7) and (8) are from the sub-sample from 2008:Q1 to 2014:Q4. From Column (3) to (8), we set the trimming parameter in Cruz-Gonzalez, Fernández-Val, and Weidner (2017) as one to estimate spectral expectations since the econometric model in equation (1.3) has the predetermined variables, CR_{t-1} and DTA_{t-1}, with respect to the dependent variable.

From Column (3) and (4), we find that ROA_t and Dividend_t are statistically significant predictors of equity capital issuance. Dividend_t maintains its statistical significance in both sub-sample regression outcomes, but ROA_t does not so after the financial crisis. The strong predictive power of Dividend_t on Issuance_t is consistent with a well-documented fact in corporate finance and financial accounting that a company raises additional funds through equity capital issuance when dividends are paid out as cash. This is because the payout of cash dividends from retained earnings decreases the amount of shareholder equity on the company's balance sheet. Also, considering that the banking industry is subject to capital requirements, banks may issue equity capital to comply with the rules, which can be captured by CR_{t-1}. However, CR_{t-1} is only significant in the sub-sample before the financial crisis. This is potentially due to the fact that banks have higher capital buffers required by more restrictive regulatory policies after the financial crisis.

An interesting observation is that Cost of Deposits_t and $\log(\text{DTA}_{t-1})$ are quantitatively important factors to predict equity capital issuance over all different models and sample periods. For example, we can compute the average marginal effect for the cost of deposits in Column (3) as follows,

$$\text{AME} = \frac{1}{KT}\sum_{k=1}^{K}\sum_{t=1}^{T}\hat{\gamma}_2 f\left(X'_{k,t}\hat{\gamma} + \hat{\theta}_k + \hat{\delta}_k\right)$$

where f is the probability density function of the logistic distribution and $\hat{\gamma}_2$ is the estimated coefficient for the cost of deposits, 0.125. As a result, the average marginal effect for the cost of deposits in Column (3) is 1.20% with z-value = 2.78. In other words, the average change in the likelihood of equity capital issuance is 1.20% when the cost of deposits marginally increases. From a similar calculation, the average marginal effect for the deposit-to-asset ratio in a logarithmic scale in Column (3) is -12.8% with z-value = -5.02, which implies that the likelihood of equity capital issuance drops by 12.8% on average when there is a small increase in $\log(\text{DTA})$.[7] This description also holds when there is a small increase in deposits for given amount of assets due to $\log(\text{DTA}) = \log(\text{Deposits}) - \log(\text{Assets}) + \log 100$.

We can interpret the aforementioned observation as follows: for given amount of deposits, an increase in the cost of deposits can reduce retained earnings, which not only decreases the amount of shareholder equity but also increases insolvency risk. Therefore, an incentive to raise additional funds through equity capital issuance can arise to protect the shareholder value by reducing insolvency risk. Also, considering that banks compete for deposits in regional markets as shown in Figure 1-2, the cost of deposits can have implications on deposit market competition, determining the amount of deposits. This interpretation is further formalized in econometric models in Section 1.2.4.

Robustness Checks

To show that the cost of deposits and the deposit-to-asset ratio are strong factors to predict equity capital issuance in different environments, we change some independent variables or econometric models. First, we use the return on equity and the tier 1 capital ratio to replace the return on assets and the total capital ratio,

$$X'_{k,t} = \begin{bmatrix} \text{ROE}_{k,t} & \text{Cost of Deposits}_{k,t} & \underbrace{\log(\text{Tier 1 CR}_{k,t-1})}_{\text{BHCA7206 (FR Y-9C)}} & \log(\text{DTA}_{k,t-1}) & \text{Dividend}_{k,t} \end{bmatrix}$$

where $\text{ROE} = \text{Net Income}/\text{Total Equity}$ and the total equity capital is RCON3210 from Call Report. Estimated outcomes are reported in Table B-2. Like our main results, Cost of Deposits_t and $\log(\text{DTA}_{t-1})$

[7] Likewise, we can compute the average marginal effect for the cost of deposits in Column (4). From our computation, it is

are quantitatively important factors to predict equity capital issuance over all different models and sample periods.

Also, we use a different definition of equity capital issuance. With common stock, we add preferred stock to consider total equity capital issuance. Preferred stock is a hybrid concept between debt and common stock since shareholders of preferred stock have a higher claim on dividends than shareholders of common stock, but they usually do not have no or limited, voting rights in corporate governance. The new dependent variable is defined as

$$\begin{aligned}\text{Issuance} = \mathbb{1}\{ &\underbrace{\text{Sale of Common Stock}}_{\text{BHCK3579}} + \underbrace{\text{Conversion or Retirement of Common Stock}}_{\text{BHCK3580}} \\ &\underbrace{\text{Sale of Preferred Stock}}_{\text{BHCK3577}} + \underbrace{\text{Conversion or Retirement of Preferred Stock}}_{\text{BHCK3578}} > 0\}.\end{aligned}$$

Table B-3 shows estimated outcomes from using the new dependent variable. Unlike the main outcomes in Table 1-2, CR_{t-1} is a strong predictor of equity capital issuance. This is because many of distressed or undercapitalized bank holding companies in our sample applied for the Capital Purchase Program (CPP) of the Troubled Asset Relief Program after the financial crisis of 2008. Under CPP, financial institutions could apply for this capital injection in amounts between 1% and 3% of their risk-weighted assets. The capital infusions were implemented through preferred stock issuance in order to be non-dilutive to common shareholders. This is consistent with Bayazitova and Shivdasani (2012) showing that the probability of bank participation in CPP is negatively related to capital adequacy. Also, these bank holding companies were not allowed to pay dividends on common shares while the preferred shares had been repaid, making Divident_t less quantitatively important. Similar to the first two robustness tests, Table B-4 is from using the new independent and dependent variables.

Finally, we add costs of other liabilities: federal funds plus securities to repurchase, subordinated debt, and trading liabilities plus other money. Federal funds are excess reserves held by financial institutions, over and above the mandated reserve requirements set by FRB. For banks, subordinated debt is junior debt that is repaid after depositors are repaid in full. Trading liabilities usually consist of derivative liabilities, the fair value of derivative instruments in a negative position as of the end of the most recent fiscal year end, as recognized and measured in accordance with generally accepted accounting principles. Using Call Report,

1.20% with z-value = 2.72. Also, the average marginal effect for the deposit-to-asset ratio in a logarithmic scale in Column (4) is -11.8% with z-value = -4.68.

we compute the cost of each liability component as

$$\text{Cost of Federal Funds \& Securities} = (\text{RIAD4180})/(\text{RCONB993} + \text{RCONB995})$$
$$\text{Cost of Subordinated Debt} = (\text{RIAD4200})/(\text{RCON3200})$$
$$\text{Cost of Trading Liabilities \& Other Money} = (\text{RIAD4185})/(\text{RCON3190} + \text{RCON3548}).$$

Table B-5 shows that the cost of deposits, among the liabilities of banks, is the only statistically significant factor to predict equity capital issuance.

1.2.4 Regression Analysis II

We use several econometric models to demonstrate (i) whether the rising cost of deposits affects insolvency risk, which is negatively related to the shareholder value of bank holding companies and (ii) whether the rising cost of deposits leads to a gain through deposit market competition. Intuitively, these arguments implies a cost-benefit approach to the cost of deposits. On top of that, since the market for deposits is compartmentalized into smaller regional units, we incorporate the diversification index in equation (1.2) into our econometric models to reflect a comprehensive view on deposit market competition.

Econometric Specification for (i)

We use annualized variables for estimating models since the data for deposit market structure from SOD is annually reported. Therefore, we only consider bank holding companies reported in our sample at least for 3 years in a row without any missing quarter. Considering the following model,

$$\log(\text{Z-Score}_{k,t}) = X'_{k,t}\boldsymbol{\eta} + \theta_k + \delta_t + \epsilon_{k,t} \tag{1.5}$$

where $X_{k,t}$ includes $\log(\text{Z-Score}_{k,t-1})$, Cost of $\text{Deposits}_{k,t}$, $\log(1/\text{DIV}_{k,t-1})$, Cost of $\text{Deposits}_{k,t} \times \log(1/\text{DIV}_{k,t-1})$, $\text{MS}_{k,t-1}$, and $\text{DTA}_{k,t-1}$. The interaction term is included to show how a well-diversified deposit funding base impacts the dependent variable given the same cost of deposits. θ_k is bank fixed effects for removing unobserved heterogeneity among bank holding companies. Similarly, δ_t is time fixed effects for removing unobserved heterogeneity over time.

This model is used to show if the rising cost of deposits affects insolvency risk. Instead of using the shareholder value from financial market data, we use Z-score to capture the probability of default of bank as

[8] Lepetit and Strobel (2015) examine the probabilistic foundation of the link between Z-score measures and banks' probability of insolvency. They find that the log of Z-score is shown to be negatively proportional to the log odds of insolvency.

a proxy for insolvency risk.[8] This is because the market-based value of banks reflects implicit government guarantees, so that our inference would be distorted.[9] Following the World Bank, we define

$$\text{Z-Score}_t = \frac{\overline{\text{ROA}_{(t-1,t)}} + \overline{\text{CR}_{(t-1,t)}}}{\text{STD}\left(\text{ROA}_{(t-1,t)}\right)}$$

where $\overline{x_{(t-1,t)}}$ means the average value between $t-1$ and t. For instance, we use the quarterly data from Call Report to calculate

$$\overline{\text{ROA}_{(2001,2002)}} = \frac{1}{4}\left(\text{ROA}_{2001:\text{Q3}} + \text{ROA}_{2001:\text{Q4}} + \text{ROA}_{2002:\text{Q1}} + \text{ROA}_{2002:\text{Q2}}\right)$$

since deposit market data from SOD reports observations in the middle of each year. We use the fixed effects estimator, also known as the within estimator, to the model in equation (1.5), and compute standard errors with two methods: clustering standard errors by bank holding company to account for serial correlation within each bank, leading to a theoretical distribution, and bootstrapping with 2,500 samples for an empirical distribution.

Econometric Specification for (ii)

Banks competes for deposits by setting deposit rates, so we use deposit market share in equation (2.12) as the dependent variable capturing quantity information. However, unlike $\text{Z-Score}_{k,t}$ in equation (1.3), $\text{MS}_{k,t}$ is measured by stock variables. Since the independent variable of our interest, $\text{Cost of Deposits}_{k,t}$, is a flow variable, we take $\Delta\text{MS}_{k,t} = \text{MS}_{k,t} - \text{MS}_{k,t-1}$ to define the following econometric model

$$\Delta\text{MS}_{k,t} = X'_{k,t}\boldsymbol{\vartheta} + \theta_k + \delta_t + \epsilon_{k,t} \tag{1.6}$$

where we replace $\log(\text{Z-Score}_{k,t-1})$ with $\log(\text{Z-Score}_{k,t})$ in $X_{k,t}$ from equation (1.5). We use the fixed effects estimator to the model in equation (1.6), and compute standard errors with two methods: clustering standard errors by bank holding company and bootstrapping with 2,500 samples.

By moving $\text{MS}_{k,t-1}$ to the right-hand side of equation (1.6), we can use another model to apply a different estimator for a robustness test. In other words, $\text{MS}_{k,t}$ is the dependent variable of the following

[9] For exmaple, Gandhi and Lustig (2015) find that the largest commercial bank stocks, ranked by total size of the balance sheet, have significantly lower risk-adjusted returns than small- and medium-sized bank stocks. They explain that government bailouts in a financial sector can protect shareholders of large banks in disaster states and absorb some of their tail risks. Also, Atkeson, D'Avernas, Eisfeldt, and Weill (2018) demonstrate that the market-to-book ratio of U.S. banks is the sum of franchise value and the value of government bailouts. They find that a large portion of the variation in this ratio over time is due to changes in the value of government bailouts.

model

$$\text{MS}_{k,t} = X'_{k,t}\boldsymbol{\varphi} + \theta_k + \delta_t + \epsilon_{k,t}. \tag{1.7}$$

Since $X_{k,t}$ includes $\text{MS}_{k,t-1}$, this model can be estimated in spirit of Arellano and Bond (1991)

$$\Delta\text{MS}_{k,t} = \Delta X'_{k,t}\boldsymbol{\varphi} + \Delta\delta_t + \Delta\epsilon_{k,t}. \tag{1.8}$$

We use the two-step estimator with GMM-type instrumental variables for the difference equation.[10] Following Windmeijier (2005), standard errors are computed by the Windmeijier biased-corrected (WC) estimator for the robust variance-covariance matrix of two-step GMM estimators.

Results

Table 1-3 shows estimated outcomes. Column (1) and (2) are from the model in equation (1.5). We find that Cost of Deposits$_t$ is not only statistically significant but also quantitatively important to explain change in Z-Score$_t$. For a financial institutions collecting deposits from only one county ($\text{DIV}_t = 1$), an increase of one unit (1%) in Cost of Deposits$_t$ is associated with 24.4% decrease in Z-Score$_t$. Considering the negative correlation between the log of the Z-score and the log odds of insolvency from Lepetit and Strobel (2015), the estimated outcomes from the first two columns in Table 1-3 validate our hypothesis that the rising cost of deposits increases insolvency risk, which can reduce the shareholder value of bank holding companies.

DIV$_t$ conceptually reflects a degree of diversification in a branch network of a bank as we show the branch network evolution of Wells Fargo in Figure 1-3. The impact of ΔCost of Deposits$_t > 0$ on Z-Score$_t$ can be amplified through this network captured by the interaction term, Cost of Deposit$_t \times \log(1/\text{DIV}_t)$. In other words, since $\log(1/\text{DIV}_t) > 0$ and it has a higher value for a bank with a well-diversified branch network, Z-Score$_t$ of this institution decreases by

$$\left(24.4 + 3.9 \times \underbrace{\log(1/\text{DIV})}_{>0}\right)\% > 24.4\%$$

for an increase of one unit in Cost of Deposits$_t$. This outcome implies that the higher cost of deposits can

[10] Let L denote the lag operator such that $LX_t = X_{t-1}$ and $L^2X_t = X_{t-2}$. The instrumental variables include lagged predetermined independent variables produced from L and L^2 and lagged non-predetermined variables produced from L^2 and L^3. The instrumental variables associated with the interaction term is generated by L^2 and L^3 since the cost of deposits is not predetermined.

Table 1-3: Impacts of the Cost of Deposits on Insolvency Risk and Market Share

	(1)	(2)	(3)	(4)	(5)
	log(Z-Score$_t$)	log(Z-Score$_t$)	Δ MS$_t$	Δ MS$_t$	MS$_t$
log(Z-Score$_t$)			0.045^{**}	0.045^{**}	0.019
			(0.019)	(0.020)	(0.097)
log(Z-Score$_{t-1}$)	0.154^{***}	0.154^{***}			
	(0.016)	(0.016)			
Cost of Deposits$_t$	-0.244^{***}	-0.244^{***}	0.445^{***}	0.445^{***}	0.610^{***}
	(0.051)	(0.052)	(0.127)	(0.124)	(0.183)
log(1/DIV$_{t-1}$)	0.123^{**}	0.123^{**}	-0.390^{***}	-0.390^{***}	-1.878^{*}
	(0.061)	(0.061)	(0.121)	(0.120)	(1.048)
Cost of Deposits$_t$ $\times$ log(1/DIV$_{t-1}$)	-0.039^{**}	-0.039^{*}	0.052	0.052	0.070^{*}
	(0.019)	(0.020)	(0.033)	(0.033)	(0.041)
MS$_{t-1}$	0.002	0.002	-0.293^{***}	-0.293^{***}	0.649^{***}
	(0.005)	(0.005)	(0.021)	(0.020)	(0.059)
DTA$_{t-1}$	0.002	0.002	-0.016^{**}	-0.016^{**}	0.002
	(0.003)	(0.004)	(0.008)	(0.008)	(0.012)
Bank FE	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	Yes
STD	Cluster	Bootstrap	Cluster	Bootstrap	WC-Robust
R-Squared	0.235	0.235	0.160	0.160	
Observations	10,761	10,761	12,588	12,588	10,761

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, and standard errors are in parentheses.

Note: Column (1) and (2) are from the model in equation (1.5), whereas Column (3) and (4) are from the model in equation (1.6). We use the fixed effects estimator to estimate the models. We compute standard errors with two methods: clustering standard errors by bank holding company to account for serial correlation within each bank, leading to a theoretical distribution, and bootstrapping with 2,500 samples for an empirical distribution. Column (5) is the model in equation (1.8) as a robustness check for the model in equation (1.6). This model is estimated by following Arellano and Bond (1991)and standard errors are computed by the Windmeijier biased-corrected (WC) estimator for the robust variance-covariance matrix of two-step GMM estimators. Also, the estimated model in Column (5) presents strong evidence against the null hypothesis of zero autocorrelation in the first-differenced errors at order 1, which means that the idiosyncratic errors in equation (1.8) are independent and identically distributed.

become more detrimental to insolvency risk through a well-diversified branch network.

On the other hand, having a well-diversified deposit funding base can reduce insolvency risk when

Cost of Deposits_t is relatively low. For example, when Cost of Deposits_t is equal to 1%, 1% increase in $1/\text{DIV}_t$, which is equivalent to a better-diversified deposit funding base, is associated with

$$\frac{\partial \log(\text{Z-Score}_{k,t})}{\partial \log(1/\text{DIV}_{k,t})}|_{\text{Cost of Deposits}_{k,t}=1} = \hat{\eta}_3 + 1 \times \hat{\eta}_4 = 0.123 - 1 \times 0.039 = 0.084\%$$

increase in Z-Score_t. This shows a positive aspect of collecting deposits from a well-diversified deposit funding base. However, if Cost of Deposits_t is high, having a better-diversified branch network could increase insolvency risk through the interaction term. For instance, when Cost of Deposits_t is equal to 5%, 1% increase in $1/\text{DIV}_t$ is associated with

$$\frac{\partial \log(\text{Z-Score}_{k,t})}{\partial \log(1/\text{DIV}_{k,t})}|_{\text{Cost of Deposits}_{k,t}=1} = \hat{\eta}_3 + 5 \times \hat{\eta}_4 = 0.123 - 5 \times 0.039 = -0.072\%$$

change in Z-Score_t. This reconfirms the potential drawback of having a wide-spread branch network to collect deposits in more regions when the cost of deposits is higher.

Column (3) and (4) are from the model in equation (1.6), whereas Column (5) is from the model in equation (1.8). In both econometric models, an increase in the cost of deposits is associated with a positive outcome on deposit market share. In Column (3) and (4), for instance, an increase of one unit in Cost of Deposits_t leads a bank to get an additional 0.445% increase in ΔMS_t, deposit market share increment. Also, in Column (5), an increase of one unit in Cost of Deposits_t is associated with an increase in MS_t by 0.610%.[11]This demonstrates that banks can achieve higher deposit market share by spending more on competing for deposits. However, this gain from deposit market competition would diminish if a bank competes for deposits through a well-diversified branch network. Therefore, Table 1-3 shows that having a well-diversified deposit funding base has benefit, the buffer for Z-score under the low cost of deposits, and cost, the reduction in deposit market share increment or even in deposit market share itself.

As a robustness check, we estimate the econometric models in equation (1.5), (1.6), and (1.8) with the sample used for Table 1-2. This is because bank holding companies with the constant dependent variable (always issuing or not issuing) are excluded for the logit and probit models with two-way fixed effects in equation (1.3), but these institutions are included for the models in Table 1-3. Table B-6 shows estimated outcomes from the same sample used for Table 1-2. The results are qualitatively as well as quantitatively similar to Table 1-3.

[11] We check that the estimated model in equation (1.8) presents strong evidence against the null hypothesis of zero autocorrelation in the first-differenced errors, $\Delta\epsilon_{k,t}$, at order 1. This means that the idiosyncratic errors in equation (1.7) are independent and identically distributed.

1.2.5 Reverse Causality Tests

From Section 1.2.3 and 1.2.4, we demonstrate that the rising cost of deposits increases insolvency risk of bank holding companies, which leads to the higher chance of raising additional funds through equity capital issuance to protect the shareholder value of financial institutions. Also, depending on a level of the cost of deposits, this negative impact can be amplified or reduced through branch networks. Therefore, the empirical outcomes give us the intuitive causal relationship between the cost of deposits and equity capital issuance. To justify our conclusion, we implement a couple of simple reverse causality tests.

Econometric Specification

To make consistency of the sample used in our analysis, we use the identical composition of bank holding companies included in Table 1-2 to guarantee variations in $\text{Issuance}_{k,t}$ for each institution over time. Consider the following model,

$$\text{Cost of Deposits}_{k,t} = \nu_0 + \nu_1 \text{Issuance}_{k,t} + \nu_2 \log(\text{DTA}_{k,t-1}) + \theta_k + \delta_t + \epsilon_{k,t} \tag{1.9}$$

where θ_k is bank fixed effects for removing unobserved heterogeneity among bank holding companies. Similarly, δ_t is time fixed effects for removing unobserved heterogeneity over time. If the estimated value of the coefficient associated with $\text{Issuance}_{k,t}$ is statistically equivalent to zero, we can confirm that the rising cost of deposits causes the higher probability of equity capital issuance, not the other way. We use the fixed effects estimator to the model in equation (1.9), and compute standard errors with two methods: clustering standard errors by bank holding company and bootstrapping with 2,500 samples.

In addition to that, we use a different version of equation (1.9) to do a reverse causality test with a different estimator. Specifically, we estimate the following model

$$\begin{aligned}\text{Cost of Deposits}_{k,t} = \upsilon_0 + \upsilon_1 \text{Issuance}_{k,t} + \upsilon_2 \text{Cost of Deposits}_{k,t-1} \\ + \upsilon_3 \log(\text{DTA}_{k,t-1}) + \theta_k + \delta_t + \epsilon_{k,t}\end{aligned} \tag{1.10}$$

by using the two-step estimator with GMM-type instrumental variables including lagged deposit-to-asset ratios from L^2 to L^5 and lagged cost of deposits and equity capital issuance from L^3 to L^6 for the difference equation. Standard errors are computed by the Windmeijier biased-corrected (WC) estimator for the robust variance-covariance matrix of two-step GMM estimators.

Table 1-4: Reverse Causality Tests

	(1) Cost of Deposits$_t$	(2) Cost of Deposits$_t$	(3) Cost of Deposits$_t$
Issuance$_t$	0.010	0.010	0.023
	(0.009)	(0.009)	(0.022)
Cost of Deposits$_{t-1}$			0.863^{***}
			(0.014)
log(DTA$_{t-1}$)	0.402^{***}	0.402^{***}	0.251
	(0.112)	(0.116)	(0.154)
Model	Simple Panel	Simple Panel	Dynamic Panel
Bank FE	Yes	Yes	
Time FE	Yes	Yes	Yes
STD	Cluster	Bootstrap	WC-Robust
Sargan Test			Valid IVs
Arellano–Bond Test			I.I.D. Errors
R-Squared	0.893	0.893	
Observations	36,770	36,770	35,720

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, and standard errors are in parentheses.

Note: Column (1) and (2) are from the model in equation (1.9) estimated by the fixed effects estimator. We compute standard errors with two methods: clustering standard errors by bank holding company and bootstrapping with 2,500. Column (3) from the model in equation (1.10) estimated by following Arellano and Bond (1991)and standard errors are computed by the Windmeijier biased-corrected (WC) estimator for the robust variance-covariance matrix of two-step GMM estimators. The estimated model in Column (3) presents strong evidence against the null hypothesis of zero autocorrelation in the first-differenced errors at order 1, which means that the idiosyncratic errors in equation (1.8) are independent and identically distributed. Also, the null hypothesis of the Sargan test is not rejected, which supports the validity of the instrumental variables in the the two-step estimator.

Results

Table 1-4 shows that equity capital issuance is not statistically significant to explain the cost of deposits. This reaffirms our conclusion on the causal direction from the cost of deposits to equity capital issuance. For Column (3), we check that the estimated model presents strong evidence against the null hypothesis of zero autocorrelation in the first-differenced errors, $\Delta\epsilon_{k,t}$, at order 1. This means that the idiosyncratic errors in equation (1.10) are independent and identically distributed. Also, the estimated model in Column (3) shows that the overidentifying restrictions are valid, which means that the null hypothesis of the Sargan test is not rejected. This result supports the validity of the instrumental variables in the the two-step estimator.

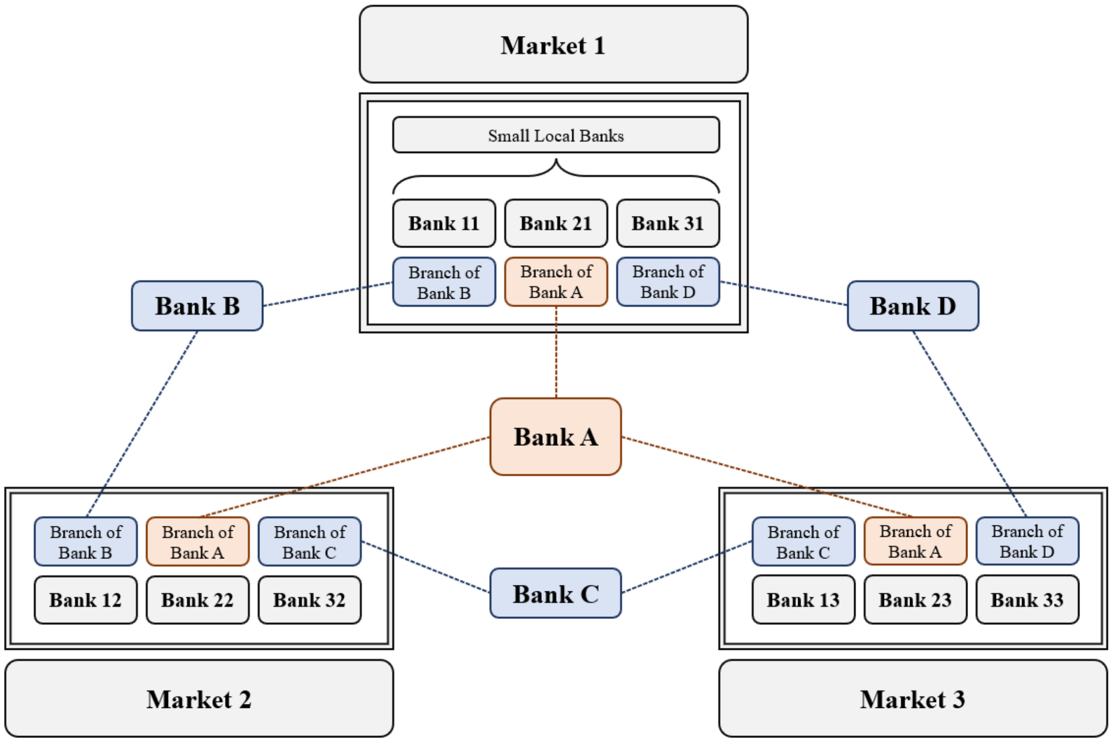


Figure 1-4: Deposit Market Structure

1.3 Model

In this section, we develop a banking industry model to show how deposit market competition can affect equity capital issuance. This give us further explanation on the outcomes from Section 1.2 with a theoretical perspective. Our model is an extended version of Egan, Hortacsu, and Matvos (2017) by incorporating multiple regional markets into deposit competition. However, unlike Egan, Hortacsu, and Matvos (2017) where banks compete for insured deposits and uninsured deposits, our model dose not differentiate between two deposit products, which means that there is only one type of deposits available to depositors in our model.

The deposit market structure in our benchmark model is described in Figure 1-4. There are three regional deposit markets: Market 1, Market 2, and Market 3. Depending on how many regional markets they are operating branches to collect deposits, there are three types of banks. Defined as a big bank holding company, Bank A operates branches in all three regional markets. Defined as medium bank holding companies, Bank B, Bank C, and Bank D operate branches in two regional markets. For example, Bank B has branches in Market 1 and Market 2 while Bank C has branches in Market 2 and Market 3. Therefore, we can consider that Bank A has a more diversified deposit funding base than the medium ones. Finally, there are three small

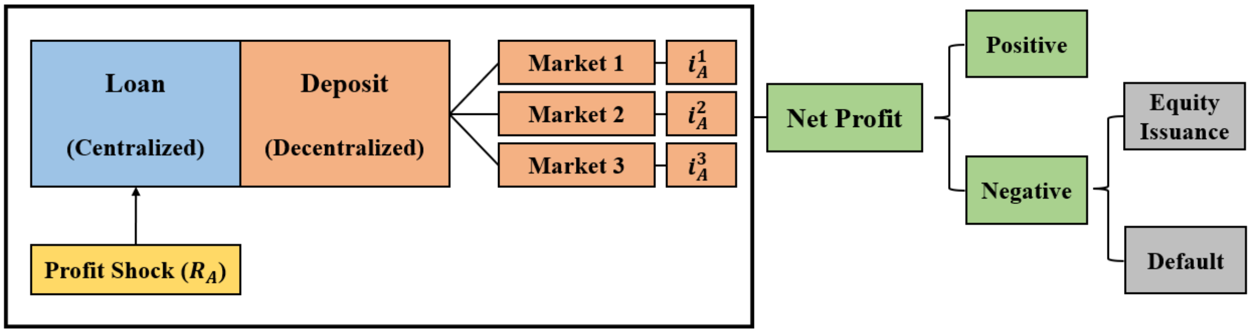


Figure 1-5: Model Environment of Bank A

bank holding companies in each regional market. Each small financial institution collects deposits from only one regional market. For a notational purpose, we put two digits into small banks. The first digit denotes a distinctive identity of small banks in each regional market and the second digit shows a regional market in which they are competing for deposits. As a result, there are six institutions in each regional market to compete for deposits. This model setup is chosen to be matched with the empirical observation in Section 1.2 that the average county-level deposit market share from our full sample period is approximately 15.8%.

The model is in discrete time. The timing of events within a period is as follows:

- Banks determine deposit rates of regional markets where they operate branches to collect deposits. We define i_k^m as a deposit rate set by Bank k in Market m. From Figure 1-4, Bank A sets deposit rates i_A^1, i_A^2, and i_A^3, whereas Bank B sets deposit rates i_B^1 and i_B^2.

- Depositors in each regional market choose where to save their funds.

- Banks invest deposits into loan projects, and profit shocks are realized. For Bank k, we define R_k as its profit shock.

- If a realized net profit is positive, Bank k can repay its deposit debt. Otherwise, Bank k can choose whether to issue equity capital or default.

To summarize, Figure 1-5 illustrates the model environment of Bank A.

1.3.1 Depositor Preference

Let $\mathcal{M}_k$ represent a set of regional markets where Bank k operates branches to collect deposits. For instance, $\mathcal{M}_A = \{\text{Market 1}, \text{Market 2}, \text{Market 3}\}$, whereas $\mathcal{M}_B = \{\text{Market 1}, \text{Market 2}\}$. We assume that $\mathcal{M}_k$ is exogenously given for each $k \in \mathcal{K} = \{A, B, C, D, 11, ..., 33\}$. In other words, we do not consider market entry-exit decisions of banks in our model.

For each regional market, there are depositors whose total funds are assumed to be one. A depositor has to decide whether to save her wealth in banks, and if so, in which one. In spirit of Hotelling (1929) and Salop (1979), depositors in Market 1 only take into account banks with operating branches in Market 1 because of transportation costs.[12] Therefore, banks can attract deposits only in regional markets where they operate branches. These banks provide differentiated deposit services and the indirect utility for depositor n living in Market m from saving her wealth in Bank k at time t is defined as follows (Market $m \in \mathcal{M}_k$):

$$u_{n,k,t}^{m} = \alpha i_{k,t}^{m} + \beta \rho_{k,t} + \varepsilon_{n,k,t}^{m} \tag{1.11}$$

where $i_{k,t}^{m}$ is the deposit rate set by Bank k which operates its branch in Market m at time t, and $\alpha > 0$ is the marginal utility of income. Also, we assume that depositors care about banks' default probabilities denoted by $\rho_{k,t}$. Even insured depositors can be concerned about an insolvency risk of banks since they need to find and switch to a new bank although the depositors could receive their funds from FDIC upon failure of banks. For example, according to FDIC, if a failed bank is acquired, all direct deposits, including Social Security payments, will automatically be re-directed to deposit accounts at the acquiring bank. However, if there is a competing option available to insured depositors in their regional market, they should close the deposit accounts at the acquiring bank and open new accounts at a different bank, leading to a switching cost. $\beta < 0$ captures the marginal disutility of default risks. The term $\varepsilon_{n,k,t}^{m}$ represents an idiosyncratic preference of depositor n living in Market m and choosing Bank k at time t. We assume that $\varepsilon_{n,k,t}^{m}$ is independently and identically distributed across markets, banks, and time with the Type I extreme value distribution following Berry, Levinsohn, and Pakes (1995). We normalize the utility from an outside alternative (for example, credit unions or saving institutions) to zero.

1.3.2 Profit Function

We consider a traditional problem of maximizing shareholder value. Suppose that bank managers have a well-aligned incentive with the interest of shareholders, so there is no agency conflict. Bank k's problem at time t is described as a two-part decision process:

(i) setting its deposit rates over regional markets ($i_{k,t}^{m}$ only for $m \in \mathcal{M}_k$) and

(ii) deciding to continue its business or declare bankruptcy.

[12] Honka, Hortacsu, and Vitorino (2017) show evidence of the importance of regional branch existence for the depositors' decision to open new bank accounts. More recently, Abrams (2019) also shows that depositors are attentive to which banks are

Banks earn profits by lending out deposits through loan investment. Bank k earns $R_{k,t}$ on deposits at time t. Conceptually, $R_{k,t}$ includes costs for loan defaults, screening and monitoring loans, and providing other services to depositors. This stochastic return specific to Bank k is independently and identically distributed across time as $R_{k,t} \sim N(\mu_k, \sigma_k)$.[13] If Bank k invests deposits in a bad loan portfolio, $R_{k,t}$ can turn out to be negative. To focus on a deposit competition mechanism, our model omits a risk choice of banks in loan investment. Since each bank has a different distribution of stochastic returns and this return is not serially correlated over time, some banks are better at investing deposits than others. This difference is persistent in our model. It arises because some banks have a better screening or monitoring technology or because some banks have relationship-based lending with a pool of more creditworthy borrowers.

Bank k whose market share of deposits is $\{s^m_{k,t}\}_{m\in\mathcal{M}_k}$ earns a gross return on deposits of

$$\sum_{m\in\mathcal{M}_k} s^m_{k,t}(1+R_{k,t}) = D_{k,t}(1+R_{k,t}), \tag{1.12}$$

where $D_{k,t} = \sum_{m\in\mathcal{M}_k} s^m_{k,t}$ denotes the total amount of deposits. A profit of Bank k is reduced by costs on deposit debt financing. Bank k has to repay deposits at the cost of

$$\sum_{m\in\mathcal{M}_k} s^m_{k,t}(1+i^m_{k,t}). \tag{1.13}$$

We implement capital requirements by requiring shareholders to invest a κ share of deposits in each period, leading to a capital ratio of $\omega = \kappa/(1+\kappa)$. This additional capital is invested along with deposits and is lost under bankruptcy, which is conceptually consistent with Basel II regime. Therefore, if a bank wants to collect more deposits, its shareholders should provide more equity capital. The net period profit of Bank k is then

$$\begin{aligned}\pi_{k,t} &= \sum_{m\in\mathcal{M}_k} s^m_{k,t}\left(R_{k,t} - i^m_{k,t}\right) + \kappa \sum_{m\in\mathcal{M}_k} s^m_{k,t}(R_{k,t} - r) \\ &= (1+\kappa)D_{k,t}R_{k,t} - \sum_{m\in\mathcal{M}_k} s^m_{k,t}(i^m_{k,t} + \kappa r) \end{aligned} \tag{1.14}$$

where r is the cost of capital conceptually equivalent to the risk-free rate.[14] In each period, Bank k disburses

present in their regions.

[13] These profit shocks can be arbitrarily correlated among banks, which can generate an equilibrium outcome where there is a systematic banking crisis.

[14] When the additional capital is invested in the risk-free assets, the net period profit of Bank k is

$$\pi_{k,t} = \sum_{m\in\mathcal{M}_k} s^m_{k,t}\left(R_{k,t} - i^m_{k,t}\right) + \kappa \sum_{m\in\mathcal{M}_k} s^m_{k,t}(r-r) = D_{k,t}R_{k,t} - \sum_{m\in\mathcal{M}_k} s^m_{k,t} i^m_{k,t}.$$

$\pi_{k,t}$ to its shareholders after paying depositors if $\pi_{k,t}$ is positive. On the other hand, Bank k is suffering operating losses in a given period if $\pi_{k,t}$ is negative. In this case, bank equity holders can decide whether to issue more equity capital (equivalent to injecting more funds) for repaying its deposit debt or to declare bankruptcy. We assume that bank equity holders are deep-pocket following Leland (1994). However, we assume that there are no direct costs of bankruptcy to simplify our model and focus on how deposit market competition can affect equity capital issuance.

1.3.3 Equilibrium

We study pure strategy Bayesian Nash equilibria. The equilibrium is characterized by the optimal behavior of banks and depositors in the model.

- Banks choose to default optimally given realized profit shocks, $R_{k,t}$.
- Depositors are fully rational, anticipating probabilities of default, $\rho_{k,t}$, and incorporate this belief when choosing where to save their funds.
- Banks choose optimal deposit rates, $\{i^m_{k,t}\}_{m \in \mathcal{M}_k}$, given demand for deposits.

In the event of bankruptcy, a failed bank is placed under new ownership with the same deposit funding base. The equilibrium of this game is stationary since the profit shock is independently and identically distributed across time. Therefore, the default decision problem is simplified in a tractable manner because a bank's decision to declare bankruptcy after a bad profit shock is independent of default decision problems of other banks. In this stationary equilibrium, banks compete with each other for deposits within periods, but not across periods. Hence, banks use the same deposit rate pricing and bankruptcy decisions in each period.

Deposit Demand

Given the distribution of $\varepsilon^m_{n,k,t}$ in equation (1.11), we employ a standard assumption in discrete choice models following Berry, Levinsohn, and Pakes (1995) to aggregate the depositor utility. With offered deposit rates and given belief in default probabilities, we derive the following demand function for deposits of Bank k in Market m:

$$s^m_{k,t}(i^m_{k,t}, \mathbf{i}^m_{-k,t}) = \frac{\mathbb{1}\{m \in \mathcal{M}_k\} \cdot \exp\left(\alpha i^m_{k,t} + \beta \rho_{k,t}\right)}{1 + \sum_{k \in \mathcal{K}} \mathbb{1}\{m \in \mathcal{M}_{k,t}\} \cdot \exp\left(\alpha i^m_{k,t} + \beta \rho_{k,t}\right)} \tag{1.15}$$

This version of capital requirements reflects Basel III regime.

where $\mathbb{1}\{\cdot\}$ is an indicator function such that $\mathbb{1}\{m \in \mathcal{M}_k\}$ indicates whether Bank k has a branch in Market m. Because depositors have rational expectations, their belief in default probabilities is correct in equilibrium.

Default Choice

Bank shareholders endogenously choose whether to default or not in our model. A bank does not declare bankruptcy simply due to a bad profit shock. If the market value of a distressed bank is high enough, shareholders of the bank can raise more equity capital to finance its business even after bad profit shocks. On the other hand, a distressed bank decides to default when its market value is lower than the amount of additional funds which shareholders of the bank should issue to support the business. Therefore, if the gross return of Bank k is lower than the required payment to its depositors after $R_{k,t}$ is realized,

$$D_{k,t}(1+R_{k,t}) + \kappa D_{k,t}(R_{k,t}-r) < \sum_{m\in\mathcal{M}_k} s^m_{k,t}(1+i^m_{k,t}),$$

shareholders of the bank have to provide additional funds through equity capital issuance to make up the shortfall to finance the bank,

$$D_{k,t}R_{k,t} + \kappa D_{k,t}(R_{k,t}-r) - \sum_{m\in\mathcal{M}_k} s^m_{k,t} i^m_{k,t} < 0.$$

Because banks are protected by limited liability in our model, shareholders can decide not to finance a shortfall, and let a distressed bank default. If a bank defaults, shareholders of the bank lose their claim to cash flows from the next period onward since they do not own the franchise. Let $E_{k,t+1}$ denote the market value of Bank k at time $t+1$. Therefore, shareholders of Bank k choose to support the bank as long as the value of staying in business is higher than the cost of default,

$$\underbrace{D_{k,t}R_{k,t} + \kappa D_{k,t}(R_{k,t}-r) - \sum_{m\in\mathcal{M}_k} s^m_{k,t} i^m_{k,t} + \frac{1}{1+r}E_{k,t+1}}_{\text{value of staying in business}} > -\kappa D_{k,t}.$$

Since we assume $R_{k,t}$ is independently and identically distributed across time, the above expression implies a cutoff strategy for the default decision of Bank k. In other words, if $R_{k,t}$ is below a certain level defined as $\overline{R}_k$, shareholders of Bank k will not issue additional equity capital and the bank will declare bankruptcy. If $R_{k,t}$ is above $\overline{R}_k$, shareholders of Bank k will choose to repay depositors by issuing additional equity capital and the bank will keep operating business in the next period. Therefore, $\overline{R}_k$ is implicitly defined as the bank profit shock at which its shareholders are indifferent between declaring bankruptcy and issuing additional equity capital,

$$D_{k,t}R_{k,t} + \kappa D_{k,t}(R_{k,t} - r) - \sum_{m \in \mathcal{M}_k} s_{k,t}^m i_{k,t}^m + \frac{1}{1+r}E_{k,t+1} = -\kappa D_{k,t}.$$

With the distributional assumption on $R_{k,t}$, we define a default probability of Bank k at time t

$$\rho_{k,t} = \Phi\left(\frac{R_{k,t} - \mu_k}{\sigma_k}\right),$$

where $\Phi(a) = \Pr(x > a)$ and x is the standard normal random variable. Following Egan, Hortacsu, and Matvos (2017), the optimal cutoff rule is directly related to the default probability

$$\kappa D_{k,t} - \underbrace{\left(D_{k,t}\overline{R}_k + \kappa D_{k,t}(\overline{R}_k - r) - \sum_{m \in \mathcal{M}_k} s_{k,t}^m i_{k,t}^m\right)}_{\text{shortfall}} \tag{1.16}$$
$$= \frac{1}{1+r}\left[-\kappa D_{k,t} + (1+\kappa)D_{k,t}\underbrace{\left(1 - \Phi\left(\frac{\overline{R}_k - \mu_k}{\sigma_k}\right)\right)}_{\text{survival probability}}\underbrace{\left((\mu_k - \overline{R}_k) + \underbrace{\sigma_k\lambda\left(\frac{\overline{R}_k - \mu_k}{\sigma_k}\right)}_{\text{limited liability}}\right)}_{\text{expected return on deposits}}\right]$$

where $\lambda(\cdot) \equiv \phi(\cdot)/\left(1 - \Phi(\cdot)\right)$ is the inverse Mills ratio. $\overline{R}_k$ is unique for a given deposit rate choice of Bank k, depositors' saving choices leading to equilibrium deposit market share derived in equation (1.15), and the market value of the bank to its shareholders. On the other hand, these choices are determined in equilibrium with expectation of the bank's default strategy, $\overline{R}_k$.

The left-hand side of equation (1.16) is the amount of equity capital that shareholders have to issue at the default threshold. The capital requirements play an important role as a buffer since it allows shareholders to raise additional funds less than the actual shortfall to finance a distressed bank. The right-hand side of equation (1.16) represents the discounted future value of the bank in equilibrium, which depends on the regulatory cost, the equilibrium survival probability, and the expected return on deposits. A portion of the future value for shareholders comes from their ability to declare bankruptcy in the future. Therefore, the term associated with limited liability can be understood as value of exercising the default option.

An important result from the bankruptcy cutoff condition is the possibility of multiple equilibria. Depositors are concerned about default probabilities of banks in equation (1.11) and bank net profits depend on deposits in equation (1.14), so there is a potential feedback loop. For example, a decrease in demand for deposits of Bank k makes the bank increase deposit rates to collect more deposits, leading to a worse level of net profits. This can raise the default probability of Bank k and this makes deposits of Bank k less attractive. This feedback loop can make depositors' belief in the default probability of Bank k self-fulling. This nature of the optimal decisions is applied to find a fixed-point in our solution algorithm.

Deposit Pricing

The financial institutions in the model compete for deposits by playing a differentiated product Bertrand-Nash price setting game in each regional market. At the start of each period, given information on the demand for deposits in equation (1.15), banks optimally determine deposit rates for regional markets where they are operating branches to maximize the expected return to shareholders. Due to limited liability, shareholders consider payoffs only if $R_{k,t}$ is realized above $\overline{R}_k$. Therefore, the market value of equity at the beginning of time t is

$$\begin{aligned}E_{k,t} = \max_{\{i^m_{k,t}\}_{m\in\mathcal{M}_k}} \int_{\overline{R}_k}^{\infty} \left[(1+\kappa)D_{k,t}R_{k,t} - \sum_{m\in\mathcal{M}_k} s^m_{k,t}(i^m_{k,t}, \mathbf{i}^m_{-k,t})(i^m_{k,t} + \kappa r) + \frac{E_{k,t+1}}{1+r}\right] dF(R_{k,t}) \\ - \int_{-\infty}^{\overline{R}_k} \kappa \underbrace{\sum_{m\in\mathcal{M}_k} s^m_{k,t}(i^m_{k,t}, \mathbf{i}^m_{-k,t})}_{D_{k,t}} dF(R_{k,t})\end{aligned}$$

where the second integral reflects the expect loss to the shareholders of the bank under bankruptcy. Applying the normal distribution of $R_{k,t}$ and the stationarity of $E_{k,t}$, we obtain

$$\begin{aligned}E_{k,t} = \max_{\{i^m_{k,t}\}_{m\in\mathcal{M}_k}} \left(1 - \Phi\left(\frac{\overline{R}_k - \mu_k}{\sigma_k}\right)\right) \left((1+\kappa)D_{k,t}\left(\mu_k + \sigma_k \lambda\left(\frac{\overline{R}_k - \mu_k}{\sigma_k}\right)\right)\right. \\ \left. - \sum_{m\in\mathcal{M}_k} s^m_{k,t}(i^m_{k,t}, \mathbf{i}^m_{-k,t})(i^m_{k,t} + \kappa r) + \frac{E_{k,t}}{1+r}\right) - \Phi\left(\frac{\overline{R}_k - \mu_k}{\sigma_k}\right) \kappa D_{k,t}.\end{aligned}$$

The choice of deposit rates can affect the market value of equity through its influence on the current period operating profit in equation (1.14) and the bankruptcy threshold $\overline{R}_k$ in equation (1.16). Because shareholders choose to default optimally, we can apply the envelope theorem,

$$\frac{\partial}{\partial i^m_{k,t}} \Phi\left(\frac{\overline{R}_k - \mu_k}{\sigma_k}\right) = 0 \;\text{ for all }\; m \in \mathcal{M}_k. \tag{1.17}$$

Therefore, by using equation (1.15) and (1.17), the first order condition characterizing the optimal deposit pricing is regional market m is

$$\left(1-\Phi\left(\frac{\overline{R}_k-\mu_k}{\sigma_k}\right)\right)\left(\underbrace{(1+\kappa)\left(\mu_k+\sigma_k\lambda\left(\frac{\overline{R}_k-\mu_k}{\sigma_k}\right)\right)}_{\text{marginal benefit}}-\underbrace{(i^m_{k,t}+\kappa r)}_{\text{marginal cost}}\right)-\Phi\left(\frac{\overline{R}_k-\mu_k}{\sigma_k}\right)\kappa$$
$$=\left(1-\Phi\left(\frac{\overline{R}_k-\mu_k}{\sigma_k}\right)\right)\underbrace{\frac{1}{\alpha(1-s^m_{k,t}(i^m_{k,t},\mathbf{i}^m_{-k,t}))}}_{\text{mark-up}}. \tag{1.18}$$

This condition is similar to a typical oligopoly Bertrand-Nash pricing condition. The marginal benefit of deposits is the same across regional markets since they are used to finance the same loan investment. This is reflected in the term in the left-hand side of equation (1.18) invariant to m. Therefore, the optimal deposit rates can be distinctive across regions for banks collecting deposits from multiple regional markets because of different equilibrium market share. Intuitively, a bank can provide a higher deposit rate in a region since it has lower market share in the region.

Equilibrium

The pure strategy Bayesian Nash equilibria are characterized by the following conditions that describe the optimal behavior of banks and depositors. Demand for deposits is characterized by the choice of depositors on banks in equation (1.15) for each bank in each regional market. Depositors anticipate default risks of banks, and take into account their belief when choosing where to save their wealth. Supply of deposits is characterized by the optimal choices of bank shareholders. Each bank sets deposit rates to maximize the market value of equity, so equation (1.18) holds for each bank in each regional market. Also, banks choose to default optimally given a profit shock to loan investment, so equation (1.16) holds for each bank. Finally, depositors have rational expectations, so their belief is correct in equilibrium. These equilibrium conditions form a foundation of our estimation and calibration.

1.4 Calibration and Estimation

1.4.1 Calibration of Supply Parameters

In our benchmark model, we have one big bank (Bank A), three medium banks (Bank B, Bank C, and Bank D), and nine small banks as depicted in Figure 1-4. Banks optimally set deposit rates and choose whether to default. For simplicity, we assume that all banks in the model have the same deposit rate denoted by i_{ss} and default probability denoted by ρ_{ss} in a steady state. Using RateWatch from S&P Global Market Intelligence, we calculate i_{ss} based on a certificate of deposit with one year maturity and $\$10,000$ minimum savings from 2001 to 2010. We also calculate the cost of deposits from Call Report for the same period. From these calculations, we set $i_{ss} = 0.025$. ρ_{ss} is set based on the annual exit rate in the U.S. banking industry from 2001 to 2010 and Audrino, Kostrov, and Ortega (2019). As a result, we get $\rho_{ss} = 0.025$. Finally, we set $\omega = 0.04$ from Basel II regime and $r = 0.01$ as the risk-free rate.

For each bank, we analytically derive two parameters, μ_k and σ_k, from the optimal behavior of banks in the model. Since the default probability is endogenously determined as the optimal default strategy,

$$\rho_{ss} = \Phi\left(\frac{\overline{R}_k - \mu_k}{\sigma_k}\right). \tag{1.19}$$

This expression is inverted to obtain the normalized endogenous bankruptcy cutoff,

$$\frac{\overline{R}_k - \mu_k}{\sigma_k} = \Phi^{-1}(\rho_{ss}). \tag{1.20}$$

We start with the bankruptcy condition from equation (1.16) showing that shareholders of Bank k is indifferent between staying in business and defaulting. Using equation (1.19) and (1.20), equation (1.16) becomes

$$\begin{aligned} & \left[(1+\kappa)(\mu_k + \sigma_k\Phi^{-1}(\rho_{ss})) - i_{ss} - \kappa r - \kappa\right] \underbrace{n(\mathcal{M}_k)\overline{s}}_{D_{k,t}} \\ = \; & \frac{1}{1+r}\left[\kappa + \sigma_k(1+\kappa)\left(1-\rho_{ss}\right)\left(\Phi^{-1}(\rho_{ss}) - \lambda\left(\Phi^{-1}(\rho_{ss})\right)\right)\right] n(\mathcal{M}_k)\overline{s} \end{aligned} \tag{1.21}$$

where $n(\mathcal{M}_k)$ is the number of regional markets in which Bank k operates branches to collect deposits. With i_{ss} and ρ_{ss}, $\overline{s}$ is from equation (1.15), which is a function of the demand-side parameters, α and β. Similarly, equation (1.18) becomes

$$(1-\rho_{ss})\left((1+\kappa)\left(\mu_k + \sigma_k\lambda\left(\Phi^{-1}(\rho_{ss})\right)\right) - i_{ss} - \kappa r\right) - \rho_{ss}\kappa = \frac{(1-\rho_{ss})}{\alpha(1-\overline{s})}. \tag{1.22}$$

Using equation (1.21) and (1.22),

$$\sigma_k = \frac{\dfrac{1}{\alpha(1-\overline{s})} + \left(\dfrac{\rho_{ss}}{1-\rho_{ss}}\right)\kappa - (2+r)\kappa}{(1+r)(1+\kappa)(r+\rho_{ss})(\lambda\left(\Phi^{-1}(\rho_{ss})\right) - \Phi^{-1}(\rho_{ss}))} \tag{1.23}$$

$$\mu_k = \frac{1}{1+\kappa}\left(i_{ss} + \kappa r + \frac{1}{\alpha(1-\overline{s})} + \left(\frac{\rho_{ss}}{1-\rho_{ss}}\right)\kappa\right) - \sigma_k \lambda\left(\Phi^{-1}(\rho_{ss})\right). \tag{1.24}$$

Since $\overline{s}$ is a function of α and β, the supply-side parameters are determined once the demand-side parameters are estimated. Also, these two parameters are same for all banks in the model. In other words, Bank A in Figure 1-4 does not have an advantage in its asset-side as a big bank. Therefore, banks in our model have the unique source of heterogeneity only in their liability-side, the number of regional markets in which they compete for deposits. One intuitive outcome with $\alpha > 0$ and $0 < \overline{s} < 1$ is

$$\frac{\partial}{\partial \kappa}\sigma_k \propto \left(\frac{\rho_{ss}}{1-\rho_{ss}} - 2 - r - \frac{1}{\alpha(1-\overline{s})}\right) < 0,$$

which means the return on loan investment becomes less volatile as the capital requirements get more restrictive. Therefore, our model conceptually reflects a traditional implication of capital requirements on riskiness of loan portfolios.

1.4.2 Estimation of Demand Parameters

We use the simulated method of moments to estimate α and β in equation (1.11). These two demand parameters determine the supply parameters from equation (1.23) and (1.24) through the mark-up term. We define two-dimensional parameter space,

$$(\alpha, \beta) \in [0.5, 1, ..., 49.5, 50] \times [-20, -19.5, ..., -0.5, 0],$$

to solve the model 50,000 times for each pair of (α, β) to obtain three moments: default rates, equity issuance rates, and deposit rates. The parameter space is designed to be consistent with empirical estimates in Table 3 from Egan, Hortacsu, and Matvos (2017). The empirical moments for default rates and deposit rates are both set by 0.025, which is from $\rho_{ss} = 0.025$ and $i_{ss} = 0.025$. The empirical moment for equity issuance rates is redefined from the dependent variable from 2001:Q1 to 2014:Q4 in Table 1-2 to exclude an effect of dividend payments on equity capital issuance,

$$\text{Issuance} = \mathbb{1}\{\underbrace{\text{Sale of Common Stock}}_{\text{BHCK3579}} + \underbrace{\text{Conversion or Retirement of Common Stock}}_{\text{BHCK3580}} \\ - \underbrace{\text{Cash Dividends Declared on Common Stock}}_{\text{BHCK4460}} > 0\},$$

and the estimated value is 0.41.

For each (α, β) in the parameter space, we solve the model as follows:

- Using the pre-determined parameters, we get σ_k and μ_k from equation (1.23) and (1.24). A return shock is generated from $N(\mu_k, \sigma_k)$ for each bank to define an initial default probability. Also, the initial deposit rate is defined as $i_{ss} = 0.025$ for all banks.

- Using equation (1.15), we calculate deposit market share and use these into equation (1.18) to get $\overline{R}_k$. Since we use i_{ss} as the optimal pricing decision for all banks, we may have different values of $\overline{R}_k$ in equation (1.18) depending on deposit markets shares of Bank k if Bank k operate its branches in multiple regional market. These different values of $\overline{R}_k$ must converge into the same value, the optimal default cutoff, as we iterate the solution process.

- Using $\overline{R}_k$ from the previous step, if Bank k collect deposits from only one regional market. we can find a new deposit rate from equation (1.16). If Bank k collect deposits from multiple regional markets, we need to use equation (1.18) as well as equation (1.16) to make a system of equations. For example, Bank A has three types of equation (1.18) since it competes for deposits in three regional markets. From these, we can derive the following two equations

$$i^1_{A,t} + \frac{1}{\alpha\left(1 - s^1_{A,t}(i^1_{A,t}, \mathbf{i}^1_{-A,t})\right)} = i^2_{A,t} + \frac{1}{\alpha\left(1 - s^2_{A,t}(i^2_{A,t}, \mathbf{i}^2_{-A,t})\right)}$$
$$i^2_{A,t} + \frac{1}{\alpha\left(1 - s^2_{A,t}(i^2_{A,t}, \mathbf{i}^2_{-A,t})\right)} = i^3_{A,t} + \frac{1}{\alpha\left(1 - s^3_{A,t}(i^3_{A,t}, \mathbf{i}^3_{-A,t})\right)}.$$

  Therefore, we can update the deposit rate pricing of Bank A by solving equation (1.16) and the above two equations simultaneously. If we have three different values of $\overline{R}_A$ from the previous step, we use the average value of them to define a value of $\overline{R}_A$ in equation (1.16).

- With the updated deposit rates, we go back to the second step and iterate the solution process until the optimal decisions of all banks converge, which is finding a fixed-point.

From this solution algorithm, we get $\alpha = 35$ and $\beta = -5$. With these parameters, simulation outcomes are described in the first row of Table 1-5. Since we have one big bank, three medium banks, and nine small banks in the model of three regional markets, the average default probability from the model simulation is

$$\frac{(1 \times 1.74 + 3 \times 1.9 + 9 \times 2.6)}{(1 + 3 + 9)} = 2.37\%,$$

Table 1-5: Simulation Results

Benchmark Model										
# of Markets		Default (%)			Equity Issuance (%)			Deposit Rate (%)		
		Big	Mid	Small	Big	Mid	Small	Big	Mid	Small
3		1.74	1.90	2.60	39.50	41.98	45.49	2.50	2.50	2.54
4		1.56	1.89	2.61	36.59	42.47	45.70	2.52	2.50	2.53
5		1.33	1.95	2.59	33.62	42.63	45.72	2.53	2.49	2.53
Capital Requirement (Basel II Type)										
ω	#	Default (%)			Equity Issuance (%)			Deposit Rate (%)		
		Big	Mid	Small	Big	Mid	Small	Big	Mid	Small
6.0 %	3	1.47	1.60	2.50	37.43	40.25	44.62	2.50	2.50	2.54
	4	1.37	1.64	2.52	33.71	40.48	44.64	2.53	2.50	2.53
	5	1.16	1.65	2.49	31.02	40.56	44.61	2.54	2.50	2.53
8.0 %	3	2.99	2.64	2.27	30.57	35.60	42.15	2.70	2.64	2.60
	4	3.66	2.53	2.22	26.31	35.99	42.09	2.78	2.63	2.60
	5	4.29	2.49	2.18	22.55	36.16	41.99	2.85	2.62	2.59
8.0 % with $\bar{i}$	3	1.83	1.99	1.98	42.90	43.18	43.02	2.46	2.46	2.47
	4	2.04	2.03	1.97	43.37	43.08	42.96	2.46	2.46	2.47
	5	2.05	1.94	1.97	44.64	42.78	42.90	2.45	2.46	2.47
Capital Requirement (Basel III Type)										
ω	#	Default (%)			Equity Issuance (%)			Deposit Rate (%)		
		Big	Mid	Small	Big	Mid	Small	Big	Mid	Small
6.0 %	3	1.48	1.58	2.50	37.02	40.18	44.52	2.51	2.50	2.54
	4	1.38	1.65	2.52	34.23	40.49	44.56	2.54	2.50	2.53
	5	1.18	1.65	2.47	30.82	40.68	44.65	2.54	2.50	2.53
8.0 %	3	3.14	2.51	2.27	30.84	35.80	42.06	2.71	2.63	2.60
	4	3.83	2.53	2.23	27.01	35.93	42.04	2.83	2.63	2.60
	5	4.35	2.53	2.20	22.36	36.24	42.15	2.86	2.62	2.59
8.0 % with $\bar{i}$	3	2.04	1.93	1.93	42.83	43.16	43.05	2.46	2.46	2.47
	4	2.17	1.95	1.92	43.70	43.05	42.92	2.50	2.46	2.47
	5	2.03	1.99	1.94	44.63	42.88	42.94	2.45	2.46	2.47

which is close to 2.50% from $\rho_{ss} = 0.025$. Similarly, the average equity issuance rate from the model simulation is 44.2% close to the empirical counter part, 41.0%. Finally, the average deposit rate is 2.53% close to 2.50% from $i_{ss} = 0.025$. Therefore, our estimates for the demand parameters make the simulated moments close enough to their corresponding empirical moments. As an external validity test, we calculated the average regional deposit market share from the estimated model, which is 16.1% close to its empirical counterpart, 15.8%.

1.5 Simulation Results

1.5.1 Benchmark Model

Using the parameter values from the previous section, we simulate the benchmark model 50,000 times. We report deposit rates, equity issuance rates, and deposit rates from the simulation in Table 1-5. Each reported number represents an average value within the same group of banks depending on their size. For instance, the benchmark model has three medium banks (Bank B, Bank C, and Bank D). Therefore, each default rate under “Mid” column with three regional markets of Table 1-5 is calculated from 150,000 default decisions of these banks. Likewise, each default rate under ”Small” column with three regional markets of Table 1-5 is calculated from 450,000 default decisions of the small banks.

The first row of Table 1-5 shows the simulated outcomes from the benchmark model described in Figure 1-4. As a bank operates its branches in more regional markets to collect deposits, the bank is less likely to issue equity capital. In addition, it is less likely for the bank to choose a default if it competes for deposits in more regional markets. Considering that the average deposit rates among three different categories of banks from the benchmark model simulation are almost same around 2.50%, the smaller chances of declaring bankruptcy and issuing equity capital are associated with the number of regional markets as deposit funding sources.[15] To understand a mechanism behind these outcomes, we simulate two different scenarios. For each scenario, we fix a vector of returns for all banks except for one:

- Example I: Bank 1 (small) in Market 1,
- Example II: Bank B (medium) in Market 1 and Market 2.

We solve the benchmark model by changing the return on assets of Bank 11 in Example I and for Bank B in Example II from 0.10 to 0.70 while maintaining a vector of the returns for the others as,

$$
\begin{aligned}
&[R_A, R_C, R_D, R_{21}, R_{31}, R_{12}, R_{22}, R_{32}, R_{13}, R_{23}, R_{33}] \\
=&[0.35, 0.47, 0.51, 0.21, 0.18, 0.18, -0.29, 0.17, -0.30, -0.80, 0.50].
\end{aligned}
$$

We also define $R_B = 0.35$ in Example I and $R_{11} = 0.35$ in Example II to make two simulation scenarios comparable to each other. Figure 1-6 shows the optimal deposit rates (%) determined by all banks and the deposit market share (%) from two simulation scenarios.

[15] Since σ_k and μ_k are same for all banks in the model, this result is hard to be interpreted as an asset-side ramification, justifying our approach to make a link between deposit market competition and equity capital issuance.

Example I

As the return on assets of Bank 11 increases, the bank chooses to provide a higher deposit rate in Market 1 for collecting more deposits. In response to this action, some banks having branches in Market 1 (Bank A, Bank B, and Bank D) try to increase their deposit rates, but not as much as Bank 11 does, if their returns are good enough. On the other hand, the other banks in Market 1 (Bank 21 and Bank 31) provide lower deposit rates in order to minimize business losses since their returns are not profitable. As a result, Bank 11 receives higher market share in Market 1 from offering a higher deposit rate while the other banks in Market 1 lose their market share as the return on assets of Bank 11 becomes better. This gives upward pressure on the cost of deposits $((\sum_{m\in\mathcal{M}_k} s_{k,t}^m i_{k,t}^m)/(\sum_{m\in\mathcal{M}_k} s_{k,t}^m))$ for Bank A, Bank B, and Bank D since they provide higher rates while losing market share.

The outcomes in Market 1 directly influence the optimal decisions of Bank A, Bank B, and Bank D in the different regional markets since they operate multiple branches. One common observation from these banks is that their market share is stable although their optimal deposit rates in Market 2 and Market 3 decreases. This is because depositors in the model cares about default risks as well as deposit rates, and a default risk is affected by the return on assets. In our first simulation scenario,

$$R_A = R_B < R_C < R_D$$

among banks with multiple branches, so Bank D has the lower default risk. This leads Bank D to decrease a deposit rate in Market 3 denoted while the bank can maintain a relatively stable deposit market share in Market 3. Therefore, this can put downward pressure on the cost of deposits for Bank D. The similar mechanism is working more significantly for Bank A as we can see how the bank sets deposit rates while protecting its market share in Market 2 and Market 3. In addition to the direct influence, banks which do not compete with Bank 11 in Market 1 can be affected by the optimal decisions of Bank A, Bank B, and Bank D. For example, Bank C competes with Bank A and Bank B in Market 2 and competes with Bank A and Bank D in Market 3. This shows that the optimal pricing decision of Bank 11 has an indirect impact on Bank C through branch networks of Bank A, Bank B, and Bank D.

Example II

As the return on assets of Bank B increases, the bank chooses to provide higher deposit rates in Market 1 and Market 2 for collecting more deposits. In response to this action, Bank A optimally chooses to decrease deposit rates in Market 1 and Market 3, but increase a deposit rate in Market 2 so that the bank can maintain

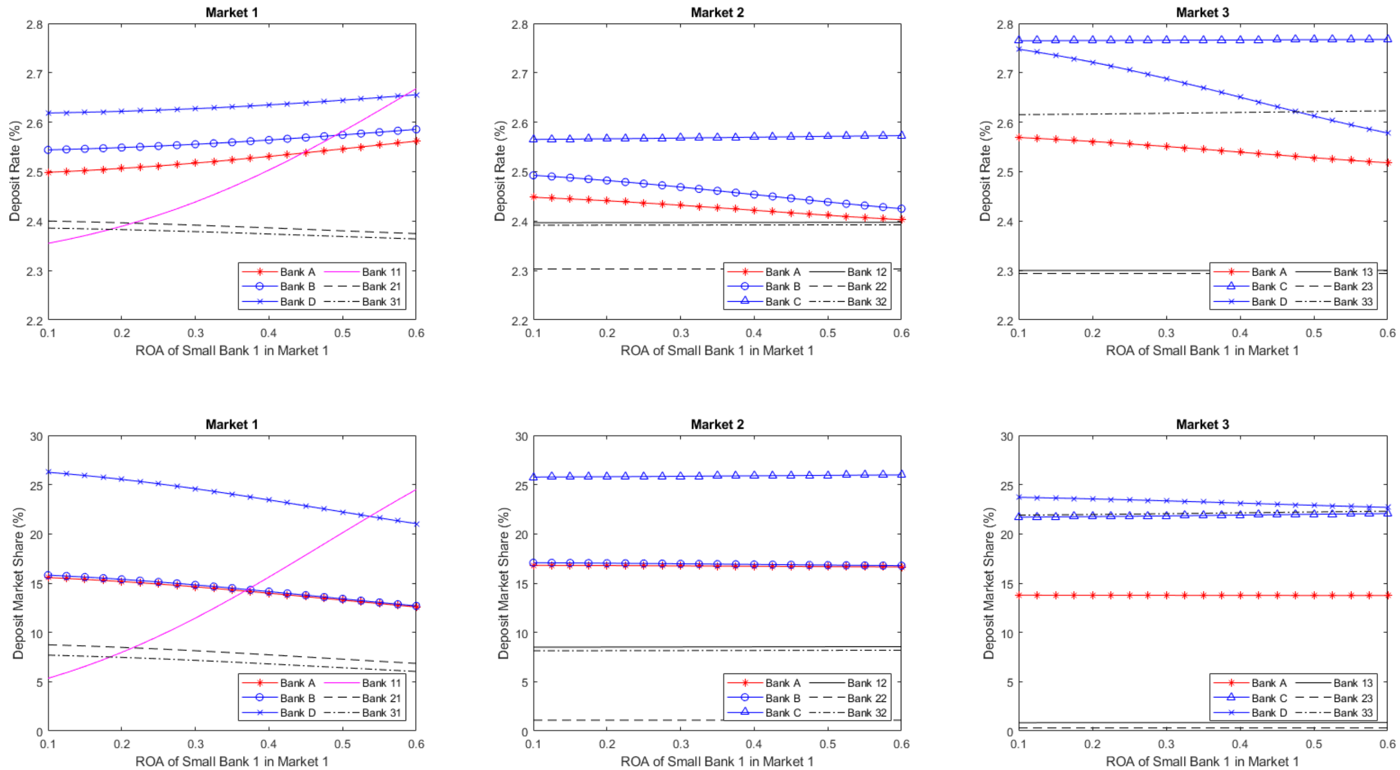


Figure 1-6: Simulation Example I

The upper panel shows the optimal deposit rates (%) determined by all banks in each regional market as the return on assets of Bank 11 increases from 0.10 to 0.70. The lower panel shows the deposit market share (%) derived from the preference of depositors under the simulation scenario. The values relevant to Bank A (big) are in red while the values relevant to Bank B, Bank C, and Bank D (medium) are in blue. Bank 11 is represented with pink lines and the other small banks are described with black lines.

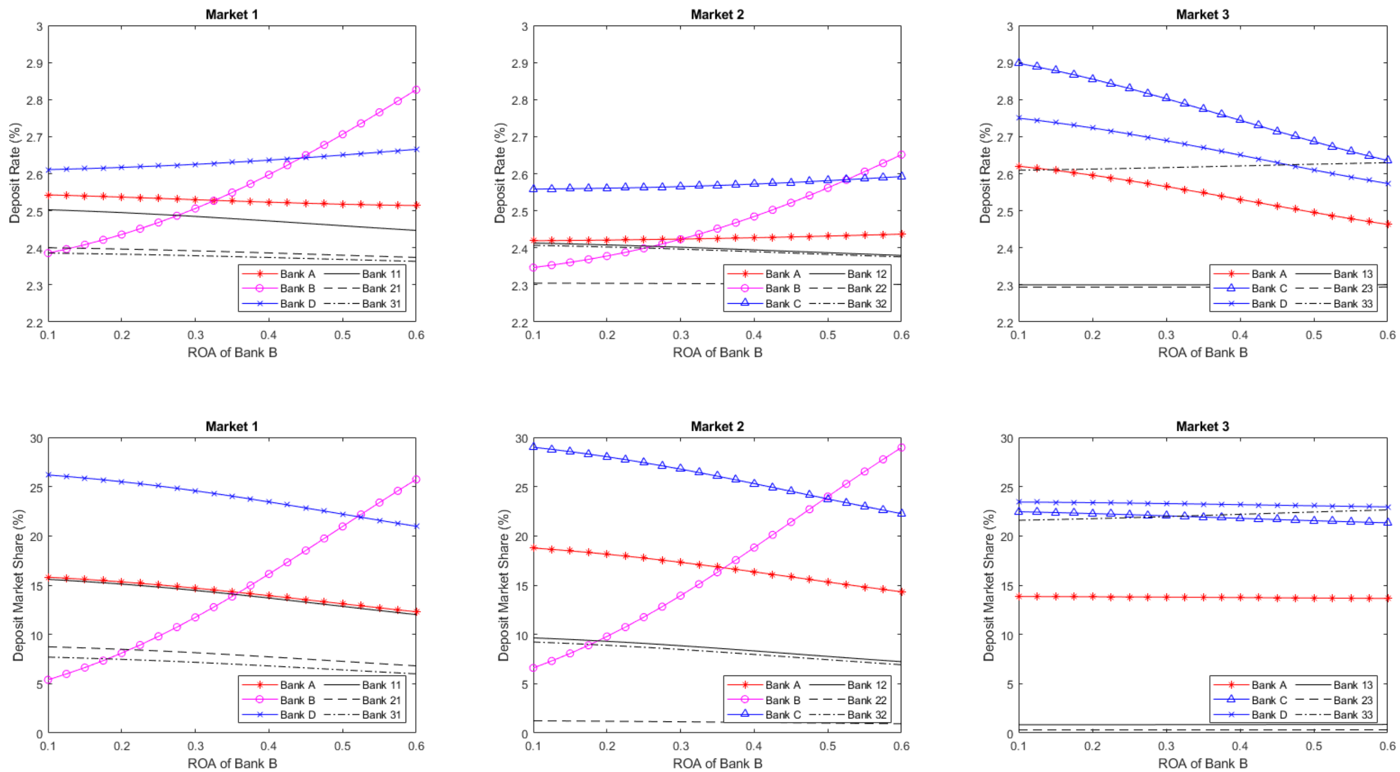


Figure 1-6: Simulation Example II

The upper panel shows the optimal deposit rates (%) determined by all banks in each regional market as the return on assets of Bank B increases from 0.10 to 0.70. The lower panel shows the deposit market share (%) derived from the preference of depositors under the simulation scenario. The values relevant to Bank A (big) are in red while the values relevant to Bank C, and Bank D (medium) are in blue. Bank B is represented with pink lines. Lastly, the small banks are described with black lines.

the flow of deposits from the diversified funding base. On the other hand, both Bank C and Bank D increase deposit rates in the regional markets where they compete with Bank B not to lose their market share too much. As a result, Bank B receives higher market share in Market 1 and Market 2 from offering higher deposit rates while the other banks in both markets lose their market share as the return on assets of Bank B becomes better.

The outcomes in Market 1 and Market 2 directly influences the optimal decisions of Bank A, Bank C, and Bank D in Market 3 since they collect deposits in the regional market. Similar to Example I, the banks are able to protect their market share although they decrease their deposit rates in Market 3. Again, banks which do not compete with Bank B neither in Market 1 nor in Market 2 can be affected by the optimal decisions of Bank A, Bank C, and Bank D in Market 3. For example, Bank 33 optimally increases a deposit rate to get higher market share since Bank A, Bank C, and Bank D decrease deposit rates in Market 3. This shows that the optimal pricing decisions of Bank B has an indirect impact on Bank 33 through branch networks of Bank A, Bank C, and Bank D.

Two simulation analyses show that a main advantage of having a well-diversified deposit funding base is the ability to control the cost of deposits. This ability is associated with managing the cost term in equation (1.14). Bank A has the lowest rate of declaring bankruptcy and and lowest of issuing equity capital in the first row of Table 1-5 from simulating the benchmark model 50,000 times because the bank is able to weaken a negative effect of the cost term in equation (1.14) on its market value. To quantify the ability to control the cost of deposits for each bank in Example I and Example II, we compute dispersion of the costs of deposits as follows

$$\text{Dispersion}_k = \frac{\text{STD}\left(\dfrac{\sum_{m\in\mathcal{M}_k} s^m_{k,t} i^m_{k,t}}{\sum_{m\in\mathcal{M}_k} s^m_{k,t}}\right)}{\text{Mean}\left(\dfrac{\sum_{m\in\mathcal{M}_k} s^m_{k,t} i^m_{k,t}}{\sum_{m\in\mathcal{M}_k} s^m_{k,t}}\right)}.$$

Table 1-6 shows a quantitative version of our analyses in Figure 1-6. A colored cell in pink indicates that the return on assets of a relevant bank is the source of variation in each panel. From the left panel of Table 1-6, there are five banks directly influenced by Bank 11: Bank A, Bank B, Bank D, Bank 21, and Bank 31. Bank A has the lowest value of the dispersion, which means it is better than the other four banks at controlling the cost of deposits. From the right panel of Table 1-6, Bank A dose not have the lowest value of the dispersion among the banks directly affected by Bank B. However, considering that Bank A competes with Bank B in

Table 1-6: Dispersion of the Costs of Deposits

	Simulation Example I			Simulation Example II		
Big	Bank A Market 1 Market 2 Market 3			Bank A Market 1 Market 2 Market 3		
	0.20			0.61		
Mid	Bank B Market 1 Market 2	Bank C Market 2 Market 3	Bank D Market 1 Market 3	Bank B Market 1 Market 2	Bank C Market 2 Market 3	Bank D Market 1 Market 3
	0.30	0.07	0.79	4.65	1.13	0.72
Small	Bank 11 Market 1	Bank 12 Market 2	Bank 13 Market 3	Bank 11 Market 1	Bank 12 Market 2	Bank 13 Market 3
	4.00	0.01	0.00	0.72	0.44	0.01
	Bank 21 Market 1	Bank 22 Market 2	Bank 23 Market 3	Bank 21 Market 1	Bank 22 Market 2	Bank 23 Market 3
	0.34	0.00	0.00	0.35	0.05	0.00
	Bank 31 Market 1	Bank 32 Market 2	Bank 33 Market 3	Bank 31 Market 1	Bank 32 Market 2	Bank 33 Market 3
	0.30	0.01	0.10	0.30	0.42	0.25

Market 1 and Market 2, the value of its dispersion is comparatively low.[16]

1.5.2 Additional Regional Markets

As an extension based on the benchmark model, we add one or two more additional regional markets to the benchmark model. For each additional market, we include one more medium bank and three more small banks. In the case of four regional markets, Bank B has branches in Market 1 and Market 2, Bank C has branches in Market 2 and Market 3, and Bank D has branches in Market 3 and Market 4, and Bank E has branches in Market 4 and Market 1. We maintain Bank A as the only big bank in each extended model but Bank A operates an additional branch in a newly added regional market. We simulate each extended benchmark model 50,000 times and report outcomes in the second row of Table 1-5 for the case of four regional markets and in the third row of the same table for the case of five regional markets. As Bank A has additional branches to collect deposits in more regional markets, the bank becomes less likely to default and less likely to issue equity capital. This result reaffirms the branch network mechanism, a novel link between deposit market competition and equity capital issuance, through which having additional branches makes Bank A better at controlling the cost of deposits. This simulation result is consistent with our empirical analysis in Table 1-3 showing a positive aspect of collecting deposits from a well-diversified deposit funding

[16] Moreover, Table 1-6 shows non-zero values of the dispersion for some banks not competing with Bank 11 in Example I and Bank B in Example II. As explained earlier, these values imply the indirect impact of Bank 11 and Bank B through the branch networks of their competitors.

base when the cost of deposit is moderate.

1.5.3 Different Capital Requirements

The capital requirements in our model affect default and equity capital issuance rates through the optimal default decision in equation (1.16) and the optimal deposit pricing in equation (1.18). If everything else is constant, having a higher capital ratio $\omega = \kappa/(1+\kappa)$ induces a bank less likely to declare bankruptcy as well as necessitate additional equity capital. However, as we show in equation (1.23) and (1.24), a different capital ratio can reshape the distribution of stochastic returns, and this change the optimal behavior of banks in the model. Therefore, we alter the capital ratio in the benchmark model from 4.0% to 6.0% and 8.0% to understand impacts of different capital requirements on default and equity capital issuance rates.

Given the number of regional markets, ranging from three to five, we simulate the model 50,000 times with a new capital ratio. The first six rows in the second panel of Table 1-5 show our simulation outcomes. When $\omega = 6.0\%$, there is a decrease in the number of default and equity capital issuance cases for all banks of different sizes. Considering that the average deposit rates are almost same around 2.50%, the higher capital ratio improves the capital buffer without increasing the cost of deposits. In other words, the optimal decision in equation (1.18) is not affected as much as in equation (1.16) from this change. Also, as Bank A operates additional branches in more regional markets, its default and equity capital issuance rates decrease further, which means that the branch network mechanism is still working positively for the bank by efficiently controlling the cost of deposits.

When $\omega = 8.0\%$, the higher capital ratio induces banks in the model less likely to issue equity capital through the improved capital buffer. This policy shift also makes the small banks in the model less likely to default. However, unlike the small banks, the banks with multiple branches are more likely to default under $\omega = 8.0\%$. Moreover, the branch network mechanism turns out to work negatively for Bank A when the bank is distressed since it has a higher default rate than the medium banks. This result can be explained by an increasing level of deposit market competition as reflected in the higher average deposit rates.

Figure 1-7 shows how $\kappa = \omega/(1-\omega)$ can reshape a distribution of R_k. Under the parameter values we calibrate and estimate, a higher capital ratio implies a higher average return with lower volatility. Quantitatively, the lower volatility is more significant than the increased average returns. This implicitly captures a key idea behind capital requirements, which makes assets in the banking system safer. Therefore, there is a higher chance out of 50,000 simulation cases for Bank A to compete with smaller banks with better returns. In this situation, Bank A encounters a number of competitors with good returns through the branch network mechanism. For example, if these smaller banks locate their branches in all regional markets, Bank A has

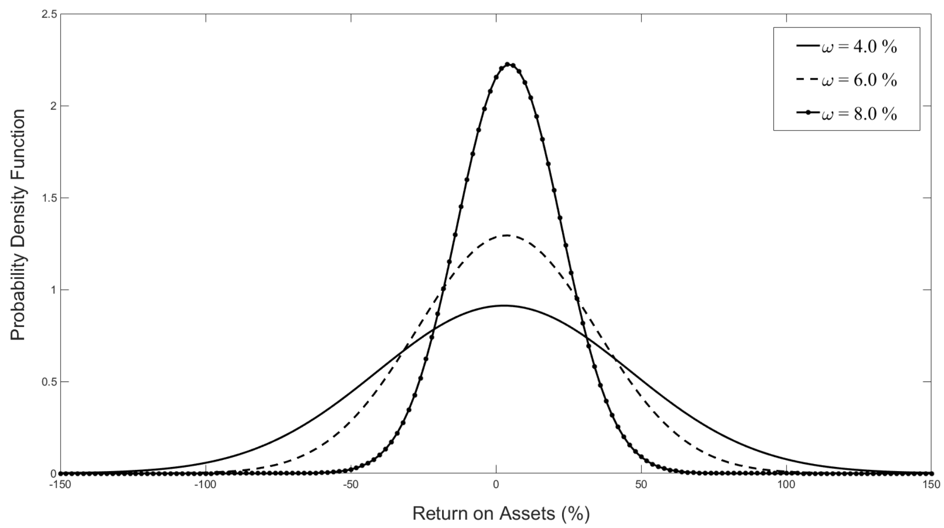


Figure 1-7: Capital Requirements and Distributions of the Return on Assets

higher competition pressure since its competitors optimally increase deposit rates in response to their good returns. Therefore, Bank A optimally increase deposit rates to compete, but the bank can lose its market share in all regional markets, leading to the higher cost of deposits. This unintended consequence of a higher capital ratio on Bank A gets worse through the branch network mechanism as Bank A operate additional branches in more regional markets. Therefore, this outcome can give a theoretical explanation on our empirical analysis in Table 1-3 showing the potential disadvantage of having a wide-spread branch network to collect deposits in more regions when the cost of deposits is higher.

As another variation of the benchmark model, we replace the capital requirements under Basel II regime with those under Basel III regime. We describe the optimal decisions of banks under this new regime in Appendix C. We set $\omega = 6.0\%$ and $\omega = 8.0\%$ to understand impacts of different capital requirements under Basel III regime on default and equity capital issuance rates. Given the number of regional markets, ranging from three to five, we simulate the model 50,000 times with a new capital ratio. The first six rows in the third panel of Table 1-5 show our simulation outcomes. Similar to the capital requirements under Basel II regime, Bank A dose not benefit from its branch network when a capital ratio becomes quite high.

1.5.4 FDIC Rate Cap

In the previous simulation, we show how a safer banking system can paradoxically lead a big bank to get in trouble due to increased deposit market competition. To remedy a potential default of Bank A under $\omega = 8.0\%$, we incorporate a rate cap rule into the model to alleviate unnecessarily intense competition. In the U.S. banking system, a similar rule is implemented by FDIC to limit a less than well-capitalized financial institution from soliciting deposits by offering rates that significantly exceed rates in its prevailing market.

To simplify our analysis, we set $\bar{i} = 3.25\%$ as the rate cap rule for all regional markets by following a calculation rule used by FDIC: the national rate, $i_{ss} = 2.50\%$ in our case, plus 75 basis points. With $\omega = 8.0\%$ and this cap, we simulate the model 50,000 times for each capital requirements regime. The last three rows in the second and third panels of Table 1-5 show our simulation outcomes. Under both Basel II and Basel III regimes, the rate cap rule decreases the average deposit rates, which results in the lower default rates for all banks of different sizes. In other words, the rate cap rule can make the branch network mechanism work positively. This outcome is also empirically supported from Table 1-3 demonstrating that having a well-diversified deposit funding base can reduce insolvency risk when the cost of deposits is relatively low. This consequence can justify the necessity for policy coordination between FRB and FDIC in the U.S. banking system.

On the other hand, since the banks with multiple branches under the rate cap rule have the limited ability to utilize their branch networks to collect deposits as much as they desire, they do not have enough funds to invest in loan portfolios. However, due to the lower default risk under the rate cap rule and the higher average return from Figure 1-7, the banks are more likely to have the higher value of staying in business than the cost of default. Therefore, bank shareholders provide additional funds to finance loan investment more often, reflected by the higher equity capital issuance rates.

1.6 Conclusion

In this paper, we shed a new light on a relationship between two liabilities of banks: deposits and equity capital. Empirically, we use the logit and probit models with two-way fixed effects to show that the cost of deposits is a quantitatively important factor to predict equity capital issuance of publicly listed bank holding companies in the U.S. banking system. To handle the incidental parameter problem in the nonlinear models, we use the analytic bias correction developed by Fernández-Val and Weidner (2016). The estimated outcomes from our full sample with both logit and probit models show that the average marginal effect for the cost of deposits is 1.20% increase in the likelihood of equity capital issuance. This finding is robust to various environments.

On top of that, using the log of Z-score as a proxy for insolvency risk, we present that an increase of one unit in the cost of deposits is associated with 24.4% decrease in Z-score even though bank holding companies can achieve higher deposit market share by spending more on the cost of deposits. This validate our hypothesis that the rising cost of deposits increases insolvency risk, so shareholders of bank holding companies are more likely to raise additional funds through equity capital issuance to protect the shareholder value of financial institutions. This impact of the cost of deposits on Z-score can be amplified or reduced through a well-diversified deposit funding base.

The empirical findings motivate us to develop a banking industry model to demonstrate how deposit market competition can affect equity capital issuance. Our model is a variation of Egan, Hortacsu, and Matvos (2017) by incorporating multiple regional markets into deposit competition. We use the simulated method of moments to estimate two demand parameters which determine two supply parameters. From the benchmark model, we show that a bank is less likely to issue equity capital as the bank competes for deposits in more regional markets. With two simulation scenarios, we explain that a main advantage of having a well-diversified deposit funding base is the ability to control the cost of deposits. However, our counterfactual simulations present a potential negative repercussion of having a well-diversified branch network under more restrictive capital requirements because intensity of deposit market competition soars. This result is consistent with our empirical analysis that the rising cost of deposits further decreases Z-score through a well-diversified branch network when the cost of deposits is already high enough.

There are several ways to extend our empirical analysis and structural model. We can study a relationship between deposit market competition and bank equity valuation. Some papers (e.g. Gandhi and Lustig (2015) and Atkeson, D'Avernas, Eisfeldt, and Weill (2018)) empirically show that the possibility of government guarantees is priced in the stock value of large financial institutions. Our paper demonstrates that there is a potential benefit or cost of having a well-diversified branch network for large financial institutions in deposit market competition. Therefore, it can be an important task to show how this diversification through branch networks is priced in the stock value of those entities. Also, we can revise our structural model to reflect entry and exit decisions of financial institutions in regional markets. Our model is built on the assumption that a deposit-taking branch is exogenously given. Considering a recent report that large bank holding companies close down numerous branches in the U.S. banking industry, this extension can allow us to understand how deposit market competition affects formation of branch networks. These are remained for the future research.

Chapter 2

Deposit Market Competition with Entry and Menu Choice

2.1 Introduction

Banks use deposits as a cheap funding source because the Federal Deposit Insurance Corporation (FDIC) guarantees the debt financing vehicle.[1] One strategy banks can use to collect more deposits is simply offering a higher interest rate to depositors. However, banks need to compete in local markets, leading to higher costs on the liability side. Since banks are not willing to offer a deposit rate higher than the rate determined by a monetary policy, managing price-based competition in the deposit market is difficult for banks when a monetary policy rate is too low. For example, Figure 2-1 shows the unprecedented policy regime in the U.S. banking system. Under the circumstance that the deposit rate competition is ineffective, our research question is to answer what the bank's strategy is to gain or maintain deposit market share. On top of the conventional optimal pricing decision, this paper sheds new light on the deposit market competition mechanism: *endogenous deposit menu choice*.

The current paper contributes to the literature in three ways. First, we highlight a substantial role of the bank's deposit menu choice on local-level market share and deposit rate, explaining why banks provide some deposit products in certain counties while not serving others. Our reduced-form and structural models combined with a noble dataset from RateWatch find that the bank's deposit product menu choice highly influences local market share and resulting deposit rate. Second, we construct a structural model incorporating the bank's entry, deposit product menu choice, and deposit rate competition mechanism. The model enables us to understand the strategic interactions among the top 5 banks in entry decisions and deposit menu choices. Third, our counterfactual analysis based on empirical observations after the financial crisis in 2008 predicts how the market structure of the banking industry changes with the change in local market

[1] In the case of deposits saved in credit unions, the National Credit Union Administration (NCUA), created by the U.S. Congress in 1970, has been responsible for protecting the members who own credit unions, chartering and regulating federal credit unions. Currently, both FDIC and NCUA insure deposits of up to $250,000.

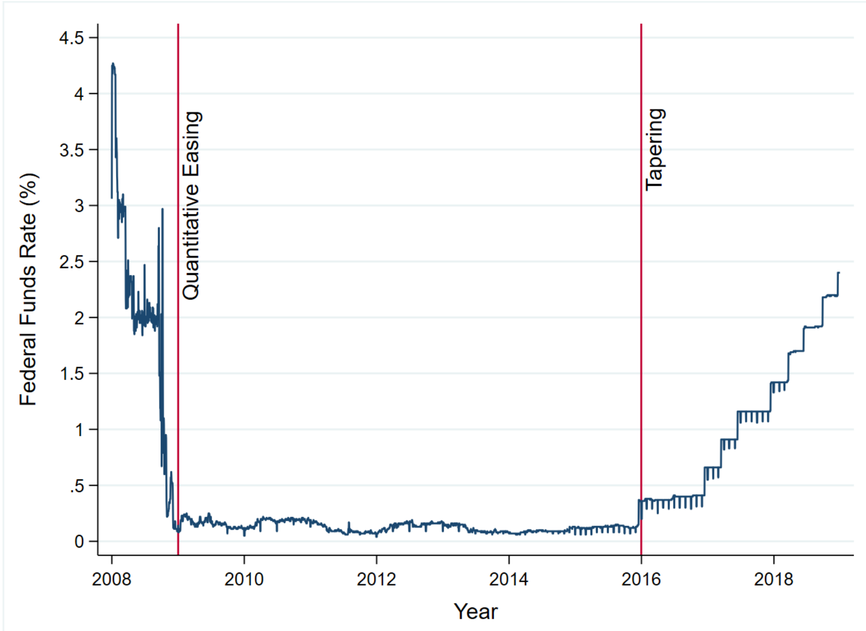


Figure 2-1: Federal Funds Rate

The federal funds rate is the interest rate at which depository institutions trade federal funds overnight. When a depository institution has surplus balances in its reserve account, it lends to other banks needing more substantial balances. The market determines the federal funds rate, but the Federal Reserve indirectly influences the rate through open market operations to reach the federal funds rate target. The data is from FRED.

characteristics. Our observation starts by finding banks serving different deposit products for each local market. Banks sell deposit products in local markets where they open and operate branches. A certificate of deposit (CD) is a savings product that earns interest on a lump sum for a fixed period. CD differs from money market (MM) or savings accounts because the money must remain untouched for the entirety of its maturity. However, a bank provides different combinations of deposit products depending on geographical regions and changes the deposit product menu over time. For example, JP Morgan Chase had temporarily stopped providing the money market accounts with \$10,000 minimum deposits in New York County for three quarters since the beginning of 2013, while the financial institution had kept providing the same deposit product in Dallas County. To understand the endogenous deposit menu choice as a potential competition strategy, our paper uses several reduced form-regression analyses and constructs an empirical game-theoretic model.

Our first reduced-form regression model shows that local and bank-level factors significantly affect the probability of adding a new deposit product in a county-level market. For example, the county population and housing price index positively affect the deposit product addition. On the other hand, banks provide fewer deposit products in a local market if there is a lack of competition. These empirical findings are robust to our econometric model, which uses the number of deposit products reflecting the degree of menu diversification as a dependent variable. The results demonstrate that the menu choice and composition affect the deposit market structure, determining market share and deposit rate. Therefore, a model of deposit market competition without considering menu choice may not fully show the competition mechanism. Our structural model complements the reduced-form analysis by handling the underlying competition mechanism.

Regarding our second contribution, we construct a structural model with static games of strategic interactions through multiple discrete choices: banks choose where to open branches, which deposit products to sell, and how much they pay to depositors. One noticeable characteristic of our model is considering bank-specific menu cost structure so that we can differentiate each bank's competitive edge in the deposit product menu choice competition. We estimate the model with the novel data set, including county-level geographical features of deposit markets. The data lets us observe the banks' county-level market share, entry, menu choice, and deposit rate decisions. Our baseline estimation result with the top 5 banks (JP Morgan Chase, Bank of America, Wells Fargo, PNC Financial, and US Bank) demonstrates a substantial role of the entry and menu costs in the deposit market structure through strategic interaction. For example, one additional top 5 competitor's entry reduces the entry probabilities of JP Morgan Chase and Bank of America by 1.65% and 1.9% on average, respectively. In contrast, the entry decisions of Wells Fargo, PNC, and US Bank are more sensitive to one rival bank's entry.

On top of that, the estimated interaction in the menu game shows that the banks are less likely to sell a deposit product if their rival banks introduce the same product in a local deposit market. Therefore, our result on the endogenous deposit product menu choice implies that banks have an additional competitive strategy other than deposit rate setting. Through the menu cost estimation, we also find that this deposit product menu choice is a bank-specific strategy, verifying that some banks are more involved in the product-space competition than others. For instance, JP Morgan Chase shows relatively high costs from adding a product from MM or savings while low costs from adding a product from CD, which implies that the institution's cost structure prefers to add a product from CD instead of MM or savings. However, not all banks strategically behaved as JP Morgan Chase did. The Bank of America shows a different cost structure and prefers a product from MM and savings over a product from CD.

Regarding our third contribution, we simulate three counterfactual scenarios motivated by empirical observations after the financial crisis of 2008: the nationwide increase in the housing price index, a decrease in the number of bank charters at a faster rate, mainly through M&A, and a reduction of bank branches. First, the rise in HPI causes less entry for all banks and provides more diversified products to the market. Still, the competition from the deposit product menu choice plays a more significant role than the direct impact of the increase in HPI. In other words, one bank's more diversified menu discourages rival banks from launching new financial products under monopolistic competition.

For the second counterfactual exercise, we assume a potential merger between PNC and US Bank, which operate branches in different geographical regions, so this hypothetical situation does not violate a relevant regulatory policy from the Bank Merger Act. The merger between two entities negatively affects the rival bank's entry probability, product diversification, and market share. The merger effect on rival banks is more evident in product diversification, and resulting market share than the overall entry since PNC and US Bank do not have many overlapped regional markets. Three rival banks decrease the probability of selling all deposit products since the merged institution has a higher capacity to serve all deposit products in many local markets. One remarkable result is that some rival banks heavily rely on menu diversification to lower deposit rates, although their market share decreases. Our model finds that the menu cost structure has a more dominant effect on deposit rate pricing than a conventional markup through market share.

Finally, the decrease in bank branches causes fewer market entries through network effects and gives the banks in our model an incentive to serve less diverse deposit products. The degree of effects also heavily relies on the current network size. For example, US Bank enters a large portion of the deposit markets with many branches, which implies that the counterfactual situation has more negative impacts on US Bank than the others.

As a robustness check, we extend the baseline model to include five additional banks (M&T Bank, Associated Bank, Fifth Third Bank, Regions Financial Corporation, and Key Corporation). The strategic interaction for the entry decision shows a bank-specific characteristic. For example, JP Morgan Chase cares more about the top 5 competitors, whereas Bank of America cares more about the top 10 competitors. Regarding the deposit product menu choice, the estimated sensitivity capturing strategic behavior demonstrates that banks react to their competitors against whom they are practically competing. For instance, PNC's decision is more sensitive to a CD product from the top 10 competitors, but US Bank's decision is more susceptible to a CD product from the top 5 competitors. The extended model with the top 10 banks not only shows validity and stability of the primary outcomes with the top 5 banks but also gives additional insights into deposit market competition between two different groups of financial institutions.

Literature Review

The current paper belongs to studies using industrial organization models to understand deposit market competition. For example, Egan, Hortacsu, and Matvos (2017) develop an empirical model of the U.S. banking sector to show how competition for uninsured deposits can lead to financial fragility. Egan, Lewellen, and

Sunderam (2022) develop novel measures of individual banks' productivity at collecting deposits and making loans relevant to bank market values. They find that deposit productivity is responsible for the most variation in value across banks. These papers only consider deposit rate pricing as a competitive strategy for banks on their liability side. Some papers investigate monetary policy transmission through deposit competition. Drechsler, Savov, and Schnabl (2017) present that when the federal funds rate rises, banks widen the spreads charged on deposits more and deposits flow out more in concentrated regional markets, which impacts bank lending. Xiao (2020) shows that monetary tightening could unintentionally increase financial fragility through the shadow banking sector since it can attract more deposits from a yield-sensitive clientele. Wang, Whited, Wu, and Xiao (2022) estimate a dynamic banking model to quantify the impact of bank market power on the transmission of monetary policy through banks to borrowers. To the best of our knowledge, no paper considers entry and menu choice in a structural model of deposit market competition.[2] Some recent studies have been carried out on menu choice as bundling in the banking industry. However, most of them concentrate on the bank's loan business (e.g., Berger, Zhang, and Zhao (2020), Berlin, Nini, and Yu (2020), Gustafson, Ivanov, and Meisenzahl (2021)).

Our paper also considers papers incorporating branch networks into structural models to describe deposit market structure. Several articles have studied branch networks in the banking industry following the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994. Calem and Nakamura (1998) show that increasing bank branch networks tend to mitigate geographical market power by broadening the spatial scope of competition among banks. Cohen and Mazzeo (2007) propose an endogenous market structure model in rural markets by bank type and show that product differentiation generates additional profits for retail depository institutions. Ho and Ishii (2011) estimate a spatial model of consumer demand for retail bank deposits to predict the effect of changes in market structure on consumer welfare. Kuehn (2018) develops a two-stage model with demand for deposit services and a branch network choice focusing on the impact of bank branching on the local competition. Aguirregabiria, Clark, and Wang (2020) recently suggested a model encompassing deposit and loan market competition. They investigate how branch networks, market power, and the scope of economies can prevent funding from flowing to high loan demand areas, leading to a geographical imbalance of deposits and loans. Kim (2021) examines the effect of the internet on deposit market structure through entry-exit and consumer welfare in the U.S. banking industry. We add menu choice into deposit market competition with branch networks to understand the nature of competition in depth.

[2] The entry game is commonly used in the empirical literature on analyzing oligopolistic market structures (e.g., Bresnahan and Reiss (1990, 1991), Berry (1992), Tamer (2003), Toivanen and Waterson (2005), Ciliberto and Tamber (2009), Sweeting (2009), Vitorino (2012), and Dunne, Klimek, Roberts, and Xu (2013)). Our model endogenizes menu choice with the entry game like Mazzeo (2002) and Seim (2006).

2.2 Empirical Analysis

2.2.1 Data Construction

For our empirical analysis and structural estimation, we combine three data sources from the U.S. banking sector from 2011 to 2018. We gather information on balance sheets and income statements of commercial banks from the Report of Condition and Income quarterly issued by FDIC, also known as the Call Report. We measure the variables associated with profitability and deposit composition. The return on assets (ROA) of bank i at time t is calculated as

$$R_{i,t} = \frac{\text{Net Income (RIAD4340)}}{\text{Total Assets (RCON2170)}}.$$

We divide the total deposits into three categories from Call Report:

$$\begin{aligned} \text{Term (CD)} &= \text{RCON6648} + \text{RCONJ473} + \text{RCONJ474} \\ \text{Money Market (MM) \& Savings} &= \text{RCON6810} + \text{RCON0352} \\ \text{Checking} &= \text{RCON2385}. \end{aligned}$$

Table 2-1 shows, on average, how much each group of financial institutions in our merged sample can account for each category of deposits reported to Call Report over the sample period. For each quarter over the sample period, we define the bottom 30% banks as “Small”, the middle 40% banks as “Medium”, the top 30% banks excluding the top 1% banks as “Large”, and the top 1% banks as “Very Large”.

A commercial bank operates branches to collect deposits in multiple markets. Geographical information on deposits is from the Summary of Deposits (SOD), the annual survey of FDIC. It is a well-documented fact that deposit markets are geographically segmented.[3] In other words, each deposit market has a different characteristic from others. As an illustration, Figure 1-2 shows county-level deposit market concentrations of the U.S. in 2015, measured by the Herfindahl-Hirschman Index (HHI). A darker shade of blue means a more concentrated deposit market with a higher level of HHI.

We utilize SOD to define variables reflecting a commercial’s performance from deposit market competition. We consider a sample from SOD as an economy with N banks, indexed by $i \in \{1, ..., N\} = \mathcal{N}$, over time $t \in \{1, ..., T\} = \mathcal{T}$. Considering entry and exit behavior in the U.S. banking sector, not every bank

[3] Drechsler, Savov, and Schnabl (2017) use county-level information to show that a branch of banks in more concentrated deposit markets increases a rate less due to its regional market power after the federal funds rate rises. Aguirregabiria, Clark, and Wang (2020) also use county-level deposit market information to investigate the geographical imbalance between deposits and loans. These papers assume that depositors only consider deposit-taking institutions in proximity due to transportation costs. This

Table 2-1: Deposit Market Share in the United States

	Deposit	**Product Type**			
	Total	CD	MM	Savings	Checking
Bank Size					
Small	0.7%	1.5%	0.3%	0.4%	1.2%
Medium	3.0%	6.1%	1.4%	2.6%	4.6%
Large	22.6%	32.0%	20.4%	23.9%	17.7%
Very Large	58.5%	35.1%	67.3%	59.3%	56.0%

This table shows how much each size group of financial institutions in our merged sample can account for each category of deposits reported to Call Report over the sample period. Our data spans from 2011 to 2018 and only covers financial institutions whose county-level deposit rates are available from RateWatch. Information on deposit categories is from Call Report. For each quarter over the sample period, we define the bottom 30% banks as "Small", the middle 40% banks as "Medium", the top 30% banks excluding the top 1% banks as "Large", and the top 1% banks as "Very Large". Globally Systematically Important Banks (GSIB) and Domestically Sysmetically Important Banks (DSIB) are all included in the "Very Large" category. Since our sample is a subset of institutions reported in the Call Report, the sum of each column is less than 100. For example, the first column implies that financial institutions in our sample covered 84.8% of domestic deposits in the U.S. between 2011 and 2018.

$i \in \mathcal{N}$ stays in the economy for all $t \in \mathcal{T}$. We denote each county-level deposit market with $m \in \{1, ..., \} = \mathcal{M}$. Therefore, $\mathcal{M}$ is the set of all counties in the United States. Let $q_{i,t}^m$ represent the amount of deposits collected by bank i in county m at time t. Then, we can define the deposit market share of bank i in market m at time t as follows

$$s_{i,t}^m = \frac{q_{i,t}^m}{\sum_{i \in \mathcal{N}_t^m} q_{i,t}^m} = \frac{q_{i,t}^m}{Q_t^m}$$

where $\mathcal{N}_t^m \subset \mathcal{N}$ is a set of financial institutions observed in market m at time t from SOD. Therefore, in order to measure county-level deposit market share, we use all financial institutions in SOD. Figure 1-3 shows the county-level deposit market share of Wells Fargo over time. It also demonstrates how Wells Fargo has expanded its deposit funding base.

For example, Figure 1-3 shows how Wells Fargo has expanded its deposit funding base as well as county-level deposit market share of the bank over time. A darker shade of green means a higher deposit market share for Wells Fargo in a county. A darker shade of green indicates a higher deposit market share for Wells Fargo in a county. From 1995 to 2005, the bank established more branches across the country and acquired other financial institutions after the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994. A

assumption is justified by Honka, Hortacsu, and Vitorino (2017), providing evidence that local branch presence is an essential factor in the decision to open new bank accounts. More recently, Abrams (2019) shows that customers are attentive to which banks are located in their regions.

critical reason behind the change in its deposit funding base from 2005 to 2015 is that Wells Fargo acquired Wachovia after the financial crisis of 2008.

Using RateWatch from S&P Global Market Intelligence, we gather information on deposit product types and rates, giving us a comprehensive deposit menu for each bank in each county. For example, we can observe how much JP Morgan Chase pays for a certificate of deposit with one-year maturity and $\$10,000$ minimum savings in Dane County, Wisconsin, over the sample period. Table D-1 shows how many different products defined by maturity-minimum deposit pairs are offered in each deposit type for each size group of banks. We merge Call Report, SOD, and RateWatch using FDIC Certificate ID numbers and Federal Information Processing System (FIPS) codes. Finally, we include personal income and population data from the Bureau of Economic Analysis of the U.S. Department of Commerce and housing price indexes from the Federal Housing Finance Agency to reflect the local characteristics of each county.

2.2.2 Reduced-Form Regression Analysis

This section presents some baseline reduced form analyses to describe how menu diversification correlates with local market characteristics. Compared with the previous literature focusing on banks' entry decisions and the deposit rate competition, we highlight the essential role of menu choice. Conditional on entry, the entrants compete in choosing an optimal menu, which endogenizes the resulting regional market share and eventually affects the deposit rate. For example, banks usually prefer term deposits to demand deposits since the deposits with maturity offer more benefits to the banks. If a local market is not competitive and a bank is the only major bank in the region, the only entrant may have an incentive to exclude demand deposit products from the menu. Generally, a bank will include a deposit product on the menu if the marginal cost is lower than the expected benefit.

We first define three dummy variables indicating CD, MM-SAV, and IRA menu diversification. The CD indicator value is one if a bank sells more than one type of CD product in addition to the standard CD. For example, Table D-1 displays Relationship CD and Business CD in addition to the standard CD product. Considering a county-year combination as a market, 47.87% of the markets in our data provide at least one more additional CD product to depositors. Similarly, 59.34% offer extra MM or Saving products, and 71.83% offer other IRA products with the standard fixed-rate IRA. Treating the three dummy variables as dependent variables, we figure out the determinants of menu diversification.

The following Table D-2 presents the OLS and Logit estimates. The first two columns of Table D-2 show the determinants of the additional CD products. Similarly, the following four columns provide estimates for additional MM-SAV and IRA products. Since the dependent variables are dummy variables, we use both

OLS (linear probability model) and the Logit model to capture the effect of covariates on menu diversification probability. We add year and bank fixed effects to all specifications. The estimated standard errors are clustered at the county level to capture the potential correlation of shocks within the same county.

One critical determinant is the county population, which positively affects the probability of adding a new CD product to the menu. The housing price index also has a positive effect on menu diversification. The county-specific covariates reveal that various products are added to the menu to support consumers with diverse financial backgrounds. The other significant covariate is the number of large banks. As expected, banks are less likely to provide a diversified menu unless there is competition in menu choice. For example, one more major bank in the market increases the probability of additional CD products on the menu by 0.40%p. On the other hand, the small bank's influence on menu diversification is limited and not statistically significant.

We also pay attention to the TD Ratio coefficient in the first two columns of Table D-2. As the bank's primary deposit source is more likely to be term deposit products, the bank is prone to decrease the variety of the menu. The DD Ratio coefficient in the third and fourth columns of Table D-2 finds the opposite effect for demand deposit (MM-Saving) products. The demand deposit menu is more diversified with the bank's actual proportion of demand deposits. The correlation structure implies that depositors may not choose to purchase a term deposit product if there are more flexible options available. The coefficients indirectly indicate that banks strategically choose deposit products to sell depending on the market structure. A bank's significant regional market power may result in fewer products, inducing depositors to purchase more profitable deposit products for the bank.

Next, Table D-3 summarizes what influence the degree of menu diversification and deposit rate. The dependent variable in the first two columns of Table D-3 is the sum of three dependent variables in Table D-2, presenting the number of additional product types from the standard CD, MM-Saving, and IRA. For example, suppose a bank's menu comprises CD, MM, Fixed IRA, Premium MM, and Business MM. In that case, the dependent variable is one since Premium MM and Business MM are non-standard MM-Saving products, while a non-standard CD or Variable IRA is not on the menu.

We conduct a linear regression and ordered logit estimation to find the correlation between market-level covariates and menu diversification. Firstly, the county population positively correlates with a more diverse menu. More population implies various depositor groups with different financial backgrounds. Thus a larger market size contributes more products on the menu to serve heterogeneous depositors. The number of major banks leads to a more competitive market structure, so banks are more likely to provide various products. The number of active counties negatively correlates with product variety, showing a trade-off between more entries and product types. Following the same context as Table D-2, the fraction of term deposits shows a significantly negative correlation with menu diversification. As term deposits are usually more favorable to banks while less attractive to depositors, a bank's magnitude of term deposits correlates with fewer products.

The last two columns of Table D-3 display the determinants of county-specific deposit rates. Conditional on bank-year-county level fixed effects, we find that more competition with other large-size banks implies a higher deposit rate. More entry decisions over the counties lower the deposit rate as a bank is more likely to become a dominant player in regional markets with no other major banks. More importantly, the deposit rate depends highly on menu composition, as the fractions of term deposits and demand deposits have relatively more explanatory power on the deposit rate.

The reduced form estimates provide insight into the relationship between the bank's entry, menu choice, and deposit rate. The results find that the endogenized menu composition considerably affects the market structure, market share, and deposit rate. Thus, a structural model without considering menu choice may not fully reflect the deposit competition mechanism. In the next section, we establish a structural model describing the bank's decision. The structural approach investigates how the strategic interactions among banks affect the resulting county-level market power, menu diversity, and deposit rate.

2.3 Model and Estimation

This section presents the structural model to describe the bank's decision to choose the entry, selling products, and deposit rate. The model includes three types of static games of strategic interactions through multiple discrete choices for each county-level deposit market $m \in \mathcal{M}$ and year $t \in \mathcal{T}$: (1) an entry game among potential entrants of the market, (2) a game to decide the selling menu among the entrants, and (3) the deposit competition conditional on entry and selling menu. The three games are within a market m and time t, but the games are independent across markets and times. Banks make entry decisions for each market, and the banks that entered the market simultaneously decide on the menu to sell, considering the expected profit and menu cost. Last, banks determine the deposit rates conditional on the given entry decisions and product space. Since all decisions in the three games are made at once, we assume that variables describing local market factors are exogenously given.

2.3.1 Model Setup

Game I: Entry Game

We denote the entry game $\left\{\mathcal{I}_{E,t}, \{\mathcal{A}_{E,i}\}_{i\in\mathcal{I}_{E,t}}, \{U_{E,i,t}\}_{i\in\mathcal{I}_{E,t}}\right\}$, where $\mathcal{I}_{E,t} = \{1, \ldots, N_{E,t}\}$ is the set of banks participating in the game in time t, $\mathcal{A}_{E,i} = \{0, 1\}$ is the player i's action set for the entry decision, and $U_{E,i,t}$ is bank i's expected utility from the entry. The utility from no-entry is normalized to zero. We specify player i's expected profit using the following function:

$$U_{E,i,t}\left(a_{E,t}, X_{E,t}\right) = \begin{cases} X'_{E,i,t}\beta_{E,i} - \left(\sum_{-i\in\mathcal{I}_{E,-i,t}} a_{E,-i,t}\right)\delta_{E,i} - \varepsilon_{E,i,t} & \text{if } a_{E,i,t} = 1 \\ 0 & \text{otherwise} \end{cases} \tag{2.1}$$

where $a_{E,t} = (a_{E,1,t}, \ldots, a_{E,N_E,t})'$ is the vector of entry decisions, $X_{E,t} = \left(X'_{E,1,t}, \ldots, X'_{E,N_E,t}\right)'$ includes regressors, and $\delta_{E,i}$ summarizes the strategic interaction between bank i and other rival banks. The payoff function parameters $\beta_{E,i}$ and $\delta_{E,i}$ differ across banks ($\delta_{E,i} \neq \delta_{E,j}$ for banks i and j) but are the same across markets and times. For bank i, bank j's entry $a_{E,j,t}$ and bank k's entry $a_{E,k,t}$ imply the same amount of loss $\delta_{E,i}$. That is, the negative entry impact from the rival bank's entry can be different, but one bank does not particularly affect the other bank differently. We assume that $\varepsilon_{E,i,t}$ follows the standard Type 1 Extreme Value distribution. The researcher observes $a_{E,t}$ and $X_{E,t}$ for $t \in \mathcal{T}$ and all markets $m \in \mathcal{M}$.

The game is an incomplete information game. $X_{E,t}$, $(\beta_{E,i}, \delta_{E,i})$, and the probability distribution of $\varepsilon_{E,i,t}$ are common knowledge among banks but the realized value of $\varepsilon_{E,i,t}$ is bank i's private information. The banks simultaneously choose actions based on their own information set: bank i's information set is $\left\{X_{E,t}, \{\beta_{E,i}, \delta_{E,i}\}_{i\in\mathcal{I}_{E,t}}, \varepsilon_{E,i,t}, F_{\varepsilon_E}\right\}$, where F_{ε_E} is the CDF of $\varepsilon_{E,i,t}$ for $i \in \mathcal{I}_{E,t}$. The market presents the joint action $a_{E,t}$ as a result. The assumption of the information structure is common in empirical game literature. Considering the assumption that the entry game outcome follows the Bayesian Nash Equilibrium (BNE), the conditional entry probability at the equilibrium is

$$P\left(a_{E,i,t} = 1 | X_{E,t}\right) = F_{\varepsilon_E}\left(X'_{E,i,t}\beta_{E,i} - \left(\sum_{-i\in\mathcal{I}_{E,-i,t}} P\left(a_{E,-i,t} = 1 | X_{E,t}\right)\right)\delta_{E,i}\right) \tag{2.2}$$

for $i \in \mathcal{I}_{E,t}$, . The equilibrium entry probabilities $\{P\left(a_{E,i,t} = 1 | X_{E,t}\right)\}_{i\in\mathcal{I}_{E,t}}$ satisfies equation (2.2) for all players in time t. We assume that the researcher knows F_{ε_E}, the equilibrium probabilities are identified up to the finite-dimensional parameters $\beta_{E,i}$ and $\delta_{E,i}$. The nonlinear mapping in equation (2.2) generates at least one BNE following the Brouwer fixed-point theorem. The multiplicity of BNE is a common issue in empirical games, but we assume the degenerate equilibrium selection mechanism for simplification.

Game II: Menu Game

With the entry decisions in each market, the entrants strategically determine the optimal menu considering the opponent's menu and menu cost. The bank's financial products in a specific market are stable across years due to menu costs. Once a bank decides to serve a CD product, for example, the bank tends to sell the same product for many years regardless of the change in the market environment. The banks rather compete with deposit rates to increase the market share instead of changing the menu composition.

The primary menu includes three deposit types: term deposits (TD), demand deposits (DD), and Individual Retirement Account (IRA). The term deposits include Certificate of Deposit (CD), and the demand deposits contain Money Market deposit (MM) and Savings (SAV). The bank can diversify the menu to attract more consumers to deposit, considering the trade-off between the additional expected deposit and menu cost. For example, a bank can provide a Relationship CD, Business CD, or Business Relationship CD in addition to the standard CD product. Similarly, some banks offer fixed- and variable-rate IRA, while others only provide a fixed IRA.

Denote a product composition game $\left\{\mathcal{I}_{P,t}, \{\mathcal{A}_{P,i}\}_{i\in\mathcal{I}_{P,t}}, \{U_{P,i,t}\}_{i\in\mathcal{I}_{P,t}}\right\}$, which is simply a menu game. $\mathcal{I}_{P,t} = \{1,\ldots,N_{P,t}\} \subseteq \mathcal{I}_{E,t}$ is the set of active banks in the market, $\mathcal{A}_{P,i}$ is the player i-specific action set containing all possible types of menus, and $U_{P,i,t}$ is bank i's profit function conditional on entry. The action set comprises multi-dimensional binary variables $\{a_{P,i,j,t}\}_{j\in\mathcal{J}}$ with $\mathcal{J} = \{\text{TD, DD, IRA}\}$, and $a_{P,i,j,t} = 1$ implies that the bank i provides more diverse options of type j deposit in addition to the standard type j product. The game's payoff presents the normalized value of the bank's profit by adding or dropping a deposit product from the menu. The product composition involves strategic interaction among banks since the banks with the same product types divide the fixed market share. For example, if Bank A is the only bank selling a variable-rate IRA, Bank A can take all deposits from the consumers demanding a variable-rate IRA. But if another Bank B is also offering a variable-rate IRA, the product composition of Bank B will decrease Bank A's IRA deposit share.

We define bank i's payoff from the product composition by the following functional form.

$$U_{P,i,t}\left(a_{P,t}, X_{P,t}\right) = \begin{cases} \sum_{j\in\mathcal{J}} a_{P,i,j,t}\left(X'_{P,i,j,t}\beta_{P,i,j} - \left(\sum_{-i\in\mathcal{I}_{P,-i,t}} a_{P,-i,j,t}\right)\delta_{P,i,j}\right) + \varepsilon_{P,i,t} \\ \qquad\qquad\qquad \text{if } a_{P,i,j,t} \neq 0 \text{ for some } j \in \mathcal{J} \\ 0 \qquad\qquad\qquad \text{if } a_{P,i,j,t} = 0 \text{ for all } j \in \mathcal{J} \end{cases} \tag{2.3}$$

where $X_{P,t} = \{X_{P,i,j,t}\}_{i\in\mathcal{I}_{P,t}, j\in\mathcal{J}}$ includes market covariates, and $a_{P,i,j,t}$ is a binary variable indicating that the bank i sells the product type j in time t. $a_{P,i,t} = (a_{P,i,TD,t}, a_{P,i,DD,t}, a_{P,i,IRA,t})' \in \{0,1\}^3$ is bank i's action and $a_{P,t} = \left(a'_{P,i,t}, a'_{P,-i,t}\right)'$ is the action profile of the game. $\varepsilon_{P,i,t}$ follows the standard Type 1 Extreme Value Distribution. The action set is a three-dimensional space presenting the menu composition strategy. The other bank's product choice for type j does not affect bank i's profit unless the type j product belongs to bank i's menu.

The menu game is also an incomplete information game. In this game, banks observe the entry decisions of all banks in the market but do not observe the other banks' products. Under the Bayesian Nash Equilibrium, $P\left(a_{P,i,t} = \bar{a} | X_{P,t}\right)$ for some $\bar{a} = (\bar{a}_{TD}, \bar{a}_{DD}, \bar{a}_{IRA})' \in \{0,1\}^3$ presents the equilibrium probability of bank i. Bank i chooses the optimal action $\bar{a}$ if the expected profit

$$\sum_{j\in\mathcal{J}} \bar{a}_j \left(X'_{P,i,j,t}\beta_{P,i,j} - \left(\sum_{-i\in\mathcal{I}_{P,-i,t}} P\left(a_{P,-i,j,t} = 1 | X_{P,t}\right) \right) \delta_{P,i,j} \right) + \varepsilon_{P,i,t}$$

is greater than the expected profits from other actions $\bar{a}' \in \{0,1\}^3 \setminus \bar{a}$. The marginal equilibrium probability $P\left(a_{P,-i,j,t} = 1 | X_{P,t}\right)$ is a function of equilibrium probabilities $\sum_{\{\bar{a}_{-i,j}=1\}} P\left(a_{P,-i,t} = \bar{a}_{-i} | X_{P,t}\right)$. At the equilibrium, $P\left(a_{P,i,t} = \bar{a} | X_{P,t}\right)$ is

$$\begin{aligned} P\Bigg(& \sum_{j\in\mathcal{J}} \bar{a}_j \left(X'_{P,i,j,t}\beta_{P,i,j} - \left(\sum_{-i\in\mathcal{I}_{P,-i,t}} P\left(a_{P,-i,j,t} = 1 | X_{P,t}\right) \right) \delta_{P,i,j} \right) + \bar{\varepsilon}_{P,i,t} \\ & \geq \sum_{j\in\mathcal{J}} \bar{a}'_j \left(X'_{P,i,j,t}\beta_{P,i,j} - \left(\sum_{-i\in\mathcal{I}_{P,-i,t}} P\left(a_{P,-i,j,t} = 1 | X_{P,t}\right) \right) \delta_{P,i,j} \right) + \varepsilon_{P,i,t} \Bigg| X_{P,t} \Bigg) \\ & = \frac{\exp\left(\sum_{j\in\mathcal{J}} \bar{a}_j \left(X'_{P,i,j,t}\beta_{P,i,j} - \left(\sum_{-i\in\mathcal{I}_{P,-i,t}} P\left(a_{P,-i,j,t} = 1 | X_{P,t}\right) \right) \delta_{P,i,j} \right) \right)}{\exp\left(\sum_{a\in\{0,1\}^3} \sum_{j\in\mathcal{J}} a_j \left(X'_{P,i,j,t}\beta_{P,i,j} - \left(\sum_{-i\in\mathcal{I}_{P,-i,t}} P\left(a_{P,-i,j,t} = 1 | X_{P,t}\right) \right) \delta_{P,i,j} \right) \right)} \end{aligned} \tag{2.4}$$

where the inequality holds for all $\bar{a}' \in \{0,1\}^3 \setminus \bar{a}$. The equilibrium product choice probability satisfies equation (2.4). The researcher observes the menu choice $a_{P,t}$, observable covariates $X_{P,t}$, and the joint distribution of $\varepsilon_{P,t}$ for markets $\mathcal{M}$. The covariates $X_{P,t}$ include some bank i and type j specific covariates $X_{P,i,j,t}$, and share common covariates with $X_{E,t}$.

Game III: Deposit Competition

Deposit market competition follows the context of Egan, Hortacsu, and Matvos (2017). Observing the entry of banks and deposit rates, depositors decide the bank to place their financial assets, primarily considering the deposit rate. The depositor k's indirect utility function from bank $i \in \mathcal{I}_{P,t}$ is

$$U_{D,k,i,t} = \alpha_D I_{i,t} + \delta_{D,i} + \eta_{D,t} + \varepsilon_{D,k,i,t},$$

where $I_{i,t}$ is the deposit rate provided by bank i in time t, $\delta_{D,i}$ is the depositor's bank preference, and $\eta_{D,t}$ is the time fixed effect. The bank-specific optimal deposit rate $I_{i,t}$ relies on the bank's profit function components in equation (2.4), which approximates the market size, market share, and cost structure. More importantly, the bank's menu affects the resulting $I_{i,t}$. Following Egan, Hortacsu, and Matvos (2017), we assume that the equilibrium deposit rates $\{I_{i,t}\}_{i\in\mathcal{I}_{P,t}}$ follows a Bertrand-Nash Equilibrium. We normalize the utility from other banks $i \notin \mathcal{I}_{P,t}$ by zero. The utility shock $\varepsilon_{D,k,i,t}$ follows the standard Type 1 Extreme Value Distribution.

Depositor k decides on a bank to maximize the utility. Then the conditional choice probability of bank i is

$$s_{i,t} = P\left(U_{D,k,i,t} \geq U_{D,k,-i,t} \middle| \{I_{i,t}\}_{i\in\mathcal{I}_{P,t}}\right) = \frac{\exp\left(\alpha_D I_{i,t} + \delta_{D,i} + \eta_{D,t}\right)}{1 + \sum_{i'\in\mathcal{I}_{P,t}} \exp\left(\alpha_D I_{i',t} + \delta_{D,i'} + \eta_{D,t}\right)} \tag{2.5}$$

and $s_{i,t}$ is bank i's market share in depositor k's county at time t. The coefficient α_D presents the sensitivity of depositor's bank choice with respect to the deposit rate. The logit demand system generates the linear relation of log market share and demand coefficients. Let $s_{0,t} = 1 - \sum_{i'\in\mathcal{I}_{P,t}} s_{i',t}$ denote the market share of small banks that do not practically participate in the entry and product games. The observable market shares enable to identify the depositor's utility parameters:

$$\log s_{i,t} - \log s_{0,t} = \alpha_D I_{i,t} + \delta_{D,i} + \eta_{D,t} \tag{2.6}$$

and taking a linear regression, we estimate coefficients α_D, $\delta_{D,i}$, and $\eta_{D,t}$ by observing market shares across many counties $\mathcal{M}$. We discuss details regarding estimation in Section 2.3.2.

In the last stage, we identify the bank's menu cost. The bank's profit level relies on the total deposit size of the county (market size), the bank's market power (market share), and menu cost. $\pi_{i,t}$ denotes bank i's net profit in time t:

$$\pi_{i,t} = Q_t s_{i,t}\left(R_{i,t} - c_{i,t}\left(a_{P,i,t}\right) - I_{i,t}\right)$$

where Q_t is the market size measured by the total deposit amount in the county and time t, $s_{i,t}$ is bank i's market share satisfying equation (2.5), $R_{i,t}$ is the return on deposits, $c_{i,t}\left(a_{P,i,t}\right)$ is the marginal cost containing the menu cost, and $I_{i,t}$ is the deposit interest rate. Since the banks simultaneously maximize the profit by choosing the optimal deposit rate $\{I_{i,t}\}_{i\in\mathcal{I}_{P,t}}$, the first order condition at the equilibrium is

$$\frac{\partial \pi_{i,t}}{\partial I_{i,t}} = -Q_t s_{i,t} + Q_t\left(\alpha_D s_{i,t}\left(1-s_{i,t}\right)\right)\left(R_{i,t} - c_{i,t}\left(a_{P,i,t}\right) - I_{i,t}\right) = 0,$$

which implies

$$1 = \alpha_D\left(1-s_{i,t}\right)\left(R_{i,t} - c_{i,t}\left(a_{P,i,t}\right) - I_{i,t}\right).$$

Since we can identify α_D from equation (2.6) and $s_{i,t}$, $R_{i,t}$, $I_{i,t}$ are observables, we can retrieve the information regarding the marginal cost $c_{i,t}\left(a_{P,i,t}\right)$. The marginal cost varies across banks, times, and menu choices. The specification of the cost structure follows

$$c_{i,t}\left(a_{P,i,t}\right) = R_{i,t} - I_{i,t} - \frac{1}{\alpha_D\left(1-s_{i,t}\right)} = \sum_{j\in\mathcal{J}} a_{P,i,j,t} c_j + \delta_{C,i} + \eta_{C,t} + \xi_{C,i,t} \tag{2.7}$$

where $\delta_{C,i}$ is bank-specific cost, $\eta_{C,t}$ is time-specific cost, and c_j is the menu cost of launching a new product type j. The identified $c_{i,t}\left(a_{P,i,t}\right)$ from the first equality of equation (2.7) is the marginal cost when bank i's selling menu is realized at $a_{P,i,t}$. The identification of c_j using cross-county menu variations enables researchers to approximate the marginal cost from adding different products to the menu.

Under the given actions $a_{P,i,t}$ and $a_{P,-i,t}$, the bank i's maximized net profit is $(Q_t s_{i,t})/(\alpha_D\left(1-s_{i,t}\right))$ when the deposit rate is optimal. The bank i's profit $\pi^*_{i,t}$ and payoff level $U_{P,i,t}\left(a_{P,t}, X_{P,t}\right)$ are equivalent at the equilibrium, while $U_{P,i,t}\left(a_{P,t}, X_{P,t}\right)$ presents a normalized profit value. The payoff function described in equation (2.3) is a normalized profit of bank i with respect to the payoff with $a_{P,i,j,t} = 0$ for all $j \in \mathcal{J}$, where the profit of selling no more than standard products is fixed at zero. We calibrate the effect of menu change to the market outcome. The payoff in the menu game is

$$\sum_{j\in\mathcal{J}} a_{P,i,j,t}\left(X'_{P,i,j,t}\beta_{P,i,j} - \left(\sum_{-i\in\mathcal{I}_{P,-i,t}} a_{P,-i,j,t}\right)\delta_{P,i,j}\right) + \varepsilon_{P,i,t}$$

for $a_{P,i,j,t} \neq 0$ for some j and is normalized to zero if $a_{P,i,j,t} = 0$ for all $j \in \mathcal{J}$. Since the normal form game's Nash Equilibrium and best responses are invariant to positive affine transformations of the payoffs, we match

$$\overbrace{\frac{Q_t s_{i,t}}{\alpha_D\left(1-s_{i,t}\right)}}^{\pi^*_{i,t}} = g\left(\sum_{j\in\mathcal{J}} a_{P,i,j,t}\left(X'_{P,i,j,t}\beta_{P,i,j} - \left(\sum_{-i\in\mathcal{I}_{P,-i,t}} a_{P,-i,j,t}\right)\delta_{P,i,j}\right) + \varepsilon_{P,i,t}\right)$$

$$= g_1 \left(\sum_{j \in \mathcal{J}} a_{P,i,j,t} \left(X'_{P,i,j,t} \beta_{P,i,j} - \left(\sum_{-i \in \mathcal{I}_{P,-i,t}} a_{P,-i,j,t} \right) \delta_{P,i,j} \right) \right) + g_2 + \xi_{\pi,i,t} \tag{2.8}$$

for some transformation parameters g_1 and g_2. For example, if $a_{P,i,j,t} = 0$ for all $j \in \mathcal{J}$,

$$\frac{Q_t s_{i,t}}{\alpha_D (1 - s_{i,t})} = g_2 + \xi_{\pi,i,t}.$$

Matching the normalized payoff with the supply side parameters enables us to predict the market share change with respect to the selling menu change.

Suppose g_1 and g_2 are identified by the linear projection of $\pi^*_{i,t}$ on the bank's indirect utility. As far as the market size Q_t is given, the change in $a_{P,i,j,t}$ directly affects the marginal cost through equation (2.7) and market share $s_{i,t}$ following equation (2.8). The change in market share affects the optimal deposit rate $I_{i,t}$ conditional on the observable return on deposits $R_{i,t}$ and marginal cost $c_{i,t}(a_{P,i,t})$, since

$$I_{i,t} = R_{i,t} - c_{i,t}(a_{P,i,t}) - \frac{1}{\alpha_D (1 - s_{i,t})}. \tag{2.9}$$

In the next section, we construct an econometric model for the three simultaneous static games with multiple discrete choices. In Section 2.5, we conduct counterfactual analyses using the calibration based on entry, menu space, and deposit demand-supply parameters.

2.3.2 Econometric Specifications

We develops econometric specifications and estimation strategies for the model described in the previous section. We observe many deposit markets across regions and times, treating each county and year as an independent market. For each county $m \in \mathcal{M}$, we collect information about active banks, entry decisions, product menus, deposit rates, market share, total deposit, and several bank-county-specific covariates. The additional control variables include the number of branches, the number of other large/small banks, population, income, the house price index (HPI), etc.

The data contains 967 counties in the U.S. for eight years (2011 to 2018), in a total of 7,736 markets for each of the top 5 banks. Denote $\left\{ a^m_{E,t}, a^m_{P,t}, X^m_{E,t}, X^m_{P,t} \right\}$ for $m \in \mathcal{M} = \{1, \ldots, 967\}$ and $t \in \mathcal{T} = \{2011, \ldots, 2018\}$ to present the observables for the first and second stage estimations. The set of potential entrants $\mathcal{I}^m_{E,t}$ is given by the top 5 financial institutions, including JP Morgan Chase, Bank of America, Wells Fargo, PNC, and US Bank. $\mathcal{I}^m_{P,t}$ is the group of active banks in county m and time t.

We estimate the first and second stages by maximum likelihood since we assume the degenerate equilibrium selection. The entry-related covariates $X_{E,t}^{m}$ include the county income per capita, county population, HPI, the number of active counties, the number of banks in the county, the number of other banks in the county, the number of own branches in the county, and year dummies. The profit-related covariates $X_{P,t}^{m}$ add the bank-specific weights on product types, the Herfindahl–Hirschman index (HHI), and the number of competitors to $X_{E,t}^{m}$. The weight on product type TD means the proportion of TD-type deposits out of the bank's total deposits. The HHI measures market concentration or summarizes the county's market structure.

Define the parameter vectors for all N_E banks $\beta_E = \left(\beta_{E,1}', \ldots, \beta_{E,N_E}'\right)'$, $\delta_E = \left(\delta_{E,1}', \ldots, \delta_{E,N_E}'\right)'$, $\beta_P = \left(\beta_{P,1}', \ldots, \beta_{P,N_E}'\right)'$, and $\delta_P = \left(\delta_{P,1}', \ldots, \delta_{P,N_E}'\right)'$ with $\beta_{P,i} = \left(\beta_{P,i,TD}', \beta_{P,i,DD}', \beta_{P,i,IRA}'\right)'$ and $\delta_{P,i} = \left(\delta_{P,i,TD}, \delta_{P,i,DD}, \delta_{P,i,IRA}\right)'$. The likelihood function in county m and time t is

$$\begin{aligned}
&\mathcal{L}_{m,t}\left(\beta_E, \delta_E, \beta_P, \delta_P | a_{E,t}^m, a_{P,t}^m, X_{E,t}^m, X_{P,t}^m\right) \\
&= \prod_{i \in \mathcal{I}_{E,t}^m} P\left(a_{E,i,t} = a_{E,i,t}^m | X_{E,t}^m; \beta_E, \delta_E\right) \prod_{i' \in \mathcal{I}_{P,t}^m} P\left(a_{P,i',t} = a_{P,i',t}^m | X_{P,t}^m; \mathcal{I}_{P,t}^m, \beta_P, \delta_P\right)
\end{aligned}$$

where the likelihood components are BNE probabilities defined in equations (2.2) and (2.4). Then, we define the log-likelihood function $\log \mathcal{L}\left(\beta_E, \delta_E, \beta_P, \delta_P | \left\{a_{E,t}^m, a_{P,t}^m, X_{E,t}^m, X_{P,t}^m\right\}_{m \in \mathcal{M}, t \in \mathcal{T}}\right)$ as

$$\sum_{m \in \mathcal{M}} \sum_{t \in \mathcal{T}} \log \mathcal{L}_{m,t}\left(\beta_E, \delta_E, \beta_P, \delta_P | a_{E,t}^m, a_{P,t}^m, X_{E,t}^m, X_{P,t}^m\right),$$

and

$$\left(\hat{\beta}_E, \hat{\delta}_E, \hat{\beta}_P, \hat{\delta}_P\right) = \operatorname{argmax}_{\left(\beta_E', \delta_E', \beta_P', \delta_P'\right)} \log \mathcal{L}\left(\beta_E', \delta_E', \beta_P', \delta_P' | \left\{a_{E,t}^m, a_{P,t}^m, X_{E,t}^m, X_{P,t}^m\right\}_{m \in \mathcal{M}, t \in \mathcal{T}}\right).$$

Thereby we simultaneously estimate the entry game and menu choice game parameters through the estimation procedure with a fixed point algorithm described in Section 4.1 and 4.2 from Bajari, Hong, Krainer, and Nekipelov (2010). We follow their estimation method twice since the model has separate conditional probabilities associated with the entry and menu choice decisions. However, unlike Bajari, Hong, Krainer, and Nekipelov (2010) using GMM as an estimator, we use the maximum likelihood method as explained above.

Next, we observe the bank-county-time specific market share in the deposit market $s_{i,t}^m$, the average return on assets $R_{i,t}^m$, the deposit rate $I_{i,t}^m$, and the total deposit size of the market Q_t^m. The estimation of depositor's utility parameter in equation (2.6) follows

$$\log s_{i,t}^{m} - \log s_{0,t}^{m} = \alpha_D I_{i,t}^{m} + \delta_{D,i} + \gamma_{D,m} + \eta_{D,t} + \xi_{D,i,t}^{m} \tag{2.10}$$

where $s_{0,t}^{m}$ is the deposit market share of the non-top 5 banks in county m and time t, and $\delta_{D,i}$, $\eta_{D,t}$, and $\gamma_{D,m}$ are bank, time, county fixed effects. We denote $\left(\hat{\alpha}_D, \hat{\delta}_{D,i}, \hat{\gamma}_{D,m}, \hat{\eta}_{D,t}\right)$ by the OLS estimates of the linear equation (2.10).

The estimation of the marginal cost $c_{i,t}\left(a_{P,i,t}\right)$ follows equation (2.7). For each county $m \in \mathcal{M}$, the feasible marginal cost estimate is

$$c_{i,t}^{m}\left(a_{P,i,t}^{m}\right) = R_{i,t}^{m} - I_{i,t}^{m} - \frac{1}{\hat{\alpha}_D\left(1 - s_{i,t}^{m}\right)}$$

and we specify the marginal cost as a function of product types. The equation with the bank, time, and county fixed effects provides the average partial effect of product choice on the marginal cost:

$$c_{i,t}^{m}\left(a_{P,i,t}^{m}\right) = \sum_{j \in \mathcal{J}} a_{P,i,j,t}^{m} c_j + \delta_{C,i} + \gamma_{C,m} + \eta_{C,t} + \xi_{C,i,t}^{m} \tag{2.11}$$

and the estimated coefficients $\hat{c}_j$ for $j \in \mathcal{J}$ capture the type-specific cost contribution. The next section presents the main estimation results.

2.4 Results

This section presents the estimation results. We follow the econometric specifications in Section 2.3.2 and compute the entry game and menu choice game parameters. Then we run the regressions following equations (2.10) and (2.11) to provide the depositor's utility and bank's revenue-cost parameters.

2.4.1 Entry Game Estimates

Table 2-2 shows estimates regarding the bank's entry decisions. The bank's pre-entry expected profit affects the entry decision, and the entry determinants include bank-county-level covariates and the strategic interaction term. The income variable is the log value of the county income per capita, and the population variable is also the log value of the county population. The number of small banks summarizes the number of active non-top 5 banks, proxying the market size. If there are many small banks in the county, the market share for

Table 2-2: Entry Game Estimates: Top 5 Banks

	Top 5 Banks				
	Chase	**BoA**	**Wells Fargo**	**PNC**	**US Bank**
Covariates					
Income	− 0.1063	− 0.1039	− 0.1017	− 0.0736	− 0.0858
	(0.0167)	(0.0153)	(0.0157)	(0.0171)	(0.0157)
Population	0.1087	0.1083	0.1061	0.0901	0.0857
	(0.0168)	(0.0161)	(0.0148)	(0.0168)	(0.0163)
HPI	− 0.0706	− 0.0723	− 0.0659	− 0.0604	− 0.0685
	(0.0128)	(0.0131)	(0.0132)	(0.0135)	(0.0125)
# Small Banks	− 0.0531	− 0.0491	− 0.0451	− 0.0231	− 0.0334
	(0.0106)	(0.0107)	(0.0098)	(0.0097)	(0.0101)
# Branches	0.1339	0.1180	0.1363	0.1746	0.1636
	(0.0306)	(0.0300)	(0.0312)	(0.0315)	(0.0304)
Constant	− 0.0756	− 0.0796	− 0.0735	− 0.0674	− 0.0758
	(0.0133)	(0.0131)	(0.0128)	(0.0133)	(0.0133)
Strategic Interactions					
Rival's Entry	− 0.0096	− 0.0093	− 0.0157	− 0.0077	− 0.0193
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0001)
Year Dummies	Yes	Yes	Yes	Yes	Yes

This table shows entry game parameter estimates. Standard errors are calculated from bootstrapping 600 samples. The bank's pre-entry expected profit affects the entry decision, and the entry determinants include various covariates and the strategic interaction term. The estimated result reveals the statistically significant correlations between determinants and entry probabilities across counties in the United States. The strategic interaction parameter estimates how sensitively banks respond to the entry of rival banks. All interaction effects are negative values and statistically significant.

the top 5 banks cannot be large enough. The number of branches refers to the network effect, as the existing branches in the county make it easier to open another branch in the same county. The strategic interaction term implies the negative entry effect from the entry of major rival banks.

Table 2-2 estimates reveal the statistically significant correlations between determinants and entry probabilities across counties in the United States. Since the population directly implies the overall market size, the county with more people increases the entry probability. Similarly, regional banks negatively affect entry, as the market is competitive and the expected market share is not high. The network effect is positive, so having more branches leads banks more likely to stay in counties where they already operate branches. This network effect also reflects the fact that banks have a strong ATM network to enhance their deposit market share in regions with more branches.

The estimates find a negative correlation between income per capita and entry decisions. Similarly, the housing price (HPI) also negatively affects entry. This outcome is consistent with Lin (2020) and Campbell (2006). Lin (2020) finds that banks in areas with greater stock ownership see a greater reduction in deposit growth during stock market booms. Campbell (2006) shows that stock ownership is strongly correlated with household income. Therefore, depositors with a higher level of income are not only less likely to save their wealth into deposit accounts but also more likely to move their wealth from bank deposits to stock accounts during the low-interest rate period during which S&P 500 delivered more than 10% annual return while deposit rates were below 1%.

The strategic interaction parameter estimates how sensitively banks respond to the entry of rival banks. All interaction effects are negative values and statistically significant. One bank's entry deters the other player's entry as the rival bank's entry affects the potential profit from the county. For example, JP Morgan Chase's empirical entry probability is 5.42%, but one more top 5 banks' entry reduces JP Morgan Chase's entry probability by 0.1% or 1.65% on average. Similarly, Bank of America responds to one more rival's entry by lowering 0.091% or 1.9% entry probability. Except for the largest two banks, Wells Fargo, PNC, and US Bank's entry decisions are more sensitive. One rival bank's entry decreases their average entry probabilites by 0.18%, 0.17%, and 0.33%, respectively. The estimates predict that these three banks will retreat from 3% of markets if one more major bank enters the market. This outcome is noticeable because JP Morgan Chase and Bank of America began expanding during our sample period by opening branches in cities where they previously did not have have a retail presence.[4]

2.4.2 Menu Game Estimates

In the menu choice game, there can be only one player in the market. The banks know the incumbent players in this game, so there is no strategic interaction if a bank is the only player in the market. Table 2-3 provides the coefficient estimates, approximated standard errors, and heterogeneous strategic interaction effects across product types.

The menu choice game's utility function contains more covariates since more information is available once the entry decisions are over. For example, a bank's number of active counties correlates with the menu

[4] For example, Bank of America opened branches in Minneapolis-Saint Paul, the home market of US Bank, in 2015 and opened branches in Pittsburgh, the home market of PNC, in 2018. In 2019, JP Morgan Chase began opening branches in Pittsburgh and other areas within Western Pennsylvania. This coincided with Bank of America starting a similar expansion within the area in the previous year.

Table 2-3: Menu Choice Game Estimates: Top 5 Banks

	Top 5 Banks				
	Chase	**BoA**	**Wells Fargo**	**PNC**	**US Bank**
Covariates					
Income	0.0303	0.0435	0.0052	0.0173	0.0261
	(0.0209)	(0.0219)	(0.0211)	(0.0228)	(0.0213)
Population	– 0.0084	– 0.0112	0.0430	– 0.0206	– 0.0055
	(0.0214)	(0.0224)	(0.0220)	(0.0208)	(0.0215)
HPI	0.0307	0.0382	0.0076	0.0301	0.0436
	(0.0142)	(0.0143)	(0.0155)	(0.0156)	(0.0147)
Active County	0.0506	0.0061	– 0.0011	– 0.0117	0.0076
	(0.0024)	(0.0024)	(0.0023)	(0.0022)	(0.0022)
# Small Banks	0.0007	0.0400	0.0216	0.0145	0.0371
	(0.0224)	(0.0188)	(0.0176)	(0.0179)	(0.0182)
# Branches	0.0029	0.0211	– 0.0062	0.0150	0.0559
	(0.0183)	(0.0159)	(0.0178)	(0.0170)	(0.0165)
TD Ratio	0.0037	0.0079	– 0.0048	0.0042	0.0065
	(0.0010)	(0.0010)	(0.0010)	(0.0009)	(0.0010)
DD Ratio	0.0215	0.0138	– 0.0051	0.0362	0.0165
	(0.0082)	(0.0085)	(0.0085)	(0.0072)	(0.0083)
Constant	0.0145	0.0185	0.0025	0.0181	0.0137
	(0.0127)	(0.0130)	(0.0133)	(0.0130)	(0.0129)
Strategic Interactions					
Rival's TD	– 0.0089	– 0.0092	– 0.0006	– 0.0008	– 0.0192
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Rival's DD	– 0.0143	– 0.0025	– 0.0063	– 0.0023	– 0.0040
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Rival's IRA	– 0.0049	– 0.0091	– 0.0149	– 0.0030	– 0.0132
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

This table shows menu choice game parameter estimates. Standard errors are calculated from bootstrapping 600 samples. The menu choice game's utility function contains more covariates since more information reveals after the entry decisions are over. The menu choice game estimates show that income and housing prices positively affect selling new products. The interaction coefficients are all statistically significant, implying that the menu choice is strategic across banks.

diversification strategy, but the value is confirmed after the entry decision. We also add TD and DD ratios as control variables, as they display banks' profit sources. For example, if a bank earns profit mostly from TD, the bank has more incentive to launch new TD products. We omit the IRA ratio due to multicollinearity.

The menu choice game estimates show that income and housing prices positively affect selling new products. The result indicates that the menu is more diverse for counties where depositors demand more financial assets. The number of small banks also influences more varied products, as the competition with regional banks incentivizes new strategies to appeal to consumers. The network variable finds that banks are more likely to sell various products in the counties with more branches. Regarding type-specific regressors, our estimates find that banks earning more from TD/DD products are more prone to diversify the TD/DD products.

The estimated interaction effects reveal a complicated competition structure of menu choice but clarify the bank's menu composition strategy. The interaction coefficients are all statistically significant, implying that the menu choice is strategic across banks. We can identify each bank's different menu choice strategy based on the magnitudes of coefficients. For example, JP Morgan Chase is more sensitive to the rival banks' new TD and DD products while relatively insensitive to the rival's IRA products. If one more rival bank launches to sell an additional TD product, JP Morgan Chase's probability of selling a new TD product decreases by 0.89%. The probability reduction influenced by the rival bank's menu is 1.42% for DD products, while only 0.49% for IRA products. On the other hand, Wells Fargo is more sensitive to the rival bank's new IRA product but relatively insensitive to the other bank's TD product. One more bank selling a new TD product does not affect Wells Fargo's menu, but Wells Fargo is 1.48% less likely to add a new IRA product if the other bank launches a new IRA product. The result implies that each bank has a different strategy for diversifying the selling menu, depending on the primary deposit source and depositor characteristics.

2.4.3 Demand and Cost Functions

The estimates in Table 2-4 provide demand estimates for depositors and menu cost estimates for banks. Depositors prefer to enjoy a higher deposit rate, thus the demand positively responds to the increase in deposit rate. The next columns discuss how the bank's cost structure correlates with the product choice. We find that a DD product is the most costly option out of all product types, while TD is the least costly menu for banks. The implication preserves with different model specifications. The county, bank, and year-specific fixed effects show high R^2 values, explaining the variation of marginal cost.

The estimation result on menu costs could be associated with characteristics of deposit products under the quantitative easing monetary policy. For example, a CD is not as liquid as MM due to its rigid maturity,

Table 2-4: Demand and Cost Estimates: Top 5 Banks

	Demand Estimates		**Cost Estimates**	
	(1)		(1)	(2)
Deposit rate	23.8968	TD	− 0.2545	− 0.1558
	(20.4092)		(0.1240)	(0.1607)
		DD	0.2310	0.2236
			(0.1318)	(0.1263)
		IRA	− 0.1933	− 0.0331
			(0.1053)	(0.1076)
Constant	− 2.1776	Constant	− 0.0850	− 0.2368
	(0.0275)		(0.0788)	(0.0931)
County FE	Yes		Yes	Yes
Year FE	Yes		Yes	Yes
Bank FE	Yes		No	Yes
Observations	3,175		3,175	3,175
R^2	0.7687		0.3926	0.7128

This table shows demand and cost parameter estimates. Depositors prefer to enjoy a higher deposit rate, thus the demand positively responds to the increase in deposit rate. The next columns discuss how the bank's cost structure correlates with the product choice. The next columns discuss how the bank's cost structure correlates with the product choice.

so banks pay a liquidity premium on CDs. Therefore, a CD is a relatively expensive funding source for banks, although banks can maintain deposits through CD over a certain maturity. However, as Figure E-1 shows, this liquidity premium decreased over the sample period because of the ultra-low Federal Funds Rate. As a result, banks were incentivized to collect deposits more through CD than MM since they did not need to pay a liquidity premium as much as before.

Considering that the product-type-specific marginal cost differs across banks, we find bank-specific strategies for product choice. For example, JP Morgan Chase shows relatively high costs from adding a DD product while low costs from adding a TD product. JP Morgan Chase's cost structure prefers to add a TD product instead of a DD product. However, not all banks strategically behaved as JP Morgan Chase did under peculiar circumstances. The Bank of America shows a different cost structure and prefers a DD product over a TD product. The estimated Bank of America-specific marginal cost is much lower when they add a new DD product. This difference between the two megabanks is described in E-2, showing that JP Morgan Chase had provided a uniform liquidity premium given a maturity regardless of counties over the sample period. In contrast, Bank of America differentiated a liquidity premium at the beginning of the quantitative easing monetary policy and gradually decreased it. This observation implies that the two banks might have different competition strategies to gain deposit market share. JP Morgan Chase utilizes the deposit product menu choice more than Bank of America does, while Bank of America specializes more in differentiated pricing strategies.

Therefore, our result on the endogenous deposit product menu choice implies that banks have an additional competitive strategy other than deposit rate setting. The practitioners can use this new mechanism in our paper to understand deposit market competition in depth. For example, there are recent papers on a uniform deposit rate pricing pattern in the U.S. banking sector (e.g., Begenau and Stafford (2022) for monetary policy transmission and Granja and Paixao (2022) for implications of bank consolidation through M&A). However, the literature does not explain why the uniform pricing pattern is observed as an equilibrium result.[5] Our paper can suggest that some banks (like JP Morgan Chase in Figure E-1) are more actively involved in the product-space competition than others (like Bank of America in the same figure).

2.5 Counterfactual Analysis and Extension

This section utilizes the estimates to simulate counterfactual scenarios motivated by empirical observations after the financial crisis of 2008. We consider three counterfactual analyses: (1) increase in housing prices, (2) two banks merging, and (3) decrease in physical branches. At the end of this section, we include five more big banks into the benchmark model to check the robustness of the outcomes in Section 2.4.

We predict new equilibrium probabilities for entry and menu choice games for each counterfactual scenario. The equilibrium entry probabilities satisfy equation (2.2), and the menu choice probabilities follow equation (2.4). The change in equilibrium probabilities causes different entry and menu choice decisions. The players may enter new markets or exit from existing markets. Conditional on the entry, a bank may add a new product or remove one from the menu. Our simulation generates a new market structure for each county, affecting new market shares and deposit rates at the equilibrium. The counterfactual market share satisfies equation (2.8) assuming the same level of Q_t and α_D. The new menu and market shares imply the corresponding equilibrium deposit rate equation (2.9). We report the change in entry probabilities, menu choice probabilities, market share, and deposit rate as a resulting table.

[5] In Figure E-3 and E-4, we show the uniform deposit rate pricing pattern in the spirit of DellaVigna and Gentzkow (2019).

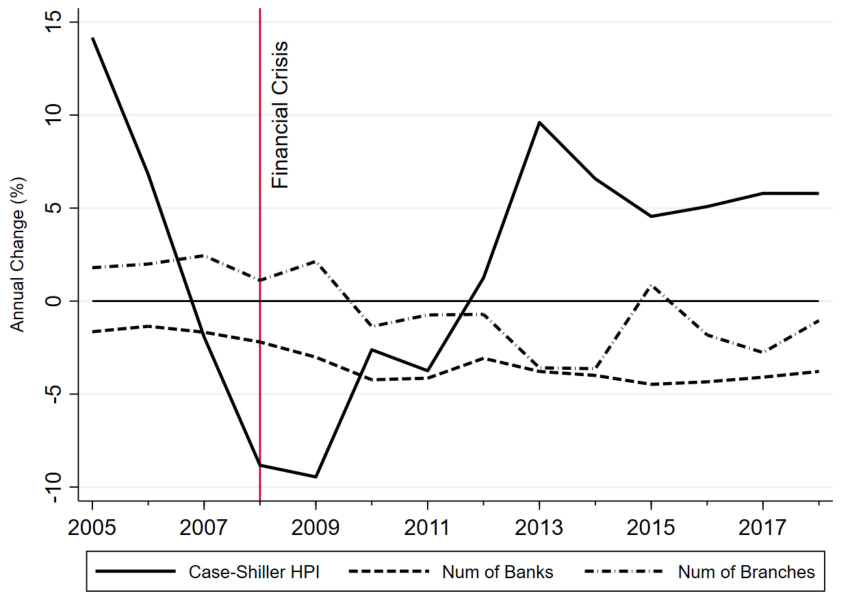


Figure 2-2: Changes in the U.S. Housing Market and Banking Sector

The above figure shows the motivational facts behind our counterfactual simulations. After the financial crisis of 2008, Case-Shiller U.S. National HPI had risen over the quantitative easing monetary policy period. In the banking sector, on the other hand, the number of commercial banks decreased at a faster rate. As Figure 1-3 shows, some failed banks were acquired. Finally, the number of bank branches per 100,000 adults peaked around 2009 and began to decrease. The data is from FRED.

2.5.1 Counterfactual Analysis 1: Increase in HPI

As Figure 2-2 shows, housing prices plummeted right before and after the financial crisis of 2008, but the housing market soon turned into a boom cycle because of the ultra-low interest rate regime. In Section 2.4, we show that the housing price negatively affects entry, consistent with Campbell (2006) and Lin (2020). To understand the implications of the rising HPI on the deposit product menu choice after the entry decision under this environment, we assume that HPI increases by 20% for each county. Table 2-5 reports the counterfactual outcome of the housing price increase. As expected, the rise in HPI causes less entry for all banks, though the magnitude of the entry effect is mediocre. Intuitively, when HPI increases, the banks in our model are less likely to enter new counties or stay in their existing regions, as shown in Table 2-2. Therefore, there is a rising incentive to collect more deposits from the smaller branch networks, leading to higher competition in regions where competitors still operate.

Conditional on new entries, banks adjust the menu composition. The primary estimation result, Table 2-3, finds that the rise in HPI provides more diversified products to the market. On the other hand, one bank's

Table 2-5: Counterfactual Analysis 1: Increase in HPI

	Top 5 Banks				
	Chase	**BoA**	**Wells Fargo**	**PNC**	**US Bank**
Game I: Entry Decision					
$\Delta P(\text{Entry})$	-0.17% (-3.21%)	-0.19% (-3.97%)	-0.21% (-3.28%)	-0.36% (-2.40%)	-0.33% (-3.13%)
Game II: Menu Choice Decision					
Joint Probability: $\Delta P(\mathbb{1}\{\text{TD}\}, \mathbb{1}\{\text{DD}\}, \mathbb{1}\{\text{IRA}\})$					
$\Delta P(1,1,1)$	-0.05% (-0.06%)	-10.01% (-17.41%)	-1.18% (-7.40%)	1.60% (68.88%)	-3.59% (-5.25%)
$\Delta P(1,1,0)$	0.24% (4.00%)	1.36% (12.53%)	-0.18% (-1.33%)	1.86% (60.91%)	0.87% (9.78%)
$\Delta P(1,0,1)$	0.28% (4.79%)	1.38% (12.91%)	-0.14% (-1.04%)	1.85% (62.20%)	0.85% (9.72%)
$\Delta P(0,1,1)$	0.24% (4.05%)	1.36% (12.54%)	-0.17% (-1.31%)	1.84% (60.17%)	0.88% (9.89%)
$\Delta P(1,0,0)$	0.42% (97.44%)	2.01% (66.79%)	0.61% (5.35%)	1.53% (17.70%)	0.67% (43.04%)
$\Delta P(0,1,0)$	0.38% (85.50%)	2.00% (65.58%)	0.57% (5.04%)	1.51% (16.98%)	0.69% (43.43%)
$\Delta P(0,0,1)$	0.42% (96.34%)	1.99% (66.25%)	0.61% (5.38%)	1.50% (17.41%)	0.67% (43.01%)
Marginal Probability					
$\Delta P(\mathbb{1}\{\text{TD}\}=1)$	0.89% (0.96%)	-5.26% (-6.41%)	-0.88% (-1.63%)	6.84% (40.27%)	-1.19% (-1.35%)
$\Delta P(\mathbb{1}\{\text{DD}\}=1)$	0.80% (0.86%)	-5.29% (-6.43%)	-0.96% (-1.78%)	6.81% (39.31%)	-1.14% (-1.30%)
$\Delta P(\mathbb{1}\{\text{IRA}\}=1)$	0.89% (0.95%)	-5.28% (-6.44%)	-0.88% (-1.64%)	6.78% (39.99%)	-1.18% (-1.34%)
Game III: Price-Setting Decision					
ΔMarket Share	-0.07% (-0.26%)	0.04% (0.08%)	-0.63% (-1.86%)	0.11% (0.66%)	-0.12% (-0.50%)
ΔDeposit Rate	0.84 bps (0.15%)	-0.14 bps (-0.01%)	46.53 bps (5.25%)	-0.60 bps (-0.05%)	0.96 bps (0.10%)

The unit for ΔP at the first two games and ΔMarket Share is a percent point. The unit for ΔDeposit Rate is bps ($1\% = 100$bps). The numbers in parentheses are percent changes.

more diversified menu discourages rival banks from launching new financial products under monopolistic competition. The competition from the deposit product menu choice plays a more significant role than the direct impact of the increase in HPI. Thus, the banks that are insensitive to the rival bank's menu choices eventually diversify their menu. For example, all banks except for PNC in Table 2-5 become less likely to sell the universal deposit products ($\Delta P(1,1,1) < 0$). PNC's counterfactual menu significantly increases diversity, with a 6.8% increase in each financial product type.

The impact of the increase in HPI on each bank is different and reflects bank-specific characteristics. For example, JP Morgan Chase generally provides more deposit products, as demonstrated in the marginal probabilities, although the institution is less likely to sell universal deposit products. JP Morgan Chase's response to the HPI rise is not substantial since only a tiny portion of JP Morgan Chase's indirect utility is from strategic interactions. JP Morgan Chase slightly decreases the number of markets providing all types of financial products but serves other counties with increasing diversity because the HPI rise induces new demand for additional financial products. The counterfactual outcome is consistent with our estimation result in the previous section that JP Morgan Chase has an advantage of selling more deposit products.

Bank of America and US Bank are sensitive to the rival's menu, causing more strategic menu composition across the markets. Bank of America becomes less likely to provide all product types and instead focuses on profitable products depending on the market environment. Bank of America's balance strategy between the menu choice and pricing implies its relatively weak competitive edge over the competition from the deposit product menu choice. This example does not show which bank is better than others but demonstrates that each bank has a different strategy to gain or maintain market share.

We also provide the expected changes in market share and deposit rates. Since the simple average of market share changes may overweight the counties with the less total deposit, we compute the weighted average in market share changes depending on the market size. In Section 2.2.1, we consider the economy with K banks, indexed by $i \in \{1, ..., N\} = \mathcal{N}$, over time $t \in \{1, ..., T\} = \mathcal{T}$. to define deposit market share of bank k in market m at time t as follows

$$s_{i,t}^{m} = \frac{q_{i,t}^{m}}{\sum_{i \in \mathcal{N}_t^m} q_{i,t}^{m}} = \frac{q_{i,t}^{m}}{Q_t^m}$$

where $\mathcal{N}_t^m \subset \mathcal{N}$ is a set of financial institutions observed in market m at time t. If bank i competes for deposits in multiple counties, we can define a set of counties where branches of bank i gather deposits at time t, $\mathcal{M}_{i,t} \subset \mathcal{M}$. As a result, we compute a weighted-average of the county-level deposit market share for bank i at time t,

$$\mathrm{s}_{i,t} = \sum_{m \in \mathcal{M}_{i,t}} \underbrace{(q_{i,t}^m / D_{i,t})}_{w_{i,t}^m} \mathrm{s}_{i,t}^m \tag{2.12}$$

where $D_{i,t} = \sum_{m \in \mathcal{M}_{i,t}} q_{i,t}^m$ is the total deposits of bank i at time t, so $\sum_{m \in \mathcal{M}_{i,t}} w_{i,t}^m = 1$. This weight reflects importance of some counties from which a bank secures a major portion of its deposits. We use this definition to report changes in market share.

The reported market shares and deposit rates show opposite signs, as predicted by theory. The rise in market share implies less deposit rate due to increased market power. The PNC's aggressive expansion on menu diversification causes a significant increase in the PNC's market share while other banks' market shares decrease accordingly. JP Morgan Chase is the least sensitive bank to the change in the market environment, and US Bank and Wells Fargo show relatively more significant changes. Notably, the HPI rise influences Wells Fargo to lose market share, causing a considerable increase in the deposit rate. Bank of America adjusts the entry and menu composition more efficiently and attains an additional market share.

2.5.2 Counterfactual Analysis 2: M&A Situation

It is a well-known fact that the number of commercial banks has decreased over the past three decades.[6] This number decreased faster during the quantitative easing monetary policy period, as Figure 2-2 shows. Some failed banks were acquired, and a large financial institution was not an exception, shown in Figure 1-3. A huge M&A deal can reshape the landscape of the banking industry. During our sample period, JP Morgan Chase and Bank of America opened new branches in Pittsburgh, the home market of PNC, and Minneapolis-Saint Paul, the home market of US Bank. The entry decisions threaten the market shares of PNC and US Bank, exposing the banks to more competition.

We implement a counterfactual simulation in which PNC and US Bank merge, which provides alternative insight. The two financial institutions operate branches in different regions, as shown in Figure F-1. For example, PNC bank has branches in 43 counties, and US Bank operates in 115 counties, according to our dataset for 2011. Out of many serving counties, the overlapped counties for both banks include only nine. The entry pattern is the same in our data in 2018. The PNC and US Bank serve 246 and 111 counties, respectively, but the two banks share the market only in 15 counties. Thus, our counterfactual simulation does not violate a fundamental idea behind the Bank Merger Act. According to the FDIC Statement of Policy on Bank Merger Transactions, the U.S. government prohibits FDIC from approving any proposed merger

[6] There are some studies on the implications of this trend. Recently, for example, Corbae and Levine (2022) provided a dynamic

transaction that would result in a monopoly in any part of the United States. The merger of PNC and US Bank does not significantly increase the market share in any regional market.

We assume that the M&A of PNC and US Bank will not change the joint entry decisions but change the profit structure of the combined bank. There are three scenarios regarding the new profit function. First, we assume that the combined bank maximizes the weighted sum of the two banks' profit functions. The case implies that two banks are associated in an equal position. PNC and US Bank merge the market shares and enter the market where either bank gains positive expected profit. Then the merged bank optimally chooses the menu of financial products to maximize the new profit function. The other scenarios include the PNC-acquiring merge and the US Bank-acquiring merge. The cases imply that one bank purchases the other; thereby, one dominating bank rules all markets that either bank currently enters. In Appendix, we also consider the case that the M&A also influences the joint entry decisions.

Table 2-6 displays the counterfactual outcome of PNC and US Bank's M&A, focusing on the responses from the rival banks. In all possible scenarios, the merger of PNC and US Bank negatively affects the rival bank's entry probability, product diversification, and market share. The overall entry effects are insignificant since PNC and US Bank's active counties do not overlap much. The merger effect on rival banks is more evident in product diversification and resulting market share. Three rival banks, JP Morgan Chase, Bank of America, and Wells Fargo, decrease the probability of selling all financial products since the merged bank has a higher capacity to serve all product types in many markets. Instead, the rival banks start providing different menus across counties.

The remarkable point is that JP Morgan Chase and Bank of America are predicted to decrease the deposit rates even though the average market shares decrease. Based on our model specification, the positive relationship between market share and deposit rate changes appears because the menu adjustment cost dominates the market share effect on the deposit rate. The merged bank will likely include all product types in the menu, around 60% of markets, almost 20% more than before. The merged bank's menu choice makes the other bank's menu diversification less profitable, crowding out other banks from selling various financial products. Therefore, the banks previously benefitted from some term deposits or IRA products cannot sell the products anymore, causing additional costs in the bank profit function. The cost increase eventually results in lower deposit rates to compensate for the profit loss. As banks previously relied more on menu diversification, the cost structure puts more pressure on lowering deposit rates.

model framework to investigate the relationship between competition and stability in the banking industry. Liu (2022) showed how a heightened regulatory burden from the Dodd-Frank Wall Street Reform and Consumer Protection Act depresses the profitability and entry of small banks in the short run while surviving banks could be more profitable in the long run. However, these papers focus on the loan business of banking while our focus is on the deposit market.

Table 2-6: Counterfactual Analysis 2: M&A Situation

	Average Between Two Banks			PNC Acquiring US Bank			US Bank Acquiring PNC		
	Chase	**BoA**	**Wells Fargo**	**Chase**	**BoA**	**Wells Fargo**	**Chase**	**BoA**	**Wells Fargo**
Game I: Entry Decision									
$\Delta P(\text{Entry})$	−0.00%	−0.00%	−0.01%	−0.00%	−0.00%	−0.01%	−0.00%	−0.00%	−0.01%
	(−0.02%)	(−0.05%)	(−0.08%)	(−0.02%)	(−0.05%)	(−0.08%)	(−0.02%)	(−0.05%)	(0.08%)
Game II: Menu Choice Decision									
Joint Probability: $\Delta P(\mathbb{1}\{\text{TD}\}, \mathbb{1}\{\text{DD}\}, \mathbb{1}\{\text{IRA}\})$									
$\Delta P(1,1,1)$	−0.28%	−11.06%	−1.40%	−0.15%	−10.32%	−1.62%	−0.28%	−10.74%	−1.49%
	(−0.34%)	(−19.22%)	(−8.59%)	(−0.19%)	(−17.94%)	(−9.90%)	(−0.35%)	(−18.66%)	(−9.10%)
$\Delta P(1,1,0)$	0.26%	1.50%	−0.25%	0.18%	1.38%	−0.35%	0.30%	1.48%	−0.25%
	(4.35%)	(13.79%)	(−1.84%)	(3.09%)	(12.67%)	(−2.62%)	(5.04%)	(13.55%)	(−1.87%)
$\Delta P(1,0,1)$	0.27%	1.49%	−0.23%	0.18%	1.38%	−0.32%	0.33%	1.47%	−0.24%
	(4.68%)	(13.94%)	(−1.73%)	(3.09%)	(12.83%)	(−2.39%)	(5.72%)	(13.76%)	(−1.77%)
$\Delta P(0,1,1)$	0.27%	1.52%	−0.22%	0.20%	1.40%	−0.28%	0.31%	1.48%	−0.26%
	(4.66%)	(13.97%)	(−1.69%)	(3.37%)	(12.88%)	(−2.15%)	(5.21%)	(13.62%)	(−2.00%)
$\Delta P(1,0,0)$	0.49%	2.08%	0.61%	0.47%	1.92%	0.65%	0.51%	2.08%	0.69%
	(111.95%)	(69.56%)	(5.34%)	(108.43%)	(64.45%)	(5.72%)	(117.83%)	(69.55%)	(6.07%)
$\Delta P(0,1,0)$	0.47%	2.11%	0.60%	0.46%	1.96%	0.67%	0.48%	2.09%	0.65%
	(107.03%)	(69.71%)	(5.37%)	(105.43%)	(64.91%)	(5.99%)	(108.35%)	(68.94%)	(5.81%)
$\Delta P(0,0,1)$	0.50%	2.08%	0.62%	0.48%	1.93%	0.70%	0.51%	2.06%	0.67%
	(113.71%)	(69.60%)	(5.49%)	(110.64%)	(64.60%)	(6.24%)	(117.57%)	(69.18%)	(5.93%)
Marginal Probability									
$\Delta P(\mathbb{1}\{\text{TD}\}=1)$	0.74%	−5.99%	−1.27%	0.68%	−5.64%	−1.63%	0.86%	−5.71%	−1.28%
	(0.79%)	(−7.29%)	(−2.34%)	(0.73%)	(−6.87%)	(−3.01%)	(0.92%)	(−6.95%)	(−2.36%)
$\Delta P(\mathbb{1}\{\text{DD}\}=1)$	0.72%	−5.93%	−1.27%	0.69%	−5.58%	−1.57%	0.80%	−5.70%	−1.35%
	(0.78%)	(−7.21%)	(−2.34%)	(0.74%)	(−6.78%)	(−2.91%)	(0.86%)	(−6.92%)	(−2.49%)
$\Delta P(\mathbb{1}\{\text{IRA}\}=1)$	0.77%	−5.98%	−1.24%	0.71%	−5.62%	−1.52%	0.87%	−5.72%	−1.32%
	(0.82%)	(−7.28%)	(−2.29%)	(0.76%)	(−6.85%)	(−2.81%)	(0.93%)	(−6.97%)	(−2.44%)
Game III: Price-Setting Decision									
ΔMarket Share	−0.17%	−0.15%	−0.59%	−0.06%	−0.08%	−0.35%	−0.26%	−0.21%	−0.80%
	(−0.65%)	(−0.31%)	(−1.76%)	(−0.23%)	(−0.16%)	(−1.04%)	(−1.01%)	(−0.43%)	(−2.39%)
ΔDeposit Rate	−0.03 bps	−4.18 bps	2.30 bps	−0.01 bps	4.43 bps	1.93 bps	−0.01 bps	−4.13 bps	1.73 bps
	(−14.72%)	(−60.78%)	(34.96%)	(−5.93%)	(−62.61%)	(29.21%)	(−5.91%)	(−59.55%)	(24.95%)

The unit for ΔP at the first two games and ΔMarket Share is a percent point. The unit for ΔDeposit Rate is bps ($1\% = 100$bps). The numbers in parentheses are percent changes.

In Appendix, Table F-1 presents the case that the merged bank only serves the markets where both PNC and US Bank are profitable. In this case, the merged bank adjusts the entry decisions across counties and does not maintain branches as many as the sum of two separate banks. Due to the entry adjustment, the merged bank exits from some counties, allowing additional entries of rival banks (JP Morgan Chase, Bank of America, Wells Fargo). However, the rival banks lose significant market shares in the counties where the merged bank operates. For all possible scenarios, the M&A eventually results in a less competitive deposit market across the country.

2.5.3 Counterfactual Analysis 3: Decrease in the Number of Branches

Unlike the number of commercial banks, the number of bank branches had increased since 1990s, but this number began to decrease after the financial crisis of 2008 as Figure 2-2 shows. One of the suggested reasons behind this trend is an introduction of online banking services as studied in Kim (2021). However, Abrams (2019) shows that customers are attentive to which banks operate branches in their regions even though they are aware of online banking services. Therefore, decreasing the number of branches could save the cost of physical branch management, but the geographical branch network could diminish. This network is an important factor for banks' entry as our estimation in Section 2.4 shows.

Table 2-7 presents the counterfactual outcome of decreasing 20% of branches in each county. The reducing network effect causes fewer market entries, implying 5 6% decreases in entry probabilities. The product diversification patterns also change correspondingly, depending on the market covariates and market competition structure. As the network effect gets less sizable, the bank generally has an incentive to serve less diverse products on the menu. However, the magnitudes of changes are heterogeneous across banks. The degree of effects also heavily relies on the current network size. For example, US Bank enters a large portion of the markets with many branches. The decrease in the number of branches mainly implies a severer impact on US Bank than other banks.

The predicted effect of the change in the number of branches benefits Wells Fargo and PNC, which do not currently have a dense network. As Bank of America and US Bank lose a significant portion of market share in the pre-existing counties and become less likely to enter new markets, Wells Fargo and PNC take advantage of fewer competitors in the existing and new markets. The predicted deposit rates inverse-proportionally respond to the market share changes. Except for Wells Fargo and PNC, other banks need to increase the deposit rates due to lower market power. JP Morgan Chase is much more robust than all the other banks, while Bank of America and US Bank adjust the deposit rates around 50 100 bps. The predicted adjustment is substantial, considering that our sample period maintains low deposit rates.

Table 2-7: Counterfactual Analysis 3: Decrease in the Number of Branches

	Top 5 Banks				
	Chase	**BoA**	**Wells Fargo**	**PNC**	**US Bank**
Game I: Entry Decision					
$\Delta P(\text{Entry})$	-0.35% (-6.51%)	-0.26% (-5.42%)	-0.38% (-6.01%)	-0.78% (-5.18%)	-0.64% (-6.01%)
Game II: Menu Choice Decision					
Joint Probability: $\Delta P(\mathbb{1}\{\text{TD}\}, \mathbb{1}\{\text{DD}\}, \mathbb{1}\{\text{IRA}\})$					
$\Delta P(1,1,1)$	-0.45% (-0.56%)	-12.00% (-20.86%)	-1.08% (-6.60%)	1.49% (65.65%)	-5.55% (-8.14%)
$\Delta P(1,1,0)$	0.35% (6.01%)	1.72% (15.80%)	-0.14% (-1.03%)	1.99% (65.34%)	1.30% (14.48%)
$\Delta P(1,0,1)$	0.39% (6.76%)	1.73% (16.18%)	-0.09% (-0.70%)	1.97% (66.63%)	1.27% (14.39%)
$\Delta P(0,1,1)$	0.36% (6.06%)	1.72% (15.83%)	-0.13% (-0.96%)	1.96% (64.61%)	1.31% (14.64%)
$\Delta P(1,0,0)$	0.45% (103.12%)	2.26% (75.70%)	0.58% (5.13%)	1.68% (19.47%)	0.88% (55.57%)
$\Delta P(0,1,0)$	0.40% (91.35%)	2.26% (74.53%)	0.55% (4.86%)	1.67% (18.76%)	0.90% (56.02%)
$\Delta P(0,0,1)$	0.44% (102.08%)	2.24% (75.19%)	0.59% (5.24%)	1.65% (19.19%)	0.88% (55.61%)
Marginal Probability					
$\Delta P(\mathbb{1}\{\text{TD}\} = 1)$	0.74% (0.80%)	-6.29% (-7.65%)	-0.73% (-1.34%)	7.12% (42.17%)	-2.10% (-2.40%)
$\Delta P(\mathbb{1}\{\text{DD}\} = 1)$	0.66% (0.71%)	-6.31% (-7.66%)	-0.80% (-1.47%)	7.11% (41.23%)	-2.04% (-2.32%)
$\Delta P(\mathbb{1}\{\text{IRA}\} = 1)$	0.74% (0.79%)	-6.31% (-7.68%)	-0.71% (-1.31%)	7.07% (41.90%)	-2.08% (-2.38%)
Game III: Price-Setting Decision					
ΔMarket Share	-2.40% (-9.31%)	-3.97% (-8.31%)	13.12% (39.60%)	5.16% (32.86%)	-5.27% (-22.15%)
ΔDeposit Rate	19.01 bps (3.31%)	91.82 bps (7.43%)	-29.02 bps (-3.47%)	-21.61 bps (-1.86%)	55.79 bps (5.64%)

The unit for ΔP at the first two games and ΔMarket Share is a percent point. The unit for ΔDeposit Rate is bps ($1\% = 100$bps). The numbers in parentheses are percent changes.

2.5.4 Extension to the Top 10 Banks

Although the top 5 banks operate branches across the United States, it is not necessarily true that they dominate deposit market share in all regions. Therefore, we add five more big commercial banks into our model and re-estimate the parameters to check the robustness of our estimates in Section 2.4. The top 10 banks include M&T Bank, Associated Bank, Fifth Third Bank, Regions Financial Corporation, and Key Corporation.

Considering other banks in the estimation, we also observe the role of regional banks reserving a significant market share within some counties. In entry games with five nationwide banks, a no-entry decision implies that the market is not profitable enough for banks due to many entrants or unfavorable county-level characteristics. Thus, observing less number of players in a market may derive a misleading conclusion that the market is not profitable. The model extension with more banks covers substantial market shares for each county. We verify that regional banks also have significant market power within their market region.

That is, the payoff functions have additional terms. Let $\mathcal{I}^B_{E,-i,t}$ and $\mathcal{I}^S_{E,-i,t}$ respectively denote the top 5 and top 10 banks except for bank i. The bank's utility function for the extended model is,

$$
\begin{aligned}
&U_{E,i,t}\left(a_{E,t}, X_{E,t}\right) \\
&= \begin{cases} X'_{E,i,t}\beta_{E,i} - \left(\sum_{-i\in\mathcal{I}^B_{E,-i,t}} a_{E,-i,t}\right)\delta^B_{E,i} - \left(\sum_{-i\in\mathcal{I}^S_{E,-i,t}} a_{E,-i,t}\right)\delta^S_{E,i} - \varepsilon_{E,i,t} & \text{if } a_{E,i,t}=1 \\ 0 & \text{otherwise,} \end{cases}
\end{aligned}
$$

where $\delta^B_{E,i}$ and $\delta^S_{E,i}$ separately capture the interaction effects from the top 1-5 and top 6-10 banks. If there are many counties where regional banks have large market shares, the nationwide bank's influence $\delta^B_{E,i}$ may not be stronger than the regional bank's effect $\delta^S_{E,i}$. The parameters $\delta^B_{E,i}$ and $\delta^S_{E,i}$ can be different across banks depending on the market structure each bank faces. Similarly, we also separately report the effects of the top 1-5 and top 6-10 banks on menu diversification. The utility function of the menu choice game is,

$$
\begin{aligned}
&U_{P,i,t}\left(a_{P,t}, X_{P,t}\right) \\
&= \begin{cases} \sum_{j\in\mathcal{J}} a_{P,i,j,t}\left(X'_{P,i,j,t}\beta_{P,i,j} - \left(\sum_{-i\in\mathcal{I}^B_{P,-i,t}} a_{P,-i,j,t}\right)\delta^B_{P,i,j} - \left(\sum_{-i\in\mathcal{I}^S_{P,-i,t}} a_{P,-i,j,t}\right)\delta^S_{P,i,j}\right) + \varepsilon_{P,i,t} \\ \qquad\qquad\qquad\qquad\qquad\qquad \text{if } a_{P,i,j,t}\neq 0 \text{ for some } j\in\mathcal{J} \\ 0 \qquad\qquad\qquad\qquad\qquad\quad\;\; \text{if } a_{P,i,j,t}=0 \text{ for all } j\in\mathcal{J}, \end{cases}
\end{aligned}
$$

where $\mathcal{I}^B_{P,-i,t}$ and $\mathcal{I}^S_{P,-i,t}$ are the market participants that belong to the top 1-5 and top 6-10 banks, other than bank i. As verified in the reduced form analysis (Section 2.2.2), the effects from the top 5 banks and top 10 banks are different in terms of deciding on what to sell on the market.

Table F-2 shows estimates regarding the bank's entry decisions. The number of small banks in the table summarizes the number of active non-top 10 banks instead of non-top 5 banks. The strategic interaction term implies the negative entry effect from the entry of major nationwide rival banks (Top 1-5 Entry) and minor region-wide rival banks (Top 6-10 Entry).

The signs of the estimates are not different from the primary estimation results in Table 2-2. The log income per capita and housing price index consistently display negative effects on entries, while the population is still a positive determinant for entry. The negative income effect may come from menu diversification and entry probability trade-offs. The high income per capita motivates banks to provide more variety of products while the entry probability is low due to expensive menu costs. The competition effect captured by the number of regional banks and the network effect preserve the same signs across banks. More competitors are associated with less chance of entry, and existing branches in the same county induce to open more branches due to the network effect.

The strategic interaction shows a bank-specific entry structure. For example, JP Morgan Chase and Bank of America's entry strategies are opposite. JP Morgan Chase's entry is highly affected by the top 5 rival entries, but Bank of America is more sensitive to regional bank entries. Observing data, JP Morgan Chase operates in a limited area, focusing on large cities. But Bank of America is trying to find more regional markets where its rivals are not having branches now. The sensitivity to the nationwide/regional bank's entry shows different values depending on the bank's strategy. Overall, the large bank's entry effect is more influential.

Next, Table F-3 presents the menu choice game estimates of the extended model. As expected, the covariates included in the indirect utility of entry show the opposite signs in the estimated coefficients. The income and housing price positively correlate with more menu diversity, and the menu is more diverse as the bank operates in many counties. The competition and network effects are positive but not statistically significant except for two mega banks (JP Morgan Chase and Bank of America). In most cases, the competition effect is evident only among the game participants. Compared with the entry decision, the small regional bank's impact on the large bank's menu choice is limited. Regarding the network effect, we find little influence on menu choice from existing branches while the branches contribute to the entry into the same county.

Allowing for heterogeneous strategic interactions between the top 5 and top 10 banks in menu choice, we observe more dramatic patterns in the bank's menu choice. Some banks respond more sensitively to the products of the top 5 banks, while the top 10 banks highly influence the other banks. The result implies that the estimated sensitivity does not rely on the bank size but depends on the banks working as practical competitors. For example, Figure F-1 displays the branch map of PNC and US Bank. PNC and US Bank belong to the top 5 banks, but their operating regions do not overlap each other. Comparing the relative magnitude of the strategic interaction effects of the top 5 banks with the top 10 banks, PNC and US Bank show opposite patterns. Regarding term deposit products, PNC's decision is more sensitively responding to the term deposit products of the top 10 banks. On the other hand, US Bank's term deposit product is more highly affected by the top 5 banks. We observe similar patterns between JP Morgan Chase and Bank of America as well.

Last, Table F-4 presents the demand and cost parameter estimates. Compared with the top 5 banks only, the demand analysis containing the top 10 banks finds that the deposit rate is not a critical factor in determining the market share. While a higher deposit rate correlates with a larger market share, the estimated value is not statistically significant. The cost structure presented in the last two columns of Table F-4 derives the same conclusion as the case of the top 5 banks. The term deposit products are the least costly option for banks as CDs are the stable and favorable deposit source for banks. IRA products also belong to profitable deposit sources since the funding does not vary much until the timing of retirement. As verified in Table 2-4, the demand term products are banks' least favorable deposit source.

2.6 Conclusion

This paper considers the endogenous deposit menu choice as an essential competition strategy to understand the deposit market competition in the U.S. banking sector. Our reduced-form regression analyses show that the endogenized menu composition significantly affects the market structure, market share, and deposit rate. In order to reflect the importance of menu choice, we construct a structural model with static games of strategic interactions in which banks choose where to open branches, which deposit products to sell, and how much they pay to depositors. We estimate the model with the novel data set, including county-level geographical features of deposit markets. The data allows us to observe the banks' entry, menu choice, and deposit rate decisions.

Our estimation result from the top 5 banks demonstrates a substantial role of the entry and menu costs in the deposit market structure through strategic interaction. For example, one additional top 5 competitor's entry reduces the entry probabilities of JP Morgan Chase and Bank of America by 1.65% and 1.9% on average, respectively. In contrast, the entry decisions of Wells Fargo, PNC, and US Bank are more sensitive to one rival bank's entry. The estimated interaction in the menu game shows that the banks are less likely to sell a deposit product if their rival banks introduce the same product in a local deposit market. Through the menu cost estimation, we find that this deposit product menu choice is a bank-specific strategy, which implies that some banks are more involved in the product-space competition than others.

Based on the estimated outcome, we simulate three counterfactual scenarios: the nationwide increase in the housing price index, a potential merger between PNC and US Bank, and a decrease in bank branches. First, the rise in HPI causes less entry for all banks and provides more diversified products to the market. Still, the competition from the deposit product menu choice plays a more significant role than the direct impact of the increase in HPI. In other words, one bank's more diversified menu discourages rival banks from launching new financial products under monopolistic competition. Second, the merger of PNC and US Bank negatively affects the rival bank's entry probability, product diversification, and market share. The merger effect on rival banks is more evident in product diversification, and resulting market share than the overall entry since PNC and US Bank's active counties do not overlap much. Finally, the reducing network effect causes fewer market entries and gives the banks in our model an incentive to serve less diverse deposit products. The degree of impact also heavily relies on the current network size. The extended model with the top 10 banks shows that the implications of our basic model with the top 5 banks are stable.

Our paper can suggest some implications for essential research topics in studies of the banking industry. First, researchers can use the result that banks have an additional competitive strategy other than a deposit rate setting to understand the uniform deposit rate pricing pattern in the U.S. banking sector. Suppose some banks have a competitive advantage of providing more deposit products to gain market share. In that case, the uniform pricing is not necessarily inefficient, in contrast to retail sectors studied in DellaVigna and Gentzkow (2019). Second, the practitioners can modify our framework to understand the impact of online banks or fintech lenders on the deposit market competition since those institutions do not physically open branches but provide higher deposit rates in general. Therefore, it is crucial to understand how conventional banks react to these newly rising competitors to maintain their market share. We leave these for future research.

Chapter 3

Government Bailouts and Bank Stock Returns

3.1 Introduction

The financial crisis of 2008 was a catastrophic event but large commercial banks or bank holding companies in the United States managed to evade collective destruction due to a package of the government bailouts including the Troubled Asset Relief Program. This government-sponsored program confirmed the old wisdom in market economy, *too-big-to-fail*.[1]

How do investors in the stock market, one of the major financial markets, perceive the notion of too-big-to-fail? In other words, what is the implication of the government bailouts on stock returns of large financial institutions? From a simple quantitative banking model with the government bailouts as a benchmark, we compare simulated results between the benchmark with the government bailouts and the model without the government bailouts as a counterfactual exercise to answer this question. We find that the government bailouts can keep the stock returns of large commercial banks and bank holding companies from further plummeting during a crisis period. Furthermore, the stock returns of large commercial banks and bank holding companies during a normal period is smaller in the model with the government bailouts. Since the stock return can be interpreted as the cost of equity, this result is consistent with Gandi and Lustig (2015), showing that large financial institutions enjoy the equity financing as a cheap source of funding because of the government bailouts reducing risk compensation priced in the stock return.

Our findings can explain heterogeneity in quarterly average stock returns of banks with different sizes. Figure 3-1 shows quarterly average stock returns of U.S. commercial banks and bank holding companies from 1986 to 2016.[2] Shaded periods in grey indicate the savings and loan crisis (1986-1995) and the recent

[1] This colloquial term was popularized by U.S. Congressman Stewart McKinney in a 1984 Congressional hearing, discussing the Federal Deposit Insurance Corporation's intervention with Continental Illinois case. In addition, Long-Term Capital Management (LTCM) case in the late 1990s is also considered as an examples of too-big-to-fail in the banking history although LTCM was a hedge fun management, not a commercial bank.

[2] In this paper, we focus on U.S. commercial banks and bank holding companies publicly listed in the stock market. We explain

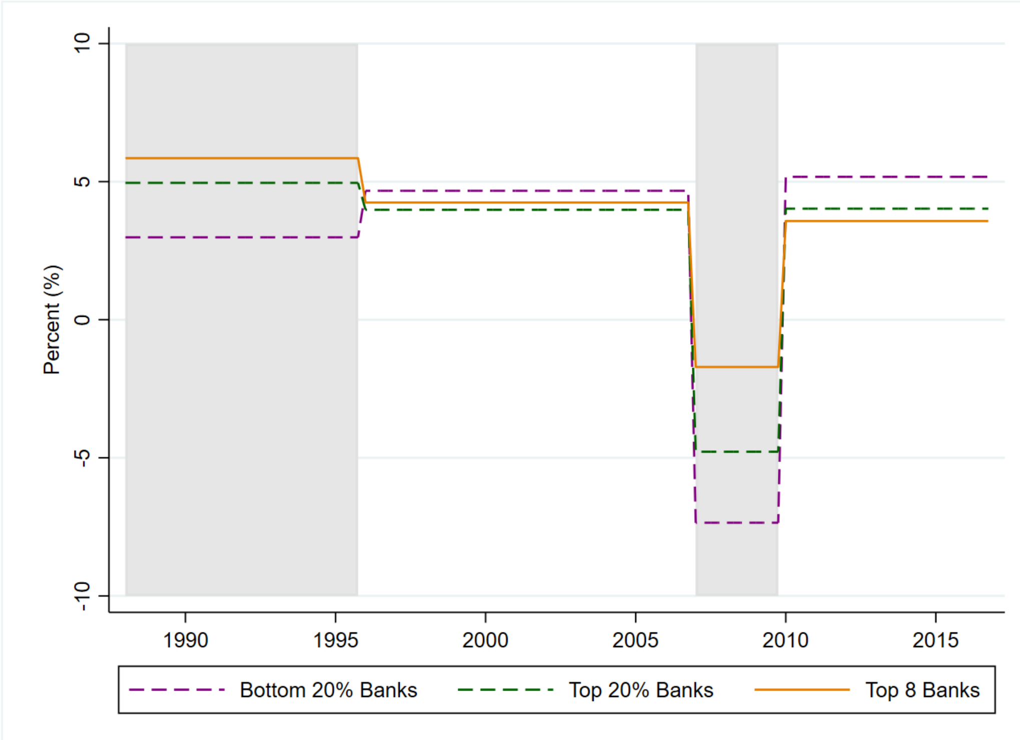


Figure 3-1: Quarterly Average Stock Returns of U.S. Commercial Banks and Bank Holding Companies

financial crisis (2007-2009). While failed or rescued financial institutions during the first crisis period in our sample were small entities, the recent financial crisis made large financial institutions into trouble, leading to the unprecedented bailout act. The quarterly average stock return during the recent financial crisis shows that the size of investment losses from bank stocks is decreasing in the size of banks. On the other hand, during both before and after the recent financial crisis, the quarterly average stock return shows that the size of investment gains from bank stocks is lower for larger banks and this is more apparent from the post-crisis period (2010-2016).[3] This heterogeneous pattern can be found from stocks of non-financial firms in Figure 3-2, which have been well explored in the empirical asset pricing literature. Therefore, the government bailouts can be an important factor to investigate the cross-sectional stock returns in the banking sector.

In this paper, we will answer the following three questions in more details: (i) How can the model with the government bailouts explain the observed heterogeneity in bank stock returns during both a crisis period and a normal period described in Figure 3-1? (ii) How much can the government bailouts affect returns of

the construction of data and size-sorted portfolios in Appendix A.

[3] This inverse relation between a size of investment gains and a size of banks during a normal time is hard to explain in traditional finance studies. From a long-term perspective, bank stock returns have information about market performance and risk compensation associated with loan investment of banks. Empirical studies have shown that large banks experience higher profitability (e.g. Regehr and Sengupta (2016)) and they engage in riskier investment (e.g. Demsetz and Strahan (1997)). Therefore, from these findings, it is predictable that the quarterly average stock return is increasing in the size of banks included in a portfolio.

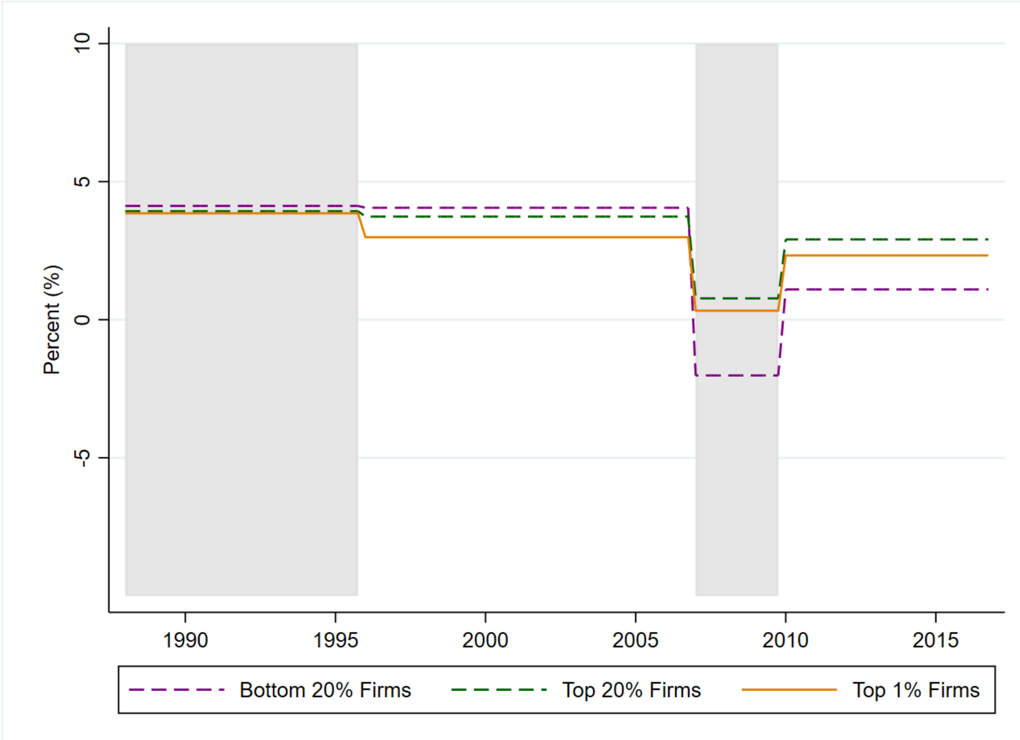


Figure 3-2: Quarterly Average Stock Returns of U.S. Non-Financial Firms

bank stocks under different capital requirements? (iii) How much can the government bailouts affect returns of bank stocks under different riskiness of loan investment? To explore the asset pricing implication of government bailouts, we use a simple quantitative banking model including dynamic investment and financing decisions. We augment the banking model with the government bailouts as exercisable options. One advantage of using a structural model is that we can conduct counterfactual exercises to answer questions such as (ii) and (iii).

From (ii), the stock return shows a less severe investment loss during a crisis period as the capital ratio becomes higher. This result is consistent with the intuition that equity holders of banks with a higher capital ratio take a low level of investment risks during a bad time. This is important since the current banking regulatory policy tries to increase the minimum capital ratio specifically designed to control large financial institutions. Moreover, from (iii), that the stock return shows a less severe investment loss as the loan investment becomes more riskier and we also find that the bailout option can be exercised not for rescuing a bank from a default but for increasing the market value of equity. From a comprehensive counterfactual exercise based on (ii) and (iii), we find that equity holders of banks in a riskier environment can benefit more from the government bailouts during a crisis period.

For matching the model to the data, we calibrate the persistence and the volatility of the idiosyncratic shock by using the simulated method of moments and borrow remaining parameters from the existing literature. We match the simulated moments of the quarterly average stock return during a crisis period with the government bailouts, the average bank profitability, and the volatility of bank profitability with the corresponding empirical moments. For the last two moments, we refer De Nicolo, Gamba, and Lucchetta (2014) to get each empirical moment. Our model is reasonably matched not only with the targeted moments but also with other moments which we do not intend to target.

Literature Review

Broadly speaking, our paper is a part of empirical studies on the cross-sectional bank stock returns. These empirical studies generally follow the approach pioneered by Fama and French (1992, 1993). Some examples in this literature are Cooper, Jackson, and Patterson (2003), Viale, Kolari, and Fraser (2009) and Baek and Bilson (2014). Among other papers, Gandhi and Lustig (2015) are associated with our research motivation. They find that the largest commercial bank stocks, ranked by total size of the balance sheet, have significantly lower risk-adjusted returns than small- and medium-sized bank stocks. They explain that government bailouts in a financial sector can protect shareholders of large banks in disaster states and absorb some of their tail risks. Therefore, our model can be complementary to their paper.

Our research is also in line with rising literature addressing government bailouts and valuation of the financial sector. Kelly, Lustig, and Van Nieuwerburgh (2016) examine the pricing of financial crash insurance during the recent financial crisis and show that show that a large amount of aggregate tail risk is missing. Gandhi, Lustig, and Plazzi (2020) show that equity is a cheap source of funding for a country's largest financial institutions. They find greater financial pricing anomalies for the largest banks in developed countries with a highly concentrated and large banking sector and fiscally strong governments. Atkeson, D'Avernas, Eisfeldt, and Weill (2018) argue that banks' market-to-book ratio is the sum of franchise value and the value of government bailouts. They find that a large portion of the variation in this ratio over time is due to changes in the value of government bailouts.

In terms of the model construction, our approach is based on the literature addressing the asset pricing implication of corporate finance. Gomes and Schmid (2010, 2021) and Kuehn and Schmid (2014) show that understanding a coordinated relationship between investment and financing decisions of corporations is important to interpret risks priced in stock and bond returns. The model we will use is based on Gomes and Schmid (2010) but incorporates a banking-specific environment and augment the model with the government bailout option, so our paper can contribute to the literature by showing how the government bailout option is priced in stock returns.

Finally, our research agenda is related to quantitative models of banking. Papers in the literature mainly address the optimal capital requirements by using a welfare criterion such as Van den Heuvel (2008), Begenau (2020), and Corbae and D'Erasmo (2021) or evaluate different regulatory policies like De Nicolo, Gamba, and Lucchetta (2014). Our paper is not about the optimal regulatory policy, but can show the impact of different regulatory environments on bank stock returns. Therefore, this paper associates a government policy with a financial variable while existing papers focus on a link between a government policy and a real variable. From our knowledge, this paper is the first approach to explain a pattern of bank stock returns by using a quantitative banking model.

3.2 Model

In this section, we will incorporate the key idea of exercising government bailout option in a simple quantitative banking model. This model includes dynamic investment and financing decisions. Time t is now discrete and the horizon is infinite. There is a finite number of heterogeneous banks indexed by i. To keep the model simple, the source of heterogeneity comes only from the idiosyncratic shock. We will explain this in the next subsection. Banks in the model can invest in loans, which are their major assets, and they can issue deposits (insured debts) and equity (bank capital) to finance the loan investment at any time. Therefore, we can define the balance sheet identity of bank i at the beginning of each period as

$$L_{it} = D_{it} + K_{it}. \tag{3.1}$$

From equation (3.1), L_{it} represents the asset side of the balance sheet and it denotes the book value of loans outstanding in the time interval between $t-1$ and t. D_{it} and K_{it} represent the liability side of the balance sheet and they denote the book value of deposits and equity respectively.

There are two policies governing investment and financing decisions of banks in the model: the capital requirements and the government bailouts. The capital requirement policy is about the minimum amount of equity K_{it}^R which an individual bank has to hold as required by financial regulators. This is usually expressed as a capital ratio k of equity that must be held as a percentage of risk-weighted assets. The government bailouts are exercisable options available to every bank in the model only if its profit becomes negative. Once a bank with a negative profit decides to get the government bailouts, its loss would be absorbed in the form of equity injection. However, the beneficiary bank has to issue equity in order to get bailed out and this

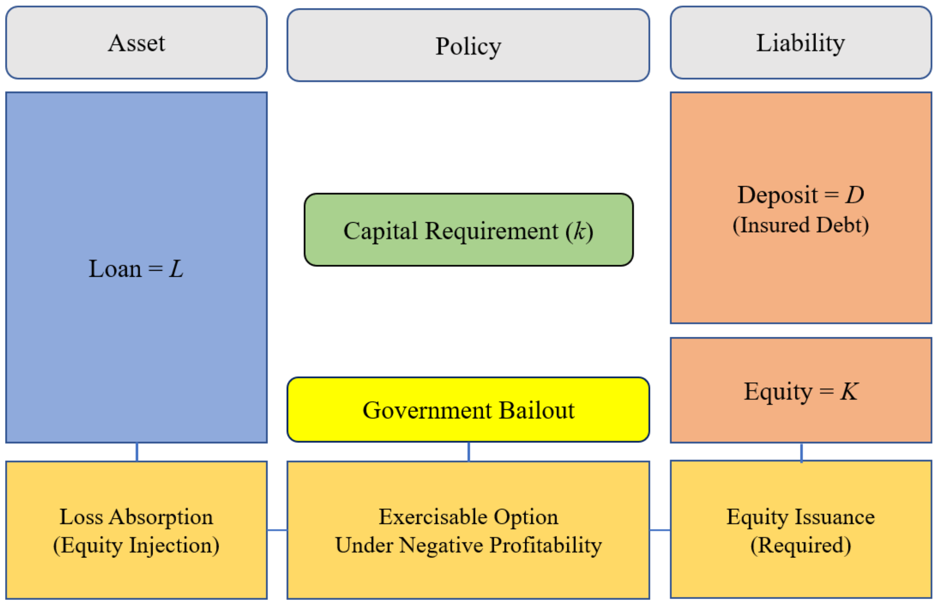


Figure 3-3: Model Structure

The model includes dynamic investment and financing decisions. Banks in the model can invest in loans L. They can issue deposits D and equity K to finance their loan investment. The capital requirements and the government bailouts govern banks' decision making.

equity issuance is costly. A structure of the model is described in Figure 3-3. In the following subsections, we will explain the model in greater detail.

3.2.1 Shocks

There are two shocks in the model: aggregate u_t and idiosyncratic v_{it}. Both u_t and v_{it} are assumed to be lognormally distributed and obey the following law of motion respectively

$$\log u_{t+1} = \rho_u \log u_t + \sigma_u \varepsilon_{t+1} \tag{3.2}$$

$$\log v_{it+1} = \rho_v \log v_{it} + \sigma_v \eta_{it+1} \tag{3.3}$$

where ε_{t+1} and η_{it+1} are truncated standard normal variables. The aggregate shock u_t reflects a general economic situation in the model. Moreover, we will use this aggregate shock to define a stochastic discount factor when determining the market value of bank equity. This is because the model is not a general equilibrium model, so we cannot endogenously derive a stochastic discount factor by solving a household utility maximization problem. The idiosyncratic shock v_{it} allows us to have cross-sectional bank heterogeneity in the form of bank specific shocks to the current profitability which we will define in the next subsection. The assumption that v_{it} is bank specific implies that

$$\mathbb{E}_t[\varepsilon_{t+1}\eta_{it+1}] = 0$$
$$\mathbb{E}_t[\eta_{it+1}\eta_{jt+1}] = 0 \text{ for } i \neq j.$$

Since we assume that there is no correlation between η_{it+1} and η_{jt+1} for $i \neq j$, we can solve the model numerically later as if we would deal with a representative banking model. Considering equation (3.1) and the assumption associated with these two shocks, we can summarize a current state with a vector

$$S_{it} = (u_t, v_{it}, L_{it}, D_{it}). \tag{3.4}$$

3.2.2 Bank Cash Flow

We will consider a typical problem of maximizing shareholder value in a perfectly competitive banking environment. We suppose that a bank manager has the incentive which is well aligned with the interest of shareholders, so there is no agency conflict. The flow of earning-after-taxes Π_{it} per unit of time for bank i is defined as

$$\Pi_{it} = (1 - \tau_{it})(Z_{it}L_{it}^{a} - r_t D_{it}) \tag{3.5}$$
$$\text{where } Z_{it} = Z(u_t, v_{it}) = \overline{z}u_t v_{it} - 1 \text{ for } \overline{z} > 1 \text{ and } 0 < a < 1.$$

Z_{it} is profitablility of bank i at time t which is assumed to be a function of both u_t and v_{it}. $(\overline{z} - 1)$ is the steady state value of this profitability. The functional form of Z_{it} reflects the intuition that bank profitability is positively high under a favorable aggregate economic situation and also under a promising bank specific investment opportunity. Debt financing in the commercial banking industry mainly includes secured by deposit insurance. r_t denotes a net deposit interest rate. Since there is no market power for an individual bank due to the perfect competition, we assume that r_t is independent of any other variables in the model and same across all states. This assumption is also reasonable since debt financing in the commercial banking industry mainly includes deposits which are insured by deposit insurance, so deposits are safe from a perspective of depositors.[4]

The assumption related to $0 < a < 1$ implies decreasing returns to scale in the amount of loans and

[4] Commercial banks or bank holding companies in the United States issue uninsured debts such as a subordinated debt. However, we do not consider an uninsured debt in our model since deposits can account for a majority of bank leverage. Sundaresan and Wang (2022) develop a dynamic model of optimal bank liability structure with insured and uninsured debts but their paper does not address the asset pricing implication.

captures the following idea: given u_t and v_{it}, suppose Z_{it} is greater than zero. Bank i has a pool of different customers. Bank i can optimally manage investment due to its monitoring technology and long-term lending relationship with its borrowers. However, there is heterogeneity in borrowers' riskiness and their creditworthiness so bank i lends to borrowers evaluated as most profitable by using the costly monitoring technology. Therefore, after the most lucrative loan investment, less profitable investment opportunities are left since the remaining customers require more monitoring and lead to higher delinquency rates. Therefore, given a positive value of Z_{it}, the marginal return from the additional loan is decreasing. On the other hand, if Z_{it} is less than zero, the last group of borrowers who renege on their loans is the most creditworthy one. Therefore, given a negative value of Z_{it}, the marginal loss from the additional loan is also decreasing. This decreasing returns to scale functional form is also assumed in some banking models such as Zhu (2008), De Nicolo, Gamba, and Lucchetta (2014), and Begenau (2020).[5]

Consistently with a dynamic model of corporate finance like Hennessy and Whited (2007), a corporate tax is introduced with the following convex function

$$\tau_{it} = \tau \cdot \mathbb{1}\{Z_{it}L_{it}^{a} - r_t D_{it} \geq 0\}. \tag{3.6}$$

This is standard in the literature and reflects reduced tax benefit on debts from negative earnings.

The net income W_{it} of each bank can be defined as the sum of the earning-after-taxes Π_{it} and the book value of equity K_{it}

$$\begin{aligned} W_{it} &= \Pi_{it} + K_{it} \\ &= (1-\tau_{it})(Z_{it}L_{it}^{a} - r_t D_{it}) + L_{it} - D_{it} \qquad (3.7) \\ &= \underbrace{(1-\tau_{it})(Z_{it}L_{it}^{a}) + L_{it}}_{\text{income from loans}} - \underbrace{(1+(1-\tau_{it})r_t)D_{it}}_{\text{cost of deposits}}. \qquad (3.8) \end{aligned}$$

As shown from equation (3.8), the net income of bank i is the difference between the gross income from loans and the total cost of deposits.

3.2.3 Investment and Financing Decisions

The maturity of deposits is set to one period. Our model embeds the bank maturity transformation from short-term debts (deposits) to long-term assets (loans). A constant proportion δ of loans at t is supposed to

[5] This concavity assumption has been tested and supported by some empirical studies. For instance, Cole, Goldberg, and White (2004), Berger, Miller, Rajan, and Stein (2005), Carter and McNulty (2005), and Dell Ariccia, Igan, and Laeven (2012).

become due at $t+1$. Therefore, the law of motion governing a stock of loans is

$$L_{it+1} = (1-\delta)L_{it} + I_{it+1} \text{ where } I_{it+1} \geq 0 \tag{3.9}$$

where I_{it+1} is investment in new loans. $I_{it+1} \geq 0$ is relevant to the investment irreversibility implying that breaking a long-term lending relationship incurs exorbitant costs.[6] When a bank decides to invest in loans, it needs to pay a information production cost for evaluating credit quality of the new loan investment. We model a loan adjustment cost as a convex function

$$m(I_{it+1}) = m \cdot (I_{it+1})^2 \text{ where } m > 0. \tag{3.10}$$

The new investment in loans as well as any distribution can be financed with deposits and equity. Therefore, the remaining cash U_{it} after bank i makes investment and financing decisions is defined as

$$\begin{aligned}
U_{it} &= W_{it} + D_{it+1} - L_{it+1} - m(I_{it+1}) && (3.11)\\
&= \underbrace{(1-\tau_{it})(Z_{it}L^a_{it} - r_t D_{it}) + \delta L_{it} - D_{it}}_{\text{liquid internal cash}} + D_{it+1} - I_{it+1} - m(I_{it+1}) && (3.12)\\
&= (1-\tau_{it})(Z_{it}L^a_{it} - r_t D_{it}) + L_{it} - D_{it} + D_{it+1} - L_{it+1} - m(I_{it+1}) && (3.13)\\
&= (1-\tau_{it})(Z_{it}L^a_{it} - r_t D_{it}) + \underbrace{K_{it} - K_{it+1}}_{\text{equity adjustment}} - m(I_{it+1}). && (3.14)
\end{aligned}$$

From the above equations, we can understand the shareholder value maximization problem in two different ways. On the one hand, bank managers are supposed to choose a future stock of loans L_{it+1} and issue deposits D_{it+1} to maximize the value of banks, which is equation (3.13). This is the traditional banking problem of the asset-liability management. On the other hand, bank managers are supposed to maximize the value of banks by choosing the new investment in loans I_{it+1} and adjusting equity holdings $(K_{it} - K_{it+1})$, which is equation (3.14). This is the conventional corporate finance problem of the optimal investment and cash holdings.

If U_{it} is positive, it is distributed to shareholders as a dividend. If U_{it} is negative, it equals the amount of newly issued equity. Similar to Gomes (2001), we assume that equity issuance is costly due to associated costs like underwriting fees. Bank i can raise its capital by issuing seasoned equity shares, which incurs a

[6] Also, it is hard for a bank to decrease a size of assets with this constraint specifically during a bad time although the bank really wants to disinvest from assets. This model feature is reminiscent of the recent financial crisis when commercial banks had a lot of toxic assets but they couldn't wipe them out from their balance sheet.

cost Λ. This cost Λ is a linear function of the book value of newly issued equity

$$\Lambda(U_{it}) = (\lambda_0 - \lambda_1 U_{it}) \cdot \mathbb{1}\{U_{it} < 0\}. \tag{3.15}$$

Hence, the actual cash flow to bank shareholders is

$$d_{it} = d(S_{it}, L_{it+1}, D_{it+1}) = U_{it} - \Lambda(U_{it}). \tag{3.16}$$

This is a function of the state vector S_{it} and the choice variables, (L_{it+1}, D_{it+1}).

3.2.4 Capital Requirements

The capital requirements in the model are similar to Basel II regime. This establishes a lower bound on the book value of equity so that the total amount of risk-weighted assets should be financed at least with the regulatory amount of equity. In the model, a capital ratio at $t+1$ is simply the book value of equity K_{it+1} over the book value of loans L_{it+1} since there is only one risky asset. Thus, the required bank equity K^R_{it+1} is a proportion k of loans outstanding at the beginning of the next period

$$K^R_{it+1} = kL_{it+1} \tag{3.17}$$

where we can also interpret k as a capital adequacy ratio. Since K^R_{it+1} is the minimum amount of bank equity, we can get the following simplified bank capital requirements by using equation (3.1)

$$\begin{gathered} L_{it+1} - D_{it+1} = K_{it+1} \geq K^R_{it+1} = kL_{it+1} \\ (1-k)L_{it+1} \geq D_{it+1}. \end{gathered} \tag{3.18}$$

As a result, we can define a feasible choice set Θ as

$$\Theta(L_{it+1}, D_{it+1}) = \big\{(L_{it+1}, D_{it+1}) \,|\, (1-k)L_{it+1} \geq D_{it+1}\big\}. \tag{3.19}$$

3.2.5 Valuation

In this subsection, we will define the market value of equity. For bank i, the market value of its equity denoted by V_{it} is the discounted sum of future dividends. We assume that bank equity holders will choose to

[7] Even though bank equity holders can default on deposit repayment, the net deposit interest rate r_t isn't priced with the consideration of the default risk due to deposit insurance. If we consider an uninsured debt in the model, the pricing mechanism of

close the bank and default on its deposit repayment if the prospect for the bank is sufficiently bad. In other words, whenever V_{it} reaches zero, bank equity holders choose a default.[7]

Since the model is not a general equilibrium model, a stochastic discount factor should be exogenously specified. This is a common way to define a pricing kernel in the literature dealing with the asset pricing implication of corporate finance decisions.[8] We will specify the following stochastic discount factor similar to Gomes and Schmid (2010)

$$M_{t,t+1} = \beta \left(\frac{u_{t+1}}{u_t} \right)^{-\gamma} \tag{3.20}$$

with $\gamma > 0$.[9] For bank i and given $S_{it} = (u_t, v_{it}, L_{it}, D_{it})$, the market value of equity is the result of the following program if $T \geq t$ is the default date

$$V(S_{it}) = \max \left[\mathbb{E}_t \sum_{j=t}^{T} d(S_{jt}, L_{jt+1}, D_{jt+1}) \prod_{k=t}^{j} M_{k-1,k} \right]$$
$$\text{subject to } (L_{j+1}, D_{j+1}) \in \Theta(L_{j+1}, D_{j+1}) \text{ and } I_{it+1} \geq 0 \text{ for } j = t, ..., T \tag{3.21}$$

where $\mathbb{E}_t$ is the conditional expectation operator associated with the state variables at time t and $M_{k-1,k}$ is a stochastic discount factor defined in equation (3.20) such that $M_{t-1,t} = 1$. Because the model is stationary and the Bellman equation involves adjacent two periods, we can drop the time index and use the notation without a prime for the current variables and with a prime for the future variables. Therefore, we can redefine the bank problem in (3.21) with the following dynamic programming problem

$$V(S_i) = \max \left\{ 0, \max_{L_i', D_i'} \left\{ d(S_i, L_i', D_i') + \mathbb{E} \left[M_{u,u'} V(S_i') \right] \right\} \right\}$$
$$\text{subject to } (L_i', D_i') \in \Theta(L_i', D_i') \text{ and } I_i' \geq 0 \tag{3.22}$$

where $\mathbb{E}$ is the conditional expectation operator associated with the current state variables and this expectation is taken by integrating over the conditional distributions of u' and v_i'. The recursive problem in (3.22) captures the possibility that bank i can default at the beginning of the current time period. In this case, bank

the debt instrument would be similar to Gomes and Schmid (2010). Therefore, a computational task to solve this model becomes easier since we do not need to endogenously determine r_t by considering a future default risk.

[8] For instance, Berk, Green, and Naik (1999), Zhang (2005), Gomes, Yaron, and Zhang (2006), and more recently Belo, Lin, and Yang (2019).

[9] An intuition behind this approximated pricing kernel is that the future market value of equity would be less discounted if the future economic situation is relatively worse than the current economic situation ($u_{t+1} < u_t$). This is because this relatively worse future economic situation is associated with a higher marginal utility state for investors, bank managers should put more weight on this state.

shareholders will get nothing, which means the market value of equity is zero. In the next subsection, we will introduce the government bailouts and define a recursive problem with this policy.

3.2.6 Government Bailouts

We incorporate some features of the Troubled Asset Relief Program from the Emergency Economic Stabilization Act of 2008 in order to model the government bailouts, but we try to keep the model as simple as possible. The government bailouts in the model are path-dependent exercisable options. It is path-dependent because it can be available to an individual bank only if the bank experiences negative profitability at any time.[10] It is also an exercisable option because a bank with negative profitability is not willing to get bailed out although the bank is eligible for exercising the government bailout option.

If bank i decides to exercise the government bailout option, its negative profitability would be absorbed in the form of equity injection.[11] This is a major benefit of the government bailouts in the model. Therefore, we can define effective profitability denoted by Z_{it}^e as

$$Z_{it}^e = (Z_{it} \cdot \mathbb{1}\{\text{Not Exercising}\} + 0 \cdot \mathbb{1}\{\text{Exercising}\}) \cdot \mathbb{1}\{Z_{it} < 0\} + Z_{it} \cdot \mathbb{1}\{Z_{it} \geq 0\}. \tag{3.23}$$

Therefore, there is one more choice variable whether bank i exercises this option or not in the model augmented with the government bailouts. Since we are interested in stock returns of large commercial banks, the probability that a bank gets bailed out if it exercises the option is assumed to be 1 for convenience.[12]

One requirement which a bank exercising the government bailout option has to follow is issuing additional equity. In the model, this requirement means that a rescued bank cannot pay any positive amount of dividends to its shareholders. A major purpose of this requirement is to increase solvency of individual bank.[13] The problem with the government bailouts is described in Figure 3-4.

---

[10] In Appendix D, we will show that our key idea is still valid under a different bailout criterion.

[11] For simplicity, we do not consider the source of funding for equity injection. If the model can be extended to a general equilibrium model, a large portion of equity injection funding would come from taxpayers.

[12] By defining a size-dependent bailout probability, we may explore the impact of too-big-to-fail on stock returns of commercial banks. However, only reason that a big bank can keep being a big bank in the model is persistently good idiosyncratic shocks. Therefore, we will interpret a bank in the model as a big bank regardless of its size and focus on two different situations depending on the existence of the government bailouts.

[13] This is one important feature of the Troubled Asset Relief Program. According to U.S. Department of the Treasury, "financial institutions selling assets to TARP are required to issue equity warrants or equity or senior debt securities to the Treasury." Since the government in the model becomes a shareholder by injecting equity to distressed banks, the government can receive positive returns from these banks in the future once they can pay dividends from better business outcomes. In the real world, U.S government used taxpayers' money to save distressed banks so tax-paying households were actually shareholders of banks regardless of their willingness to be. According to U.S. Department of the Treasury, "Treasury has already recovered an amount that is greater than what was invested in banks under TARP. Taxpayers began to see a positive return on their bank investments in March 2011."

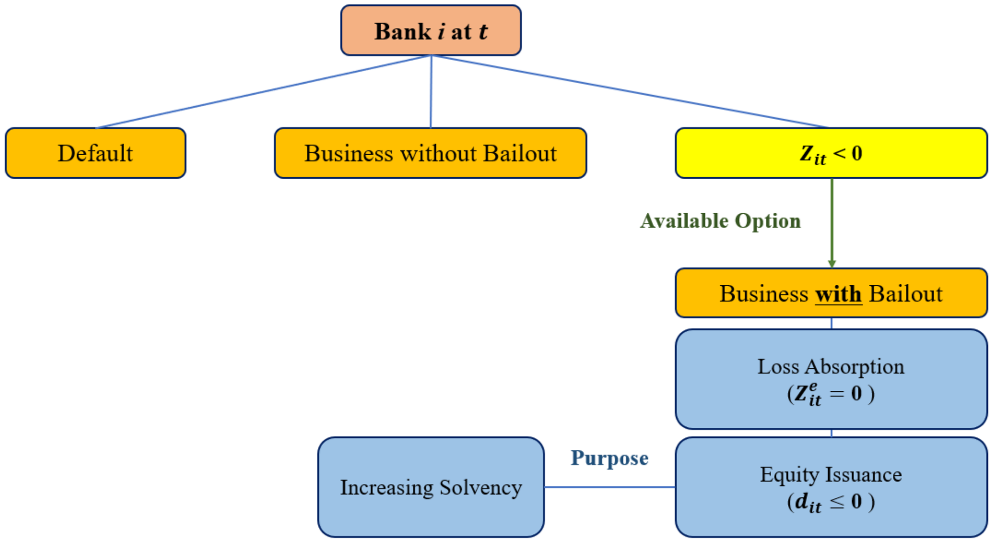


Figure 3-4: Problem with the Government Bailout Option

The government bailouts are exercisable options available to every bank in the model only if its profitability becomes negative. Once a bank with a negative profit decides to get the government bailouts, its loss would be absorbed in the form of equity injection. However, the beneficiary bank has to issue equity in order to get bailed out and this equity issuance is costly.

Unlike equation (3.22), the market value of equity with the government bailout option is

$$
\begin{aligned}
V(S_i) &= \max\left\{0,\ V_0(S_i),\ \underbrace{V_1(S_i)\cdot \mathbb{1}\{Z_i<0\}}_{\text{government bailout option}}\right\} \quad \text{where} \\
V_0(S_i) &= \max_{L_i',D_i'}\left\{d(S_i,L_i',D_i') + \mathbb{E}\left[M_{u,u'}V(S_i')\right]\right\} \\
&\qquad \text{subject to } (L_i',D_i') \in \Theta(L_i',D_i') \ \text{ and } \ I_i' \geq 0 \\
V_1(S_i) &= \max_{L_i',D_i'}\left\{d(Z_i^e=0,L_i,D_i,L_i',D_i') + \mathbb{E}\left[M_{u,u'}V(S_i')\right]\right\} \\
&\qquad \text{subject to } (L_i',D_i') \in \Theta(L_i',D_i'),\ I_i' \geq 0, \text{and } d(Z_i^e=0,L_i,D_i,L_i',D_i') \leq 0. \qquad (3.24)
\end{aligned}
$$

In the dynamic programming problem in (3.24), $V_0(S_i)$ is the market value of equity if bank i does not choose to exercise the government bailout option. On the other hand, $V_1(S_i)$ is the market value of equity if bank i chooses to exercise the government bailout option. The government bailout option is path-dependent, so $V_1(S_i)$ can be achievable only if bank i experiences negative profitability. Therefore, bank i can have a chance to evaluate both $V_0(S_i)$ and $V_1(S_i)$ under the condition $\mathbb{1}\{Z_i < 0\} = 1$. If bank i with negative profitability finds that $V_1(S_i) > V_0(S_i)$ and $V_1(S_i) > 0$, it decides to exercise the government bailout option. From the above problem, $Z_i^e = 0$ means that negative profitability is wiped out. This is equivalent

Table 3-1: Market Value of Equity of Bank i with the Government Bailouts

		Profitability	
		$Z_i < 0$	$Z_i \geq 0$
Bank Decisions	Default	0	0
	Business without Bailout	$V_0(S_i)$	$V_0(S_i)$
	Business with Bailout	$V_1(S_i)$	Not Available

$V_0(S_i)$ is the market value of equity if bank i does not choose to exercise the government bailout option. On the other hand, $V_1(S_i)$ is the market value of equity if bank i chooses to exercise the government bailout option. The government bailout option is path-dependent, so $V_1(S_i)$ can be achievable only if bank i experiences negative profitability.

to saying that $Z_{it} = 0$ in equation (3.5) when we define the earning-after-taxes. Finally, $d(Z_i^e = 0, L_i, D_i, L_i', D_i') \leq 0$ is associated with equity issuance requirement. The market values of equity of bank i are summarized in Table 3-1.

3.3 Choice and Estimation of Parameters

Considering the assumption on functional forms in our model, the dynamic programming problems (3.22) and (3.24) have a unique solution respectively. However, we must resort to a numerical method since these problems cannot be solved in a closed form.

3.3.1 Parameter Choices

In this paper, our choice of parameter values closely follows the existing literature.[14] We will use annualized parameter values and they are summarized in Table 3-2. The parameters can be divided into two sets. The first set of parameters is associated with the shocks in the model and the stochastic discount factor. The persistence, ρ_u, and conditional volatility, σ_u, of the aggregate shock are set close to the corresponding values reported in Gomes and Schmid (2010) whose values are also matched with Cooley (1995). Since Gomes and Schmid (2010) use the conditional volatility in a quarterly basis, we adjust σ_u to make it annualized. The persistence, ρ_v, and conditional volatility, σ_v, of the idiosyncratic shock are calibrated to match three

[14] For the later work, we will try to calibrate some parameters to match key moments of investment, dividends, and cash flows both in the cross-section and at the aggregate level based on banking data. For this stage of the paper, we borrow parameter values from Gomes and Schmid (2010) and De Nicolo, Gamba, and Lucchetta (2014).

Table 3-2: Parameter Choices

Parameter	Explanation	Value	Source
ρ_u	Persistence of aggregate shocks	0.98	Cooley (1995)
σ_u	Volatility of aggregate shocks	0.008	Cooley (1995)
ρ_v	Persistence of idiosyncratic shocks	0.90	Bank Stock Returns & Profitability
σ_v	Volatility of idiosyncratic shocks	0.01	Bank Stock Returns & Profitability
$\overline{z}$	Steady-state profitability	1.0717	De Nicolo et al. (2014)
β	Time discount factor	0.99	Gomes and Schmid (2010)
γ	Stochastic discount factor	15	Gomes and Schmid (2010)
τ	Corporate tax rate	0.20	Gomes and Schmid (2010)
a	Return to scale for loan investment	0.65	Cooper and Ejarque (2003)
r_d	Deposit interest rate	0.01	Corbae and D'Erasmo (2021)
δ	Loan maturity	0.20	Van den Heuvel (2008)
m	Adjustment cost	0.08	De Nicolo et al. (2014)
λ_0	Equity issuance cost (fixed)	0.02	Hennessy and Whited (2005, 2007)
λ_1	Equity issuance cost (proportional)	0.06	Hennessy and Whited (2005, 2007)
k	Capital requirement	0.04	Basel II regulatory policy

Our choice of parameter values closely follows the existing literature. We borrow parameter values mainly from Gomes and Schmid (2010) and De Nicolo, Gamba, and Lucchetta (2014). The persistence, ρ_v, and conditional volatility, σ_v, of the idiosyncratic shock are calibrated to match three numerical values: the average quarterly stock returns during crisis periods with the government bailouts, the average bank profitability, and the volatility of bank profitability.

numerical values: the average quarterly stock returns during crisis periods with the government bailouts, the average bank profitability, and the volatility of bank profitability. We will explain how to get these two parameters, ρ_v and σ_v, in the next subsection. The steady-state value of profitability, $\overline{z}$, is close to the corresponding value constructed by De Nicolo, Gamba, and Lucchetta (2014). They estimate this parameter by using the return on bank investments before taxes, given by the ratio of interest and non-interest revenues to total lagged assets. The stochastic discount factor parameters β and γ are close to Gomes and Schmid (2010) whose values are chosen to match the risk-free rate and the average equity premium.

The second set of parameters is associated with investment and financing decisions of banks in a context of corporate finance. With regard to corporate taxation, the tax function in equation (3.6) is defined by the marginal tax rate τ for positive income. The marginal tax rate for negative income is assumed to be zero, allowing for convexity in the corporate tax schedule. We take the value of the marginal tax rate τ from Gomes and Schmid (2010), which is also close to Graham (2000). For the degree of decreasing returns to scale, a, we use the value based on the evidence in Cooper and Ejarque (2003). The annual net deposit interest rate, r_d, is consistent with Corbae and D'Erasmo (2021). We use the value of the percentage of reimbursed loan, δ, consistent with the fact that the average maturity of outstanding loans is four years in line with the assumption made by Van den Heuvel (2008). The value for the adjustment cost, m, is close to the calibrated value from De Nicolo, Gamba, and Lucchetta (2014). One important difference between this paper and De Nicolo, Gamba, and Lucchetta (2014) is that they allow disinvestment from loans in their model and assume that the associated adjustment costs are asymmetric. In other words, they have one more parameter in order to define the adjustment cost.[15] The reason we do not allow disinvestment in the model is to make a crisis period much disastrous by keeping banks in the model from decreasing a stock of loans swiftly. Equity issuance costs are set to values similar to those measured by Hennessy and Whited (2005, 2007). Finally, the capital ratio, k, is consistent with the Basel II regulatory policy.

3.3.2 Simulated Method of Moments

We calculate nine aggregate states defined in equation (3.2) by following Tauchen (1986) and define the worst two states as a crisis period in the model. For the results presented in the next section, we define the next three states as a normal period in the model. These definitions are important to match simulated moments with the corresponding empirical moments. We use the simulated method of moments approach to choose reasonable values for ρ_v and σ_v. Since we have two parameters to be calibrated, we need to have at least two moment conditions for the parameter identification. The moment conditions to be matched are (i) the quarterly average stock return during a crisis period with the government bailouts, (ii) the average bank profitability, and (iii) the volatility of bank profitability. The last two moments are from De Nicolo, Gamba, and Lucchetta (2014). Before explaining a detailed procedure to determine ρ_v and σ_v, we need to mention two important identification assumptions.

Assumption 1 The government bailout option is only available to top 20% and top 8 banks.

Assumption 2 The magnitude of σ_v is same across different sizes of banks.

[15] Specifically, De Nicolo, Gamba, and Lucchetta (2014) have m^+ and m^- in their model and obtain calibrated values for these two parameters by matching two moments from empirical data. The first moment is the average ratio of bank credit over deposits and the second moment is bank's book leverage defined as deposits plus other financing liabilities over loans and other financial investments. Their calibration result delivers per-unit loan liquidation (disinvestment) costs higher than per-unit costs of loan extensions (investment), which means $m^- > m^+$.

The first assumption is associated with measuring the empirical moment of the quarterly average stock return during a crisis period with the government bailouts. From the data, we define a crisis period as between 2007 and 2009. During this period, there were approximately 1200 commercial banks and bank holding companies publicly listed in the stock market annually. Therefore, this assumption implies that only less than 250 banks were accessible to the government bailout option. According to TARP on which the government bailouts in the model is based, the number of rescued financial institutions in 2008 and 2009 is around 210 and 510 respectively. Among these financial institutions, a proportion of publicly listed commercial banks and bank holding companies is reported as less than 33%.[16] Therefore, if we assume this 33% as the upper bound, it is reasonable to believe that only some big banks have the government bailout option to be exercised.[17] Based on the first assumption, once we solve the model with the government bailouts, we will target the simulated quarterly average stock return during a crisis period with the weighted quarterly average stock return between top 20% banks and top 8 banks between 2007 and 2009, which are reported in Table G-2.

The second assumption is related to a mapping between De Nicolo, Gamba, and Lucchetta (2014) and this paper. When estimating the volatility of the idiosyncratic shock, De Nicolo, Gamba, and Lucchetta (2014) use the whole samples of commercial banks in the United States regardless of whether each individual commercial bank is publicly listed in the stock market or not. However, the sample of commercial banks and bank holding companies in this paper is only based on publicly listed entities, so we deal with a sub-sample of De Nicolo, Gamba, and Lucchetta (2014). Therefore, only under the second assumption, we can guarantee a similar process of bank profitability between their model and our model. Conceptually, σ_v is an important parameter since it can capture both how risky bank loan investment is and how diversifiable a risk of bank loan investment is. Demsetz and Strahan (1997) show that large bank holding companies are better diversified than small bank holding companies. However, they also find that this better diversification dose not translate into reductions in risk since large bank holding companies engage in riskier investment. In the same line with this empirical finding, therefore, we assume that the magnitude of σ_v is same across different sizes of banks. Based on these two assumptions, we calibrate ρ_v and σ_v with the following steps.

- Define grids of ρ_v and σ_v. For given ρ_v and σ_v, calculate nine idiosyncratic states in equation (3.3)

[16] A majority of beneficiary financial institutions of TARP were small and community banks and some certified community development financial institutions. However, the amount of funds granted to these institutions was not large and these institutions were not usually publicly listed.

[17] As 33% as the upper bound, we may say that at most around 70 and 170 publicly listed commercial banks and bank holding companies were saved due to TARP in 2008 and 2009 respectively, both of which are less than 250. Therefore, the first assumption is reasonable in a numerical sense although we need to check a list of beneficiary banks manually in order to validate this assumption. We couldn't check whether beneficiary banks of TARP are mainly top 20% banks, but top 8 commercial banks were all participants of this program.

using Tauchen (1986) .

- After solving the model with parameter values in Table 3-2, construct an artificial cross-sectional panel of 1000 banks by simulating the optimal investment and financing policies implied by the model solution over 500 periods. We do not use the first 50 periods in order to avoid dependence from initial conditions.
- Repeat constructing an artificial cross-sectional panel 50 times for different shock processes.
- Define a stock return as follows

$$1 + r^s_{it,t+1} = \frac{V_{it+1}}{V_{it} - d_{it}} \tag{3.25}$$

where s is the simulation number (from 1 to 50).

- Take the average of stock returns across all simulations and all banks conditional on

$$u^s_t \geq u^s_{t+1} \text{ and } u^s_{t+1} \in \text{Crisis Periods}$$

where the two conditions above mean that we are interested in negative net returns (losses).

- Take the unconditional average and volatility of bank profitability defined in equation (3.5).
- Repeat this procedure from Step 1 to Step 6 for every pair of ρ_v and σ_v.
- Choose reasonable estimates which minimize a criterion function.

As a result of these steps, we can find the reasonable values for ρ_v and σ_v reported in Table 3-2. The idiosyncratic shock is less persistent than the aggregate shock, but still persistent enough. In terms of the volatility, the idiosyncratic shock is more volatile than the aggregate shock. This implies that even under the same aggregate states, especially during a crisis period, the idiosyncratic shock plays an important role in determining the market value of equity and the stock return.

3.4 Results

In this section, we will show the main result based on the parameter values in Table 3-2 and discuss two counterfactual numerical exercises. When we introduce a table including stock returns and volatility, reported numbers are based on net returns, $r^s_{it,t+1}$ in equation (3.25).

3.4.1 Main Results

The main purpose of this subsection is to compare between the quarterly average stock return during a crisis period with the government bailouts and the quarterly average stock return during a crisis period without the government bailouts. The former is calculated from the problem in (3.24) and the simulation method described in the previous section and the latter is calculated from the same simulation method, but it is based on the problem in (3.22). Therefore, the only difference between two simulation results is the existence of the government bailout option in the model.

Bailout Choices

Since exercising the government bailout option is one of the choices of banks, it is important to show in which cases banks choose to get bailed out. Considering Figure 3-4, if a bank decides to get the government bailouts, it is required to issue equity, so the beneficiary bank cannot pay a dividend to its shareholder. Therefore, there is a trade-off between a benefit, loss absorption from equity injection, and a cost, a negative dividend due to the mandated equity issuance, from a perspective of bank managers who are supposed to maximize the shareholder value of banks. Intuitively, banks whose leverage ratio ($= D/L$ in the model) is low are more likely to run their business without using the government bailouts because they have less deposits but much equity which we can see in equation (3.14). In other words, they have a sufficient amount of capital buffers to pay a dividend.[18]

The intuition regarding the bailout choice can be confirmed in Figure 3-5. We have three cases, all of which are in the worst aggregate state. Among the nine idiosyncratic states, the top sub-figure is in the worst idiosyncratic state, so banks in this situation experience the largest negative profitability in the model. The middle sub-figure is in the third worst idiosyncratic state and the bottom sub-figure is in the fifth (therefore median) worst idiosyncratic state. Dark blue cells corresponding to 0 in a color bar indicate that these are infeasible. There are two reasons for the infeasibility. First, the dark blue cells situated along a diagonal line with vivid blue cells violate the capital requirements. Second, the dark blue cells below the diagonal line violate the balance sheet identity in equation (3.1) in the sense that the book value of equity should be negative. Vivid blue cells corresponding to 1 in a color bar indicate that banks in these cells choose to exercise the government bailout option. Green cells corresponding to 2 in a color bar indicate that banks in

[18] When we design the initial conditions for running the simulation, we have well-defined heterogeneity in term of the leverage ratio. However, after dropping the first 50 periods simulated results, the leverage ratio of each bank is close to $1 - k$ irrespective of its loan size. It means each bank in the model tries to utilize the full leverage capacity under the capital requirements. This is because the cost of debts is assumed to be constant, so there is no leverage risk. Also, due to the tax benefit of debts, debt financing is a cheaper source (and actually the cheapest in the model) of funding. Therefore, Figure 3-5 should be understood as an illustrative complement. Instead, we will check the impact of different capital ratios in the first counterfactual exercise.

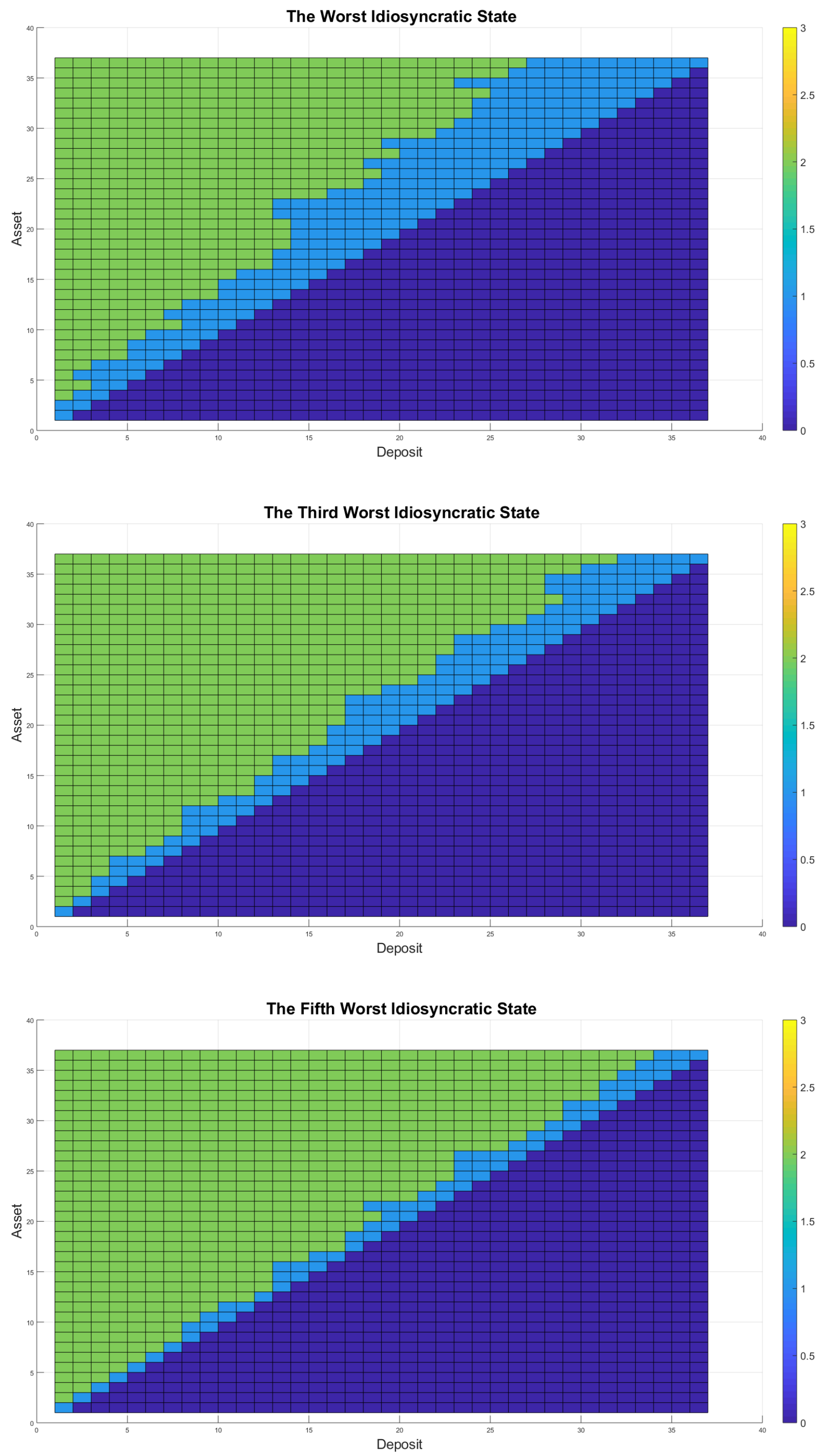


Figure 3-5: Bailout Option Exercise Decision

Three cases are all in the worst aggregate state. The top sub-figure is in the worst idiosyncratic state, the middle sub-figure is in the third worst idiosyncratic state, and the bottom sub-figure is in the median idiosyncratic state. Dark blue cells indicate the infeasibility. Vivid blue cells indicate that banks choose to exercise the government bailout option and green cells indicate that banks choose not to exercise the government bailout option. There is no case where banks choose to default indicated by yellow cells even in the worst situation.

these cells choose not to exercise the government bailout option. Interestingly, there is no case where banks choose to default indicated by yellow cells corresponding to 3 in a color bar even in the worst situation (see the top sub-figure). As the idiosyncratic state becomes better, the banks that do not have a sufficient amount of equity buffers choose to exercise the government bailout option because negative profitability is not severe enough to make banks reliant on the government bailouts.

Comparison between with and without the Government Bailouts

Following the simulation method with parameter values in Table 3-2, we can summarize comparisons between the model with the government bailouts and the model without the government bailouts in Table 3-3. Among others, it is the quarterly average stock return during a crisis period with the government bailouts that we try to match with the corresponding empirical measure based on the first identification assumption. From the simulated result, we get -3.89%, which is close to the weighted quarterly average stock return of top 20% and top 8 banks during a crisis period calculated from Table G-2.

First, the average stock return with the government bailouts is less negative during a crisis period than the counterpart without the government bailouts.[19] An interesting result is that the average stock return without the government bailouts, -7.04%, is close to the average stock return of bottom 20% banks during the recent financial crisis, -7.35%, which is not our target moment for the calibration. Since theses banks were not usually beneficiaries of TARP, based on the second identification assumption, it is reasonable to say that the government bailout option can keep the stock returns of large commercial banks and bank holding companies from further plummeting during a crisis period. On top of that, the average stock return with the government bailouts during a normal time is less than the counterpart without the government bailouts.[20] Since the stock return can be interpreted as the cost of equity, we can understand this result such that large banks enjoy the equity financing as a cheap source of funding because of the government bailouts reducing risk compensation priced in the stock return. This simulated result is consistent with empirical findings of Gandi and Lustig (2015).

In terms of volatility, the result in Table 3-3 is not well matched with the corresponding empirical measure since we do not use the second moment of stock returns for the calibration. Also, the volatility

[19] When we calculate the quarterly average stock return without the government bailouts, we do not consider defaulted stocks. This is the same way in which we construct empirical measures introduced in Table G-2.

[20] We define the average stock return during a normal as follows: take the average of stock returns across all simulations and all banks conditional on

$$u_t^s \leq u_{t+1}^s \text{ and } u_{t+1}^s \in \text{Normal Periods.}$$

Therefore, by construction, the average stock return during a normal period is associated with the economy going to good situations deviating from a crisis period, reflecting the post-crisis period.

Table 3-3: Benchmark Model Result

	Crisis Time		Normal Time	
	With Bailout	Without Bailout	With Bailout	Without Bailout
Stock Returns (%)	- 3.89	- 7.04	1.97	2.21
Volatility (%)	8.95	12.19	11.18	14.19
Bailout Ratio (%)	51.31	Not Available	9.41	Not Available
Default Ratio (%)	0.00	9.07	0.00	0.00

The key results of the paper is summarized in this table, especially on the first row. Stock returns and volatility are quarterly basis while bailout and default ratios are yearly basis. The average stock return with the government bailouts is less negative during a crisis period than the counterpart without the government bailouts. Therefore, we can say that the government bailout option can keep the stock returns of large banks from further plummeting during a crisis period. On top of that, the average stock return with the government bailouts during a normal time is less than the counterpart without the government bailouts. This result is consistent with Gandi and Lustig (2015) in the sense that large banks enjoy the equity financing as a cheap source of funding.

from the simulated result shows a different pattern compared to the empirical counterpart. In the data, the volatility of quarterly stock returns of large banks is higher than that of small banks during both a crisis period and a normal period. However, if we assume that the model without the government bailouts represents a problem of small banks, our simulated result is inconsistent with the data when it comes to the volatility.[21] This is one puzzling result from the simulation. However, it is worth explaining why the volatility of stock returns is lower in the model with the government bailouts during both a crisis period and a normal period.

Figure 3-6 shows two examples from a simulated result. Blue asterisks indicate that the bailout option available to the bank in the example is exercised. Both examples include a crisis period and the second example is especially in the same aggregate state during the whole selected periods. A return difference is defined as the difference between a quarterly stock return with the government bailouts and the counterpart without the government bailouts. Therefore, if a quarterly stock return with the government bailouts is negative (loss) and a return difference is positive, we can say that the government bailouts prevent equity holders of the bank in the example from experiencing severer investment losses. On the other hand, if a quarterly stock return with the government bailouts is positive (gain) and a return difference is negative, we can say that the government bailouts allow the bank in the example to use the equity financing in a cheaper price.

[21] We report the quarterly stock returns of U.S. commercial banks in Appendix B. From Figure H-1 and Figure H-2, we can confirm that the stock returns of large banks are more volatile than those of small banks.

From both examples, we find that once the bailout option is exercisable, the market values of equity with the government bailouts are higher than those without the government bailouts. This is qualitatively consistent with Atkeson, D'Avernas, Eisfeldt, and Weill (2018). More importantly, once the bank's future profitability becomes better due to either aggregate shocks or idiosyncratic shocks, we find that return differences are negative. The opposite is also true. One implication of this finding is that the stock return with the government bailouts is less negative in bad times and less positive in good times, leading to a mild fluctuation. This is the major reason associated with the volatility pattern from the simulation and well illustrated from the fourth quadrant in the second example in Figure 3-6.

The last two rows in Table 3-3 report bailout and default ratios. These values are yearly basis. During a crisis period, around a half of banks in the simulation choose to get bailed out. Considering the first identification assumption for the calibration in the previous section, 51.31% is a reasonable value.[22] Also, it is interesting to find that some banks exercise the bailout option during a normal period even though the default ratio during a normal period is zero. This non-zero bailout ratio during a normal time is consistent with the report of TARP that some banks received capital injection even after the recent financial crisis. Finally, as we see from Figure 3-5, the default ratio from the model with the government bailouts is zero. In the model without government bailouts, the default ratio during a crisis period is 9.07%, which is a conditional value. If we translate this conditional default ratio into the unconditional one, it is around 1% close to the value reported in Corbae and D'Erasmo (2021).[23] Therefore, our model is well fitted with the values which we do not use for the calibration, making the benchmark result more reliable.

3.4.2 Counterfactual I: Different Capital Requirements k

In the benchmark model, we assume that the cost of debts (deposits) is constant, so the capital ratio is an important factor to determine the capital structure of banks. In other words, banks in the model choose their maximum deposit financing capacity, implying that they do not accumulate equity more than suggested by the capital requirements. However, Figure I-1 and Figure I-2 in Appendix C show that there has been heterogeneity in capital ratios not only among banks with different sizes but also over different time periods. These figures show that top 8 banks have consistently lower levels of capital than top 20% and bottom 20%

[22] In the previous section, we assume that the government bailout option is only available to top 20% and top 8 banks. As we guess, if at most around 70 and 170 publicly listed commercial banks and bank holding companies were saved due to TARP in 2008 and 2009 respectively, the upper bound for the average bailout ratio would be $0.5 \cdot (70+170)/240 = 0.5$ where 240 comes from one fifth of the number of publicly listed commercial banks and bank holding companies in the stock market which is 1200 on average.

[23] From the discretized Markov process for the aggregate state, we can calculate the stationary probability. Since we define the worst two aggregate states as a crisis period, the unconditional default ratio can be calculated by $9.07 \cdot (0.0750 + 0.1249) = 1.013\%$. The numbers inside the parenthesis indicate the unconditional probability of the worst aggregate state and the second worst aggregate state respectively.

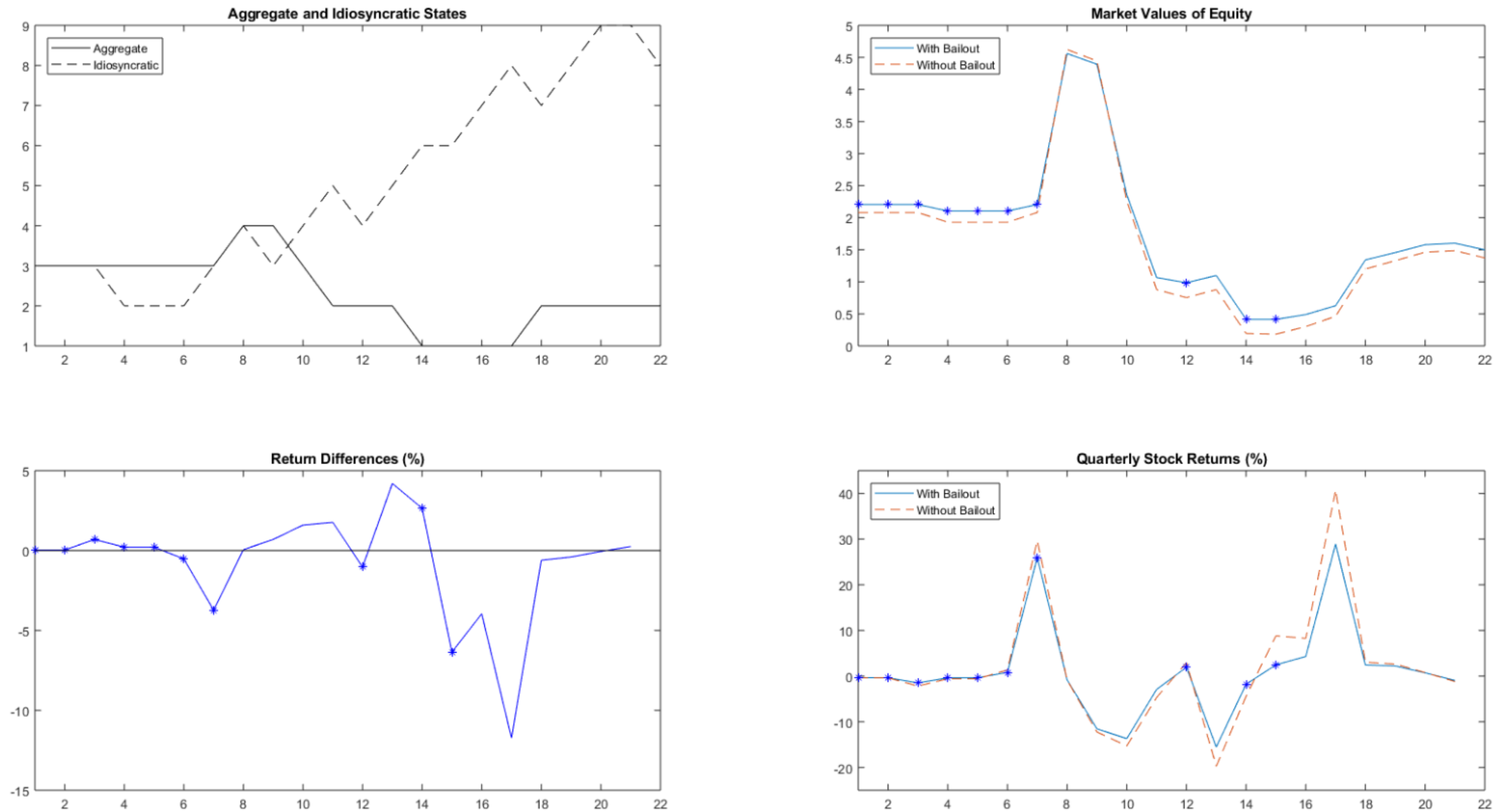


Figure 3-6: Examples of Simulated Results

Blue asterisks indicate that the bailout option available to the bank in the example is exercised. Once the bank's future profitability becomes better due to either aggregate shocks or idiosyncratic shocks, we find that return differences are negative. On the other hand, return differences are positive when the bank's future profitability becomes worse. This can explain the volatility pattern from the simulation.

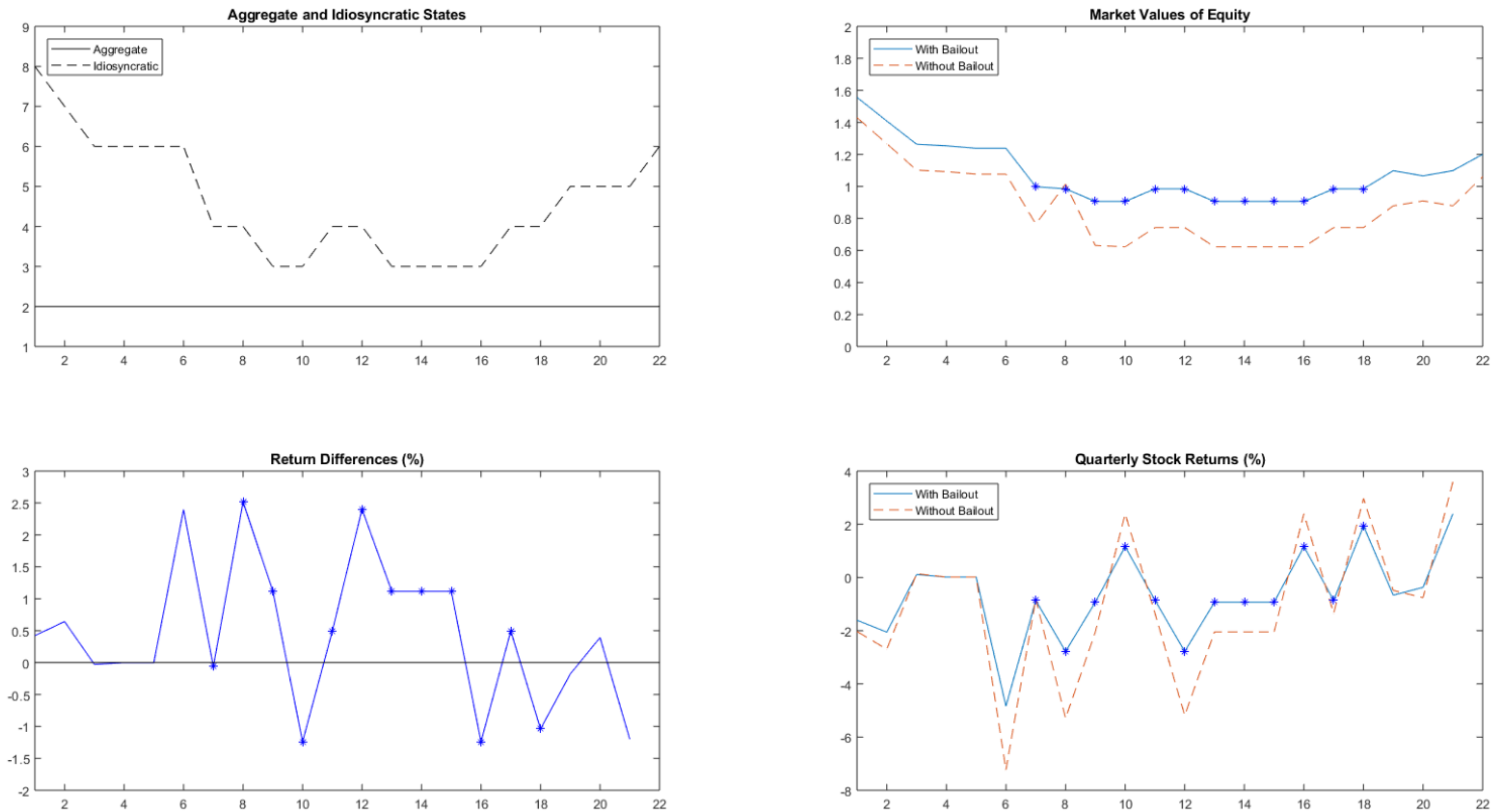


Figure 3-6: Examples of Simulated Results

Blue asterisks indicate that the bailout option available to the bank in the example is exercised. Once the bank's future profitability becomes better due to either aggregate shocks or idiosyncratic shocks, we find that return differences are negative. On the other hand, return differences are positive when the bank's future profitability becomes worse. This can explain the volatility pattern from the simulation.

Table 3-4: Counterfactual I: Different Capital Requirements k

Quarterly Average Stock Return (%)				
	Crisis Time		Normal Time	
k	With Bailout	Without Bailout	With Bailout	Without Bailout
0.04	- 3.89	- 7.04	1.97	2.21
0.06	- 3.86	- 6.84	1.94	2.18
0.08	- 3.77	- 6.59	1.90	2.16
0.10	- 3.69	- 6.40	1.88	2.13

This table is the result of a counterfactual exercise by solving the model for different capital ratios. The quarterly average stock return shows a less severe investment loss when banks experience an adverse economic situation and shows a less investment gain as the capital ratio becomes higher.

banks before the recent financial crisis. Noticeably, Figure I-2 makes clear that there has been an increasing trend in the capital ratio of large financial institutions. A part of this trend can be explained by the evolution of a banking regulatory policy specifically designed to control the largest financial institutions (e.g. Dodd-Frank Wall Street Reform and Consumer Protection Act). Among other regulatory policies, we focus on the capital requirements in this paper. In this subsection, therefore, we do a counterfactual exercise in order to investigate impacts of different capital ratios.

With the parameter values in Table 3-2, we solve the model again for different capital ratios and construct a simulated panel by following the steps described in the last section. We use the identical panel of shocks and the same initial conditions as the benchmark model. The result is summarized in Table 3-4. From the first two columns, we confirm that the quarterly average stock return shows a less severe investment loss when banks experience an adverse economic situation in the next period as the capital ratio becomes higher. This result holds in the model both with and without the government bailouts and is in accord with the intuition that equity holders of banks with a higher capital ratio take a low level of investment risks during a bad time. On the other hand, the quarterly average stock return is decreasing during a normal time as the capital requirements become tighter. Since we define a normal period as the time during which the model

[24] We can also understand the result in Table 3-4 from a perspective of leverage. Considering equation (3.1), the leverage ratio is inversely related to the capital ratio. With a less leverage ratio (a higher capital ratio), banks have sufficient cash holdings to pay the cost of debts senior to the dividend payout. Therefore, it is more likely that banks distribute a dividend, reducing a risk of holding equity. Since our model dose not have a default debt, we cannot explicitly define a leverage risk priced in the cost of debts. With dynamic corporate finance models, the association between stock returns and a leverage risk is studied in Gomes and Schmid (2010, 2021) and Kuehn and Schmid (2014).

economy would be at least as good as the current period in terms of the aggregate state, we can interpret the last two columns as that equity holders of banks with a higher capital ratio bear a less risk priced in a stock return.[24] Lastly, the implication of the government bailouts on stock returns explicated in the benchmark holds in each different capital ratio.

3.4.3 Counterfactual II: Different Idiosyncratic Volatility σ_v

In Section 3.3, to calibrate the persistence ρ_v and the volatility σ_v, we assume that the idiosyncratic shock processes are same across different sizes of banks. Especially, the volatility σ_v is conceptually important in the model since it can capture both the riskiness of loan investment and the diversification of the risk pertaining to loan investment. Therefore, if σ_v becomes higher, it can be understood as either an increase in the riskiness, or a decrease in the diversification, or both. In this subsection, we do a counterfactual exercise in order to investigate impacts of different idiosyncratic volatility. However, since we do not decompose σ_v, we cannot explain why this value is higher in some banks and lower in other banks.[25]

With the parameter values in Table 3-2, we solve the model again for different idiosyncratic volatility and construct a simulated panel by following the steps described in the last section. The result is summarized in Table 3-5. From the first column, we find that the quarterly average stock return shows a less severe investment loss as the idiosyncratic shock becomes more volatile. In the model with the government bailouts, any amount of losses would be absorbed once bank managers choose to exercise the government bailout option. Therefore, even though bank profitability becomes more dispersed, bank managers can ignore negative parts below a threshold due to the loss absorption. This makes an investment loss less severe in the model with higher idiosyncratic volatility since banks can experience much better idiosyncratic shocks even under a crisis period. In this sense, banks without the government bailout option should receive more negative profitability as the idiosyncratic volatility becomes increasing, leading to the result in the second column.[26] On the other hand, the quarterly average stock return show a decreasing pattern during a normal time regardless of the government bailouts. Since there is no default from all simulations during a normal time, we

[25] There are some papers endogenously modeling volatility of idiosyncratic shocks in equilibrium settings. Begenau (2020) considers that a representative bank can choose the amount of risk, which is modeled as volatility of the productivity level in the bank-dependent production sector. Corbae and D'Erasmo (2013) consider that big banks (national banks in their model) can have more than one branch, so they implicitly assume the notion of geographical diversification.

[26] Intuitively, if the positive profitability is also more positive, the quarterly average stock return during a crisis can become less negative during a crisis period in the model with the higher idiosyncratic volatility. However, the result in Table 3-5 is closely associated with how we define the bank profitability in equation (3.5).

$$Z_{it} = \overline{z} u_t v_{it} - 1$$

From the above definition, a negative effect of higher σ_v on v_{it} is more substantial than a positive one in terms of percentage changes in Z_{it}.

Table 3-5: Counterfactual II: Different Idiosyncratic Volatility σ_v

Quarterly Average Stock Return (%)				
	Crisis Time		Normal Time	
σ_v	With Bailout	Without Bailout	With Bailout	Without Bailout
0.010	- 3.89	- 7.04	1.97	2.21
0.015	- 3.63	- 7.18	1.82	2.16
0.020	- 3.36	- 7.18	1.68	2.10
0.025	- 3.06	- 7.26	1.53	2.00

This table is the result of a counterfactual exercise by solving the model for different idiosyncratic volatility. The quarterly average stock return shows a less severe investment loss as the idiosyncratic shock becomes more volatile. Bank managers can ignore negative profitability due to the government bailouts. This makes an investment loss less severe in the model with higher idiosyncratic volatility since banks can experience much better idiosyncratic shocks even under a crisis period.

can interpret that bank stocks underperform due the same reason mentioned in the previous footnote. Like the first counterfactual exercise, the implication of the government bailouts on stock returns holds in each different idiosyncratic volatility.

3.4.4 Impact of the Government Bailouts on Return Differences

One common finding from two counterfactual exercises is that the government bailouts can decrease a size of losses during a crisis period and can decrease a size of gains during a normal time from investing in bank stocks. Therefore, the average of return differences shown in Figure 3-6 from the first subsection can be positive during a crisis period and be negative during a normal period. The policy implication of this result is that the government bailouts can change the cost of equity of large financial institutions. Empirically, this financing advantage due to the government bailouts is reported among banks with different sizes by Gandhi and Lustig (2015) and between large financial institutions and large non-financial firms in major countries by Gandhi, Lustig, and Plazzi (2020). In this last subsection, we examine how much the government bailouts can change the average quarterly stock return which we can also interpret as the cost of equity. This analysis is done in a two-dimensional sense: we solve the model again not only with different capital ratios k but also with different idiosyncratic volatility σ_v. Instead of reporting stock returns, we focus on return differences in order to analyze the quantitative impact of the government bailouts.

Table 3-6: Mean of Quarterly Stock Return Differences

Crisis Time (%)				
	$\sigma_v = 0.010$	$\sigma_v = 0.015$	$\sigma_v = 0.020$	$\sigma_v = 0.025$
$k = 0.04$	3.15	3.55	3.82	4.21
$k = 0.06$	2.98	3.36	3.63	4.12
$k = 0.08$	2.81	3.30	3.55	4.04
$k = 0.10$	2.71	3.22	3.51	3.99

Normal Time (%)				
	$\sigma_v = 0.010$	$\sigma_v = 0.015$	$\sigma_v = 0.020$	$\sigma_v = 0.025$
$k = 0.04$	- 0.24	- 0.34	- 0.42	- 0.47
$k = 0.06$	- 0.24	- 0.35	- 0.43	- 0.49
$k = 0.08$	- 0.25	- 0.35	- 0.43	- 0.48
$k = 0.10$	- 0.25	- 0.34	- 0.43	- 0.48

During a crisis period, a size of losses from investing in bank stocks is much more alleviated due to the government bailouts as the capital ratio is lower. Moreover, the government bailouts diminish a size of losses more as the idiosyncratic shock becomes more volatile.

The result is summarized in Table 3-6. During a crisis period (the upper panel), a size of losses from investing in bank stocks is much more alleviated due to the government bailouts as the capital ratio is lower. In other words, given the same idiosyncratic volatility, equity holders of safer banks benefit less from the government bailouts. This is consistent with the bailout ratio decreasing in the capital ratio in Table 3-7 (the upper panel). Moreover, the government bailouts diminish a size of losses more as the idiosyncratic shock becomes more volatile.[27] Since σ_v conceptualizes the riskiness and the diversification of loan investment, it can be said that equity holders of banks in a riskier environment can benefit more from the government bailouts during a crisis period.

During a normal period (the lower panel), we cannot find any quantitative difference among models with different capital ratios in term of a decrease in the quarterly average stock return due to the government

[27] One caution we want to make is that the result from the idiosyncratic volatility dimension should be understood carefully because the model with higher volatility shows a severer investment loss by construction. Therefore, it is possible that the numbers reported in Table 3-6 along the different idiosyncratic volatility are large than they should be. This concern is also reasonable when considering the fact that there is no clear linear relation between the idiosyncratic volatility and the bailout ratio in Table 3-7 (the upper panel).

Table 3-7: Mean of Bailout Ratios

Crisis Time (%)

	$\sigma_v = 0.010$	$\sigma_v = 0.015$	$\sigma_v = 0.020$	$\sigma_v = 0.025$
$k = 0.04$	51.31	52.35	49.58	51.77
$k = 0.06$	48.96	48.46	47.14	49.90
$k = 0.08$	46.80	47.16	46.40	48.72
$k = 0.10$	42.72	46.97	45.98	48.27

Normal Time (%)

	$\sigma_v = 0.010$	$\sigma_v = 0.015$	$\sigma_v = 0.020$	$\sigma_v = 0.025$
$k = 0.04$	9.41	9.82	19.29	21.01
$k = 0.06$	6.92	9.42	14.52	19.87
$k = 0.08$	6.16	8.58	11.97	17.71
$k = 0.10$	5.56	7.45	11.56	17.37

During a crisis period, the bailout option is exercised to prevent banks from defaulting, so the bailout ratio is decreasing in the capital ratio. On the other hand, during a normal time, the bailout option is exercised not for rescuing a bank from a default but for increasing the market value of equity.

bailouts. Also, the magnitude of the reduction in stock returns during a normal time is significantly smaller than the magnitude of the rise in stock returns during a crisis time. This is because the government bailouts are available not only to banks close to a default but also any bank with negative profitability in the model. From the simulation, we find that defaults happen only during a crisis period for all k and σ_v in the model with the government bailouts. However, as we can see from Table 3-7, the bailout option is exercised during a normal time even though banks exercising this option are not actually very close to a default. Therefore, in those cases, the quantitative effectiveness of the government bailouts is not substantially different depending on the capital ratio since the bailout option is exercised not for rescuing a bank from a default but for increasing the market value of equity. Finally, we find that the government bailouts diminish a size of gains more as the idiosyncratic shock becomes more volatile, which is similar with the implication during a crisis period. However, unlike a crisis period, the bailout ratio is increasing in the idiosyncratic volatility as we can see from Table 3-7 (the lower panel). Therefore, we can associate the magnitude of the reduction in stock returns along the idiosyncratic volatility dimension with the rise in bailout ratios although the bailout option exercised during a normal period is not directly relevant to saving banks from being bankrupt. Consequently, we find that the government bailouts can change stock returns more both positively and negatively under a riskier banking environment.

3.5 Conclusion

We use a simple quantitative banking model including dynamic investment and financing decisions to show that the observed heterogeneity in bank stock returns during both a crisis period and a normal period can be explained by the government bailouts. The government bailouts can keep the stock returns of large commercial banks and bank holding companies from further plummeting during a crisis period. Furthermore, the stock returns of large commercial banks and bank holding companies during a normal period is smaller in the model with the government bailouts. This is consistent with Gandhi and Lustig (2015), showing that these institutions can enjoy the equity financing as a cheap source of funding due to the safety net provided by the government bailouts.

There are several ways to extend this model. In our model, banks decide to default because profitability becomes negative enough to erode the market value of equity. This type of crises is caused by the asset side of banks' balance sheet. However, incorporating a withdrawal risk from the liability side is also important since this can capture a conventional bankruptcy of financial institutions. One recent paper by Boualam and Cororaton (2020) shows an empirically positive relationship between higher funding liquidity risks and lower expected stock returns. However, they cannot explain this pattern from a multi-factor model. Therefore, adding liquidity management and liability-side shocks to a simple quantitative banking model like our paper can shed a new light on the mechanism how investors in financial markets price funding liquidity risks. Also, with a more elaborated model incorporating liquidity management, we can also study the impact of Basel III liquidity coverage ratios on bank stock returns. Finally, modeling the volatility of idiosyncratic shocks as an endogenous choice of banks in an equilibrium setting can be another interesting extension to decompose the stock return into the riskiness of loan investment and the diversification. These are remained for the future research.

A Sample Description on Bank Holding Companies

Figure A-1: Bank Capital Structure (Mean from 2001:Q1 to 2014:Q4)

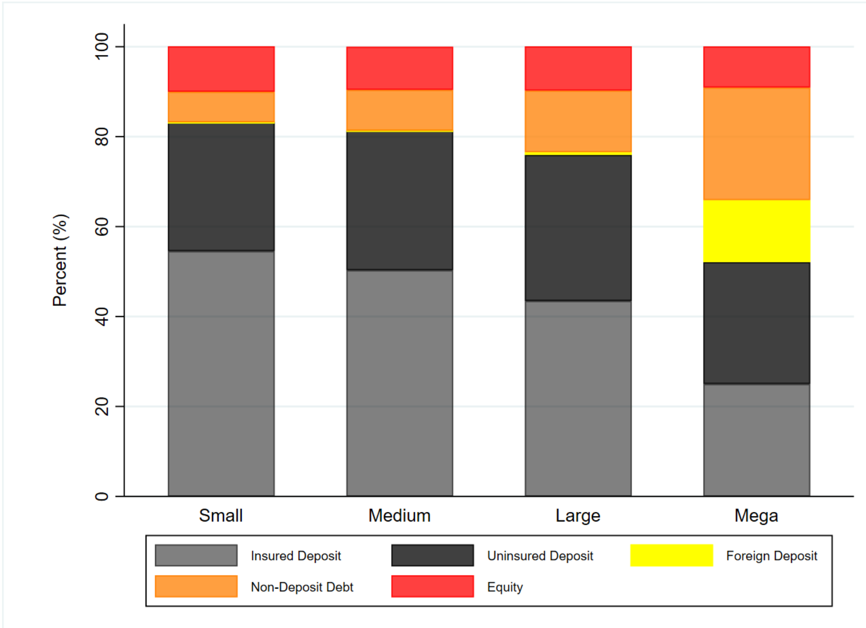
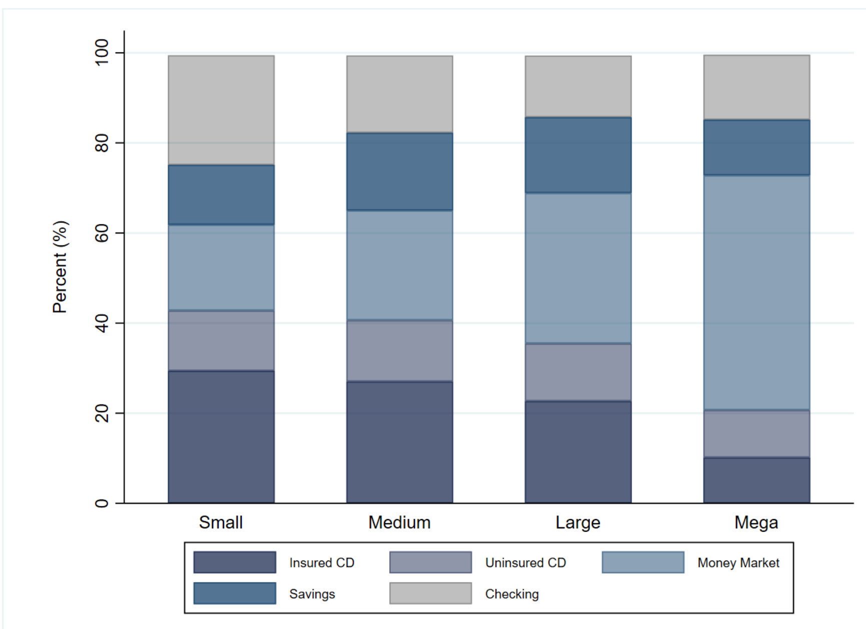


Figure A-2: Deposit Composition (Mean from 2001:Q1 to 2014:Q4)



Note: Balance sheet information is from Call Report. For each quarter over the sample period, we define the bottom 30% banks as Small, the middle 40% banks as Medium, the top 30% banks excluding the top 1% banks as Large, and the top 1% banks as Mega. GSIB and DSIB are all included in Mega category. Information on insured status of each category of deposits is only available for time deposits (CD) from Call Report.

B Empirical Analysis and Robustness Checks

Table B-1: Prediction Models of Equity Capital Issuance without the Bias Correction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Issuance_t	Issuance_t	Issuance_t	Issuance_t	Issuance_t	Issuance_t	Issuance_t	Issuance_t
ROA_t	-0.078^{***}	-0.039^{***}	0.000	-0.001	-0.047^{***}	-0.024^{***}	0.043^{***}	0.025^{***}
	(0.007)	(0.003)	(0.008)	(0.005)	(0.007)	(0.004)	(0.010)	(0.006)
Cost of Deposits_t	-0.207^{***}	-0.122^{***}	-0.204^{***}	-0.116^{***}	-0.164^{***}	-0.096^{***}	0.132^{***}	0.073^{***}
	(0.009)	(0.006)	(0.016)	(0.009)	(0.018)	(0.011)	(0.047)	(0.027)
$\log(\text{CR}_{t-1})$	-1.188^{***}	-0.709^{***}	0.027	-0.003	-1.232^{***}	-0.725^{***}	-0.038	-0.049
	(0.036)	(0.021)	(0.082)	(0.048)	(0.037)	(0.021)	(0.086)	(0.050)
$\log(\text{DTA}_{t-1})$	-2.461^{***}	-1.497^{***}	-1.150^{***}	-0.613^{***}	-2.436^{***}	-1.469^{***}	-1.328^{***}	-0.704^{***}
	(0.083)	(0.050)	(0.234)	(0.136)	(0.084)	(0.051)	(0.255)	(0.147)
Dividend_t	0.283^{***}	0.162^{***}	0.367^{***}	0.206^{***}	0.296^{***}	0.174^{***}	0.390^{***}	0.234^{***}
	(0.020)	(0.012)	(0.046)	(0.026)	(0.020)	(0.012)	(0.048)	(0.027)
Model	Logit	Probit	Logit	Probit	Logit	Probit	Logit	Probit
Bank FE	No	No	Yes	Yes	No	No	Yes	Yes
Time FE	No	No	No	No	Yes	Yes	Yes	Yes
Error Correction	No	No	No	No	No	No	No	No
Observations	55,852	55,852	36,770	36,770	55,852	55,852	36,770	36,770

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, and standard errors are in parentheses.

Table B-2: Prediction Models of Equity Capital Issuance (Robustness I)

	(1)	(2)	(3)	(4)	(5)	(6)
	Issuance_t	Issuance_t	Issuance_t (Before)	Issuance_t (Before)	Issuance_t (After)	Issuance_t (After)
ROE_t	0.0027^{***}	0.0015^{***}	0.0046^{**}	0.0026^{*}	0.0004	0.0003
	(0.0006)	(0.0003)	(0.0024)	(0.0014)	(0.0008)	(0.0005)
$\text{Cost of Deposits}_t$	0.128^{***}	0.071^{***}	0.140^{**}	0.068^{*}	0.216^{*}	0.124^{**}
	(0.047)	(0.027)	(0.065)	(0.035)	(0.112)	(0.063)
$\log(\text{Tier 1 CR}_{t-1})$	0.041	0.000	-0.818^{***}	-0.485^{***}	-0.052	-0.041
	(0.074)	(0.043)	(0.160)	(0.090)	(0.127)	(0.072)
$\log(\text{DTA}_{t-1})$	-1.251^{***}	-0.663^{***}	-1.543^{***}	-0.845^{***}	-1.397^{***}	-0.718^{***}
	(0.253)	(0.146)	(0.443)	(0.253)	(0.479)	(0.275)
Dividend_t	0.361^{***}	0.200^{***}	0.364^{***}	0.201^{***}	0.322^{***}	0.176^{***}
	(0.048)	(0.027)	(0.075)	(0.042)	(0.086)	(0.049)
Model	Logit	Probit	Logit	Probit	Logit	Probit
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Error Correction	Two-Way	Two-Way	Two-Way	Two-Way	Two-Way	Two-Way
Trimming	1	1	1	1	1	1
Pseudo R-Squared	0.374	0.374	0.346	0.345	0.384	0.384
Observations	36,770	36,770	19,102	19,102	12,115	12,115

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, and standard errors are in parentheses.

Note: ROE $=$ Net Income/Total Equity and the total equity capital is RCON3210 from Call Report. The tier 1 capital ratio is BHCA7206 from FR Y-9C. Column (1) and (2) are the logit and probit models, respectively, over the full sample periods. Column (3) and (4) are estimated outcomes from the sub-sample from 2001:Q1 to 2007:Q4, whereas Column (5) and (6) are from the sub-sample from 2008:Q1 to 2014:Q4. For all results, we set the trimming parameter in Cruz-Gonzalez, Fernández-Val, and Weidner (2017) as one to estimate spectral expectations since the econometric model in equation (1.3) has the predetermined variables, Tier 1 CR_{t-1} and DTA_{t-1}, with respect to the dependent variable.

Table B-3: Prediction Models of Equity Capital Issuance (Robustness II)

	(1)	(2)	(3)	(4)	(5)	(6)
	Issuance_t	Issuance_t	Issuance_t	Issuance_t	Issuance_t	Issuance_t
			(Before)	(Before)	(After)	(After)
ROA_t	0.035^{***}	0.018^{***}	0.047^{*}	0.028^{*}	-0.015	-0.008
	(0.010)	(0.006)	(0.025)	(0.015)	(0.014)	(0.008)
Cost of Deposits_t	0.149^{***}	0.082^{***}	0.153^{**}	0.074^{**}	0.320^{***}	0.186^{***}
	(0.046)	(0.026)	(0.064)	(0.035)	(0.100)	(0.056)
$\log(\text{CR}_{t-1})$	-0.186^{**}	-0.137^{***}	-0.861^{***}	-0.468^{***}	-0.540^{***}	-0.312^{***}
	(0.087)	(0.049)	(0.179)	(0.094)	(0.145)	(0.082)
$\log(\text{DTA}_{t-1})$	-1.060^{***}	-0.550^{***}	-1.433^{***}	-0.786^{***}	-1.188^{**}	-0.610^{**}
	(0.252)	(0.145)	(0.444)	(0.252)	(0.475)	(0.271)
Dividend_t	0.288^{***}	0.159^{***}	0.326^{***}	0.179^{***}	0.165^{**}	0.086^{*}
	(0.046)	(0.026)	(0.074)	(0.042)	(0.081)	(0.046)
Model	Logit	Probit	Logit	Probit	Logit	Probit
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Error Correction	Two-Way	Two-Way	Two-Way	Two-Way	Two-Way	Two-Way
Trimming	1	1	1	1	1	1
Pseudo R-Squared	0.374	0.373	0.349	0.348	0.388	0.388
Observations	38,141	38,141	19,335	19,335	13,534	13,534

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, and standard errors are in parentheses.

Note: Issuance_t is redefined to combine common and preferred stock issuance. Column (1) and (2) are the logit and probit models, respectively, over the full sample periods. Column (3) and (4) are estimated outcomes from the sub-sample from 2001:Q1 to 2007:Q4, whereas Column (5) and (6) are from the sub-sample from 2008:Q1 to 2014:Q4. For all results, we set the trimming parameter in Cruz-Gonzalez, Fernández-Val, and Weidner (2017) as one to estimate spectral expectations since the econometric model in equation (1.3) has the predetermined variables, CR_{t-1} and DTA_{t-1}, with respect to the dependent variable.

Table B-4: Prediction Models of Equity Capital Issuance (Robustness III)

	(1)	(2)	(3)	(4)	(5)	(6)
	Issuance_t	Issuance_t	Issuance_t	Issuance_t	Issuance_t	Issuance_t
			(Before)	(Before)	(After)	(After)
ROE_t	0.0029^{***}	0.0016^{***}	0.0042^{*}	0.0024^{*}	0.0007	0.0004
	(0.0006)	(0.0003)	(0.0023)	(0.0014)	(0.0007)	(0.0004)
Cost of Deposits_t	0.153^{***}	0.086^{***}	0.140^{**}	0.067^{*}	0.347^{***}	0.201^{***}
	(0.046)	(0.026)	(0.064)	(0.035)	(0.100)	(0.055)
log(Tier 1 CR_{t-1})	-0.107	-0.089^{**}	-0.894^{***}	-0.525^{***}	-0.371^{***}	-0.221^{***}
	(0.073)	(0.042)	(0.160)	(0.090)	(0.121)	(0.068)
log(DTA_{t-1})	-1.006^{***}	-0.524^{***}	-1.364^{***}	-0.763^{***}	-1.147^{**}	-0.590^{**}
	(0.251)	(0.144)	(0.442)	(0.251)	(0.472)	(0.269)
Dividend_t	0.281^{***}	0.155^{***}	0.331^{***}	0.184^{***}	0.157^{*}	0.082^{*}
	(0.046)	(0.026)	(0.074)	(0.042)	(0.081)	(0.046)
Model	Logit	Probit	Logit	Probit	Logit	Probit
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Error Correction	Two-Way	Two-Way	Two-Way	Two-Way	Two-Way	Two-Way
Trimming	1	1	1	1	1	1
Pseudo R-Squared	0.374	0.373	0.349	0.348	0.388	0.388
Observations	38,141	38,141	19,335	19,335	13,534	13,534

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, and standard errors are in parentheses.

Note: Issuance_t is redefined to combine common and preferred stock issuance. ROE $=$ Net Income/Total Equity and the total equity capital is RCON3210 from Call Report. The tier 1 capital ratio is BHCA7206 from FR Y-9C. Column (1) and (2) are the logit and probit models, respectively, over the full sample periods. Column (3) and (4) are estimated outcomes from the sub-sample from 2001:Q1 to 2007:Q4, whereas Column (5) and (6) are from the sub-sample from 2008:Q1 to 2014:Q4. For all results, we set the trimming parameter in Cruz-Gonzalez, Fernández-Val, and Weidner (2017) as one to estimate spectral expectations since the econometric model in equation (1.3) has the predetermined variables, Tier 1 CR_{t-1} and DTA_{t-1}, with respect to the dependent variable.

Table B-5: Prediction Models of Equity Capital Issuance (Robustness IV)

	(1)	(2)	(3)	(4)	(5)	(6)
	Issuance$_t$	Issuance$_t$	Issuance$_t$	Issuance$_t$	Issuance$_t$	Issuance$_t$
			(Before)	(Before)	(After)	(After)
ROA$_t$	0.038^{***}	0.020^{***}	0.054^{**}	0.030^{**}	-0.006	-0.002
	(0.010)	(0.006)	(0.026)	(0.015)	(0.014)	(0.008)
Cost of Deposits$_t$	0.125^{***}	0.069^{***}	0.174^{***}	0.084^{**}	0.194^{*}	0.113^{*}
	(0.047)	(0.027)	(0.064)	(0.035)	(0.112)	(0.063)
Cost of Federal Funds & Securities$_t$	0.00092^{*}	0.00053	0.00105	0.00058	0.00079	0.00045
	(0.00055)	(0.00033)	(0.00144)	(0.00086)	(0.00067)	(0.00041)
Cost of Subordinated Debt$_t$	-0.00064	-0.00033	0.00132	0.00083	-0.01020	-0.00618
	(0.00106)	(0.00055)	(0.00123)	(0.00076)	(0.02180)	(0.00954)
Cost of Trading Liabilities & Other Money$_t$	-0.00027	-0.00016	-0.00020	-0.00012	-0.00018	-0.00009
	(0.00031)	(0.00019)	(0.00030)	(0.00019)	(0.00119)	(0.00066)
log(DTA$_{t-1}$)	-1.299^{***}	-0.678^{***}	-1.394^{***}	-0.751^{***}	-1.377^{***}	-0.706^{***}
	(0.253)	(0.146)	(0.441)	(0.252)	(0.477)	(0.273)
Dividend$_t$	0.367^{***}	0.202^{***}	0.335^{***}	0.185^{***}	0.329^{***}	0.179^{***}
	(0.048)	(0.027)	(0.075)	(0.042)	(0.086)	(0.049)
Model	Logit	Probit	Logit	Probit	Logit	Probit
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Error Correction	Two-Way	Two-Way	Two-Way	Two-Way	Two-Way	Two-Way
Trimming	1	1	1	1	1	1
Pseudo R-Squared	0.374	0.373	0.345	0.344	0.385	0.385
Observations	36,770	36,770	19,102	19,102	12,115	12,115

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, and standard errors are in parentheses.

Note: We add costs of other liabilities: federal funds plus securities to repurchase, subordinated debt, and trading liabilities plus other money. Federal funds are excess reserves held by financial institutions, over and above the mandated reserve requirements set by FRB. For banks, subordinated debt is junior debt that is repaid after depositors are repaid in full. Trading liabilities which usually consist of derivative liabilities, the fair value of derivative instruments in a negative position as of the end of the most recent fiscal year end, as recognized and measured in accordance with generally accepted accounting principles. Column (1) and (2) are the logit and probit models, respectively, over the full sample periods. Column (3) and (4) are estimated outcomes from the sub-sample from 2001:Q1 to 2007:Q4, whereas Column (5) and (6) are from the sub-sample from 2008:Q1 to 2014:Q4. For all results, we set the trimming parameter in Cruz-Gonzalez, Fernández-Val, and Weidner (2017) as one to estimate spectral expectations since the econometric model in equation (1.3) has the predetermined variable, DTA$_{t-1}$, with respect to the dependent variable.

Table B-6: Impacts of the Cost of Deposits on Insolvency Risk and Market Share

	(1)	(2)	(3)	(4)	(5)
	log(Z-Score$_t$)	log(Z-Score$_t$)	Δ MS$_t$	Δ MS$_t$	MS$_t$
log(Z-Score$_t$)			0.052^{**}	0.052^{**}	0.043
			(0.022)	(0.022)	(0.088)
log(Z-Score$_{t-1}$)	0.164^{***}	0.164^{***}			
	(0.018)	(0.018)			
Cost of Deposits$_t$	-0.253^{***}	-0.253^{***}	0.458^{***}	0.458^{***}	0.405^{**}
	(0.058)	(0.057)	(0.147)	(0.147)	(0.198)
log(1/DIV$_{t-1}$)	0.123^{*}	0.123^{*}	-0.315^{**}	-0.315^{**}	-0.967
	(0.067)	(0.072)	(0.125)	(0.123)	(0.792)
Cost of Deposits$_t$ $\times$ log(1/DIV$_{t-1}$)	-0.043^{**}	-0.043^{**}	0.061	0.061	0.060
	(0.020)	(0.022)	(0.037)	(0.039)	(0.045)
MS$_{t-1}$	0.001	0.001	-0.286^{***}	-0.286^{***}	0.694^{***}
	(0.005)	(0.005)	(0.024)	(0.025)	(0.060)
DTA$_{t-1}$	0.004	0.004	-0.021^{**}	-0.021^{**}	-0.001
	(0.004)	(0.004)	(0.009)	(0.009)	(0.014)
Bank FE	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	Yes
STD	Cluster	Bootstrap	Cluster	Bootstrap	WC-Robust
R-Squared	0.249	0.249	0.154	0.154	
Observations	8,148	8,148	9,370	9,370	8,148

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, and standard errors are in parentheses.

Note: As a robustness check, we use the sample used used for Table 1-2 to estimate the econometric models in equation (1.5), (1.6), and (1.8). This is because bank holding companies with the constant dependent variable (always issuing or not issuing) are excluded for the logit and probit models with two-way fixed effects in equation (1.3), but these institutions are included for the models in Table 1-3. Column (1) and (2) are from the model in equation (1.5), whereas Column (3) and (4) are from the model in equation (1.6). We use the fixed effects estimator to estimate the models. We compute standard errors with two methods: clustering standard errors by bank holding company and bootstrapping with 2,500 samples. Column (5) is the model in equation (1.8). This model is estimated by following Arellano and Bond (1991)and standard errors are computed by the Windmeijier biased-corrected (WC) estimator for the robust variance-covariance matrix of two-step GMM estimators. Also, the estimated model in Column (5) presents strong evidence against the null hypothesis of zero autocorrelation in the first-differenced errors at order 1, which means that the idiosyncratic errors in equation (1.8) are independent and identically distributed.

C Model with the Risk-Free Capital Requirements

Profit Function

Under the risk-free capital requirements by Basel III regime, shareholders are required to invest a κ share of deposits in the risk-free asset. The net period profit of Bank k is then

$$\begin{aligned}\pi_{k,t} &= \sum_{m\in\mathcal{M}_k} s^m_{k,t}\left(R_{k,t} - i^m_{k,t}\right) + \underbrace{\kappa \sum_{m\in\mathcal{M}_k} s^m_{k,t}(r-r)}_{\text{capital requirement}} \\ &= D_{k,t}R_{k,t} - \sum_{m\in\mathcal{M}_k} s^m_{k,t} i^m_{k,t} \end{aligned} \tag{C.1}$$

which is identical to the case in the benchmark model with $\kappa = 0$.

Default Choice

Bank shareholders endogenously choose whether to default or not. Because banks are protected by limited liability in our model, shareholders can decide not to finance a shortfall, and let a distressed bank default. If a bank defaults, shareholders of the bank lose their claim to cash flows from the next period onward since they do not own the franchise. Let $E_{k,t+1}$ denote the market value of Bank k at time $t+1$. Therefore, shareholders of Bank k choose to support the bank as long as the value of staying in business is higher than the cost of default,

$$\underbrace{D_{k,t}R_{k,t} - \sum_{m\in\mathcal{M}_k} s^m_{k,t} i^m_{k,t} + \frac{1}{1+r}E_{k,t+1}}_{\text{value of staying in business}} > -\kappa D_{k,t}.$$

Since shareholders must forfeit the required capital in the event of a default, the risk-free capital requirements still make bankruptcy more costly. Following Egan, Hortacsu, and Matvos (2017), the optimal cutoff rule is

$$\begin{aligned}&\kappa D_{k,t} - \left(D_{k,t}\overline{R}_k - \sum_{m\in\mathcal{M}_k} s^m_{k,t} i^m_{k,t}\right) \\ =&\frac{1}{1+r}\left[-\kappa D_{k,t} + D_{k,t}\left(1-\Phi\left(\frac{\overline{R}_k-\mu_k}{\sigma_k}\right)\right)\left((\mu_k - \overline{R}_k) + \sigma_k \lambda\left(\frac{\overline{R}_k-\mu_k}{\sigma_k}\right)\right)\right]\end{aligned} \tag{C.2}$$

where $\lambda(\cdot) \equiv \phi(\cdot)/\left(1-\Phi(\cdot)\right)$ is the inverse Mills ratio.

Deposit Pricing

Banks compete for deposits by playing a differentiated product Bertrand-Nash price setting game in each regional market. At the start of each period, banks optimally determine deposit rates for regional markets where they are operating branches to maximize the expected return to shareholders. Due to limited liability, shareholders consider payoffs only if $R_{k,t}$ is realized above $\overline{R}_k$. Therefore, the market value of equity at the beginning of time t is

$$\begin{aligned} E_{k,t} = \max_{\{i^m_{k,t}\}_{m\in\mathcal{M}_k}} \int_{\overline{R}_k}^{\infty} \left[D_{k,t}R_{k,t} - \sum_{m\in\mathcal{M}_k} s^m_{k,t}(i^m_{k,t}, \mathbf{i}^m_{-k,t}) i^m_{k,t} + \frac{E_{k,t+1}}{1+r} \right] dF(R_{k,t}) \\ - \int_{-\infty}^{\overline{R}_k} \kappa \underbrace{\sum_{m\in\mathcal{M}_k} s^m_{k,t}(i^m_{k,t}, \mathbf{i}^m_{-k,t})}_{D_{k,t}} dF(R_{k,t}). \end{aligned}$$

Applying the normal distribution of $R_{k,t}$ and the stationarity of $E_{k,t}$, we obtain

$$\begin{aligned} E_{k,t} = \max_{\{i^m_{k,t}\}_{m\in\mathcal{M}_k}} \left(1 - \Phi\left(\frac{\overline{R}_k - \mu_k}{\sigma_k}\right)\right) \Bigg(D_{k,t}\left(\mu_k + \sigma_k\lambda\left(\frac{\overline{R}_k - \mu_k}{\sigma_k}\right)\right) \\ - \sum_{m\in\mathcal{M}_k} s^m_{k,t}(i^m_{k,t}, \mathbf{i}^m_{-k,t})(i^m_{k,t} + \kappa r) + \frac{E_{k,t}}{1+r} \Bigg) - \Phi\left(\frac{\overline{R}_k - \mu_k}{\sigma_k}\right) \kappa D_{k,t}. \end{aligned}$$

The choice of deposit rates can affect the market value of equity through its influence on the current period operating profit in equation (C.1) and the bankruptcy threshold $\overline{R}_k$ in equation (C.2). Using equation (1.15) and (1.17), the first order condition characterizing the optimal deposit pricing is regional market m is

$$\begin{aligned} \left(1 - \Phi\left(\frac{\overline{R}_k - \mu_k}{\sigma_k}\right)\right) \left(\left(\mu_k + \sigma_k\lambda\left(\frac{\overline{R}_k - \mu_k}{\sigma_k}\right)\right) - i^m_{k,t} \right) - \Phi\left(\frac{\overline{R}_k - \mu_k}{\sigma_k}\right)\kappa \\ = \left(1 - \Phi\left(\frac{\overline{R}_k - \mu_k}{\sigma_k}\right)\right) \frac{1}{\alpha(1 - s^m_{k,t}(i^m_{k,t}, \mathbf{i}^m_{-k,t}))}. \end{aligned} \tag{C.3}$$

Calibration of Supply Parameters

For each bank, we analytically derive two parameters, μ_k and σ_k, from the optimal behavior of banks in the model. We start with the bankruptcy condition from equation (C.2) showing that shareholders of Bank k is indifferent between staying in business and defaulting. Using equation (1.19) and (1.20), equation (C.2) becomes

$$\begin{aligned}
&\left[(\mu_k + \sigma_k \Phi^{-1}(\rho_{ss})) - i_{ss} - \kappa\right] \underbrace{n(\mathcal{M}_k)\overline{s}}_{D_{k,t}} \\
= \ & \frac{1}{1+r}\left[\kappa + \sigma_k\left(1-\rho_{ss}\right)\left(\Phi^{-1}(\rho_{ss}) - \lambda\left(\Phi^{-1}(\rho_{ss})\right)\right)\right] n(\mathcal{M}_k)\overline{s} \qquad \text{(C.4)}
\end{aligned}$$

where $n(\mathcal{M}_k)$ is the number of regional markets in which Bank k operates branches to collect deposits. With i_{ss} and ρ_{ss}, $\overline{s}$ is from equation (1.15), which is a function of the demand-side parameters, α and β. Similarly, equation (C.3) becomes

$$(1-\rho_{ss})\left(\left(\mu_k + \sigma_k\lambda\left(\Phi^{-1}(\rho_{ss})\right)\right) - i_{ss}\right) - \rho_{ss}\kappa = \frac{(1-\rho_{ss})}{\alpha(1-\overline{s})}. \qquad \text{(C.5)}$$

Using equation (C.4) and (C.5),

$$\sigma_k = \frac{\dfrac{1}{\alpha(1-\overline{s})} + \left(\dfrac{\rho_{ss}}{1-\rho_{ss}}\right)\kappa - (2+r)\kappa}{(1+r)(r+\rho_{ss})(\lambda\left(\Phi^{-1}(\rho_{ss})\right) - \Phi^{-1}(\rho_{ss}))} \qquad \text{(C.6)}$$

$$\mu_k = i_{ss} + \frac{1}{\alpha(1-\overline{s})} + \left(\frac{\rho_{ss}}{1-\rho_{ss}}\right)\kappa - \sigma_k\lambda\left(\Phi^{-1}(\rho_{ss})\right). \qquad \text{(C.7)}$$

Similar to the benchmark model,

$$\frac{\partial}{\partial\kappa}\sigma_k \propto \left(\underbrace{\frac{\rho_{ss}}{1-\rho_{ss}} - 1}_{<0} - 2r - \frac{1}{\alpha(1-\overline{s})}\right) < 0.$$

Under the risk-free capital requirements,

$$\frac{\partial}{\partial\kappa}\mu_k \propto \frac{\rho_{ss}}{1-\rho_{ss}} > 0.$$

Therefore, the return on loan investment becomes not only less volatile but also more profitable on average as the capital requirements get more restrictive.

D Empirical Analysis

Table D-1: The Number of Maturity-Minimum Deposit Pairs

	Bank Size				
	Small	**Medium**	**Large**	**Very Large**	**Total**
	Mean	Mean	Mean	Mean	Mean
Deposit Product					
CD	200.1	212.2	237.4	501.0	220.4
Relationship CD	132.8	103.3	88.3	120.7	101.9
Business CD	31.1	32.0	33.3	49.6	32.7
MM	23.9	24.1	25.2	27.8	24.4
Premium MM	16.7	17.0	17.8	20.0	17.3
Relationship MM	16.1	15.5	14.6	16.0	15.3
Business MM	19.0	18.4	18.1	19.8	18.5
Business Premium MM	16.4	16.2	15.4	16.8	16.0
Business Relationship MM	6.5	6.2	6.0	6.6	6.4
Savings	16.4	16.3	16.4	17.5	16.4
Relationship Savings	10.7	10.5	10.7	10.2	10.6
Business Savings	11.9	11.9	11.8	12.3	11.9
Electronic Savings	2.0	2.0	2.0		2.0
Checking	21.3	21.1	21.0	22.2	21.2
Electronic Checking	8.4	8.0	7.5	4.8	7.8
Premium Checking	15.7	15.6	15.0	16.7	15.4
Relationship Checking	13.5	13.6	13.3	13.7	13.5
Business Checking	18.3	18.3	18.2	19.6	18.3
Business Relationship Checking	4.0	4.0	4.0		4.0
Fixed IRA	67.6	67.5	66.8	90.6	68.2
Variable IRA	6.3	5.7	5.6	9.0	5.9
Corporate Sweep	14.0	13.4	13.3	14.5	13.5
Earn Credit	5.2	5.3	5.4	5.8	5.4
Total	132.9	140.7	153.4	262.8	144.5

This table shows how many different products defined by maturity-minimum deposit pairs are offered in each deposit type for each size group of banks. Data is from RateWatch and size groups are consistent with Table 2-1. Types associated with certificates of deposit (CD, Relationship CD, and Business CD) and interest-bearing retirement accounts (Fixed IRA and Variable IRA) have a variety of maturities. Therefore, the number of pairs for other deposit types indicate the number of different minimum deposits.

Table D-2: Determinants of Adding Each Deposit Product

	(1) CD	(2) CD	(3) MM-SAV	(4) MM-SAV	(5) IRA	(6) IRA
Income	-0.0627	-0.5810	0.0300	0.2480	-0.0453	-0.9190
	(0.0601)	(0.6740)	(0.0658)	(0.4620)	(0.0520)	(0.8860)
Population	0.0672^{***}	0.8840^{***}	0.0907^{***}	0.6750^{***}	0.0099	0.0756
	(0.0138)	(0.1680)	(0.01670)	(0.1370)	(0.0108)	(0.159)
HPI	0.0009^{*}	0.0123^{**}	-0.0003	-0.0031	0.0011^{***}	0.0174^{***}
	(0.0005)	(0.0060)	(0.0006)	(0.0038)	(0.0004)	(0.0059)
Active County	-0.0003^{*}	-0.0054	-0.0012^{***}	-0.0067^{***}	-0.0036^{***}	-0.0230^{***}
	(0.0002)	(0.0034)	(0.0002)	(0.0015)	(0.0002)	(0.0018)
# Big Banks	0.0040^{**}	0.0432^{*}	0.0070^{***}	0.0641^{***}	0.0028^{*}	0.0567^{*}
	(0.0020)	(0.0234)	(0.0022)	(0.0191)	(0.0015)	(0.0295)
# Small Banks	-0.0024	-0.0314	-0.0018	-0.0111	-0.0027^{*}	-0.0419
	(0.0019)	(0.0224)	(0.0021)	(0.0173)	(0.0015)	(0.0264)
# Branches	-0.0003	-0.0010	0.0007	0.0061	-0.0001	0.0114
	(0.0005)	(0.0066)	(0.0007)	(0.0064)	(0.0003)	(0.0094)
# Other Branches	-0.0002	-0.0015	-0.0005^{***}	-0.0039^{***}	-0.0000	-0.0010
	(0.0001)	(0.0017)	(0.0001)	(0.0013)	(0.0001)	(0.0018)
TD Ratio	-0.0384^{***}	-0.2240^{***}	-0.0076	0.0487	-0.0028	-0.3040^{*}
	(0.0106)	(0.0828)	(0.0143)	(0.0841)	(0.0042)	(0.1820)
DD Ratio	-0.0015	0.0076	0.0285^{***}	0.2650^{***}	-0.0089^{***}	-0.3020^{*}
	(0.0039)	(0.0471)	(0.0056)	(0.0586)	(0.0015)	(0.1770)
Model	OLS	Logit	OLS	Logit	OLS	Logit
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.675		0.457		0.653	
Observations	3,227	3,227	3,227	3,227	3,227	2,797

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, and standard errors are in parentheses.

Table D-3: Determinants of the Number of Products and Deposit Rates

	(1)	(2)	(3)	(4)
	# of Products	# of Products	Rate	Rate
Income	0.0404	0.1180	-0.0111	0.0868^{*}
	(0.0820)	(0.4190)	(0.0234)	(0.0463)
Population	0.0927^{***}	0.5810^{***}	0.0014	-0.0040
	(0.0188)	(0.1220)	(0.0026)	(0.0792)
HPI	-0.0009	-0.0065^{*}	0.0000	-0.0001
	(0.0008)	(0.0038)	(0.0001)	(0.0002)
Active County	-0.0055^{***}	-0.0229^{***}	-0.0002^{***}	-0.0002^{***}
	(0.0003)	(0.0020)	(0.0000)	(0.0000)
# Big Banks	0.0078^{***}	0.0564^{***}	-0.0002	0.0015^{*}
	(0.0028)	(0.0203)	(0.0005)	(0.0009)
# Small Banks	0.0041	0.0210	0.0004	-0.0007
	(0.0027)	(0.0176)	(0.0006)	(0.0008)
# Branches	0.0001	0.0020	-0.0000	-0.0000
	(0.0009)	(0.0064)	(0.0001)	(0.0002)
# Other Branches	-0.0006^{***}	-0.0040^{**}	0.0000	-0.0001
	(0.0002)	(0.0016)	(0.0000)	(0.0001)
TD Ratio	-0.0687^{***}	-0.2770^{***}	0.0303^{***}	0.0307^{***}
	(0.0195)	(0.0929)	(0.0016)	(0.0018)
DD Ratio	-0.0139^{*}	-0.0609	0.0175^{***}	0.0176^{***}
	(0.0071)	(0.0600)	(0.0006)	(0.0010)
Model	OLS	Ordered Logit	OLS	OLS
County FE	No	No	No	Yes
Time FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
R^2	0.855		0.433	0.594
Observations	3,018	3,018	3,227	3,175

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, and standard errors are in parentheses.

E Further Figures on Deposit Interest Rate Pricing

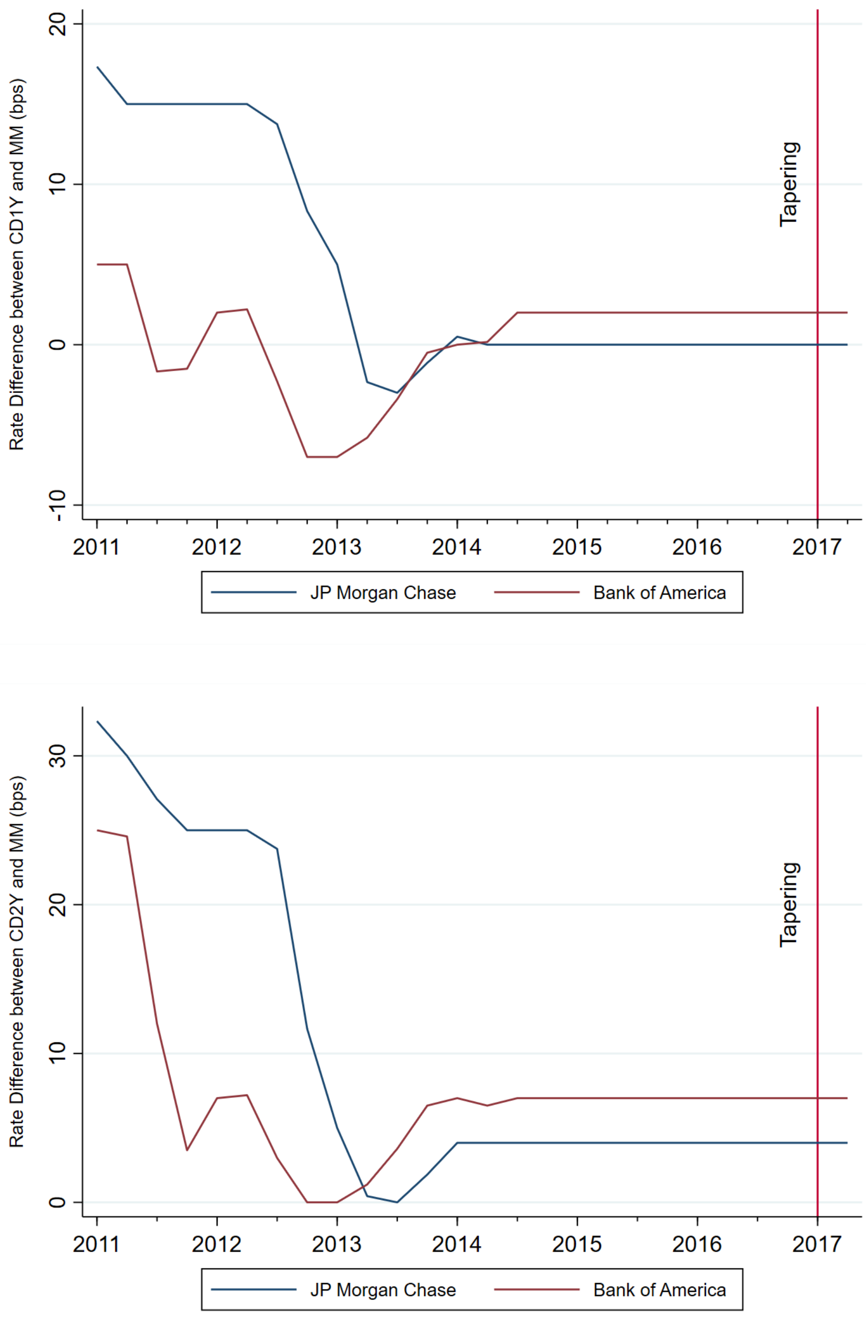
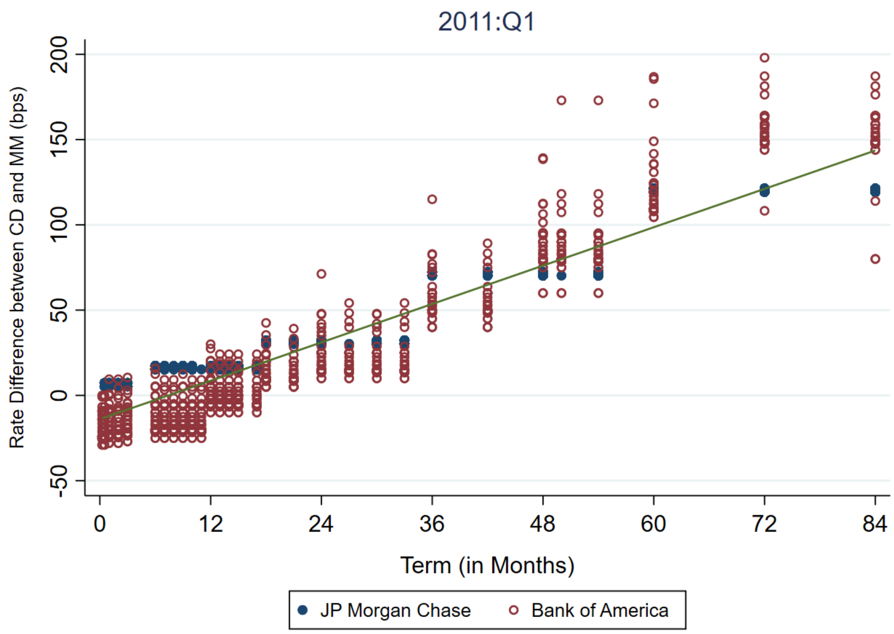


Figure E-1: Rate Difference Between CD and MM at Dallas County of Texas

The above two graphs show the difference in deposit rates between CD (upper figure is one-year maturity and lower figure is two-year maturity) and MM with $10,000 minimum deposits at Dallas County of Texas. Therefore, the difference is conceptually understood as a liquidity premium since CD is a term deposits product whereas MM is a demand deposits product. During the quantitative easing monetary policy period, both JP Morgan Chase and Bank of America decrease the liquidity premium paid to CD. This implies that CD became a cheap source of stable funding for financial institutions. The data is from RateWatch from S&P Global Market Intelligence.



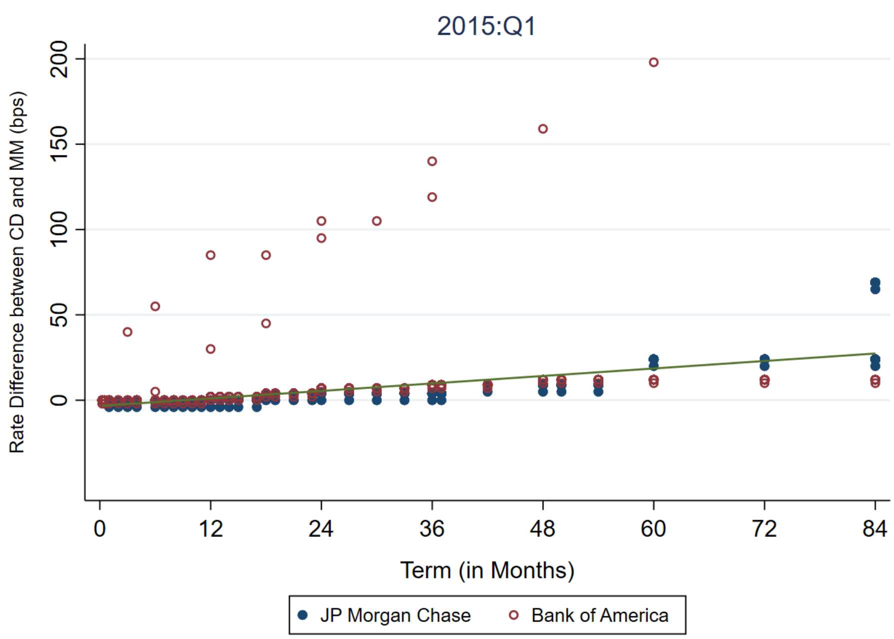
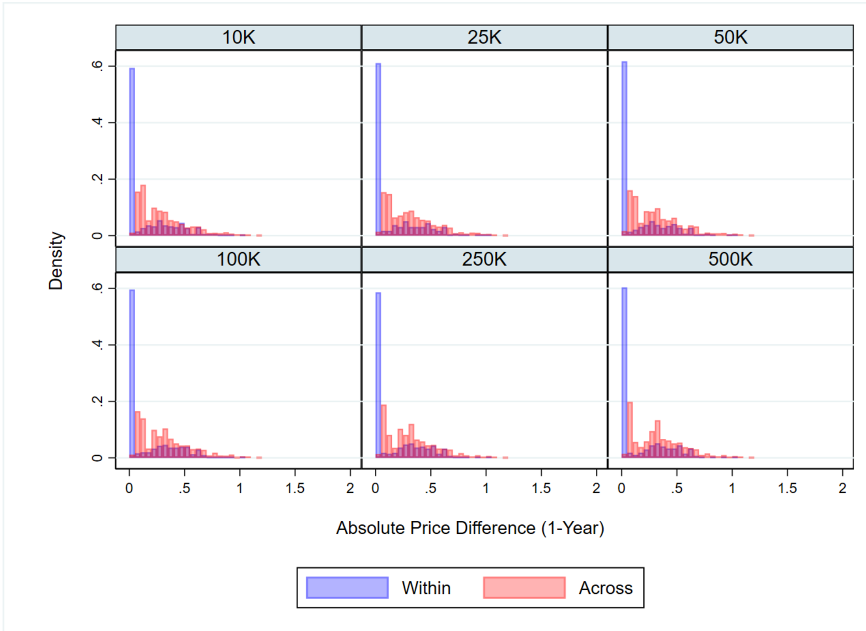


Figure E-2: Rate Difference Between CD and MM across the United States

The above two graphs show the difference in deposit rates between CD for different maturities and MM with $10,000 minimum deposits across the United States. The green lines are linear fitted values from both financial institutions. At the first quarter of 2011 (upper figure), as the maturity gets longer, both JP Morgan Chase and Bank of America pay a higher liquidity premium on CD. However, at the first quarter of 2015 (lower figure), this upward sloping relationship between the maturity and the liquidity premium becomes weaker. Bank of America has only two local markets (San Francisco in California and San Antonia in Texas) where the relationship the maturity and the liquidity premium significantly holds. Therefore, this confirms that CD became a cheap source of stable funding for financial institutions at the center of the quantitative easing monetary policy period. The data is from RateWatch from S&P Global Market Intelligence.



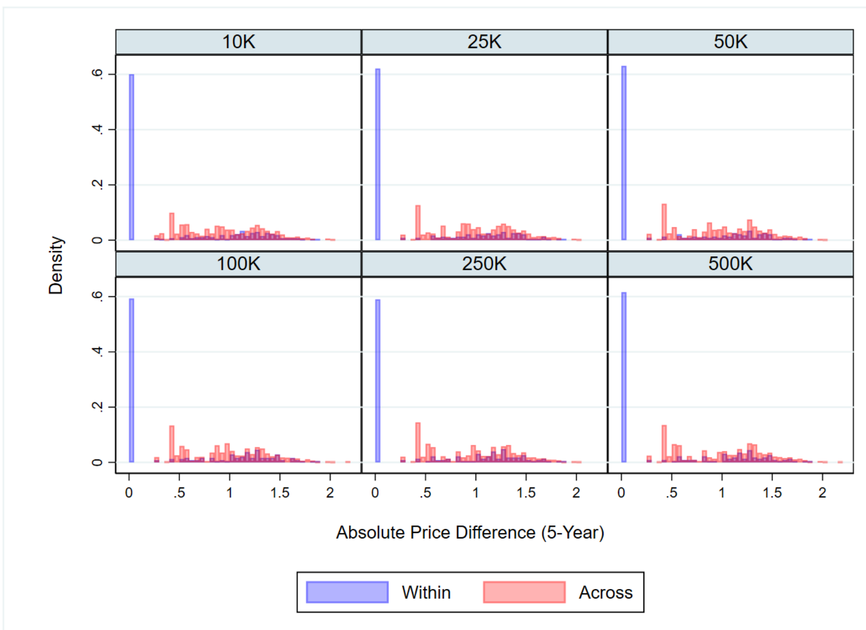


Figure E-3: Within and Across Price Dispersion (CD)

For the within difference, we only use banks which operate branches at least more than two metropolitan statistical areas (MSA) during our sample period. For each bank and each product in MM and Savings, we choose a pair of MSAs and then calculate the absolute difference and take the average over time. We repeat this process 10,000 times for each bank and for each deposit product. Finally, we take the average of these 10,000 values to get the within difference for each bank. Therefore, the unit observation of blue histograms is a bank. For the across difference, we randomly choose a pair of branches of two different banks at two different MSAs. For example, JP Morgan Chase in Chicago MSA and Bank of America in Charlotte MSA. Then, we calculate the absolute difference and take the average over time. This mean is the unit observation for red histogram representing the across difference. We repeat this process 25,000 times to select different banks and different MSAs for each deposit product in MM and Savings. The data is from RateWatch from S&P Global Market Intelligence.

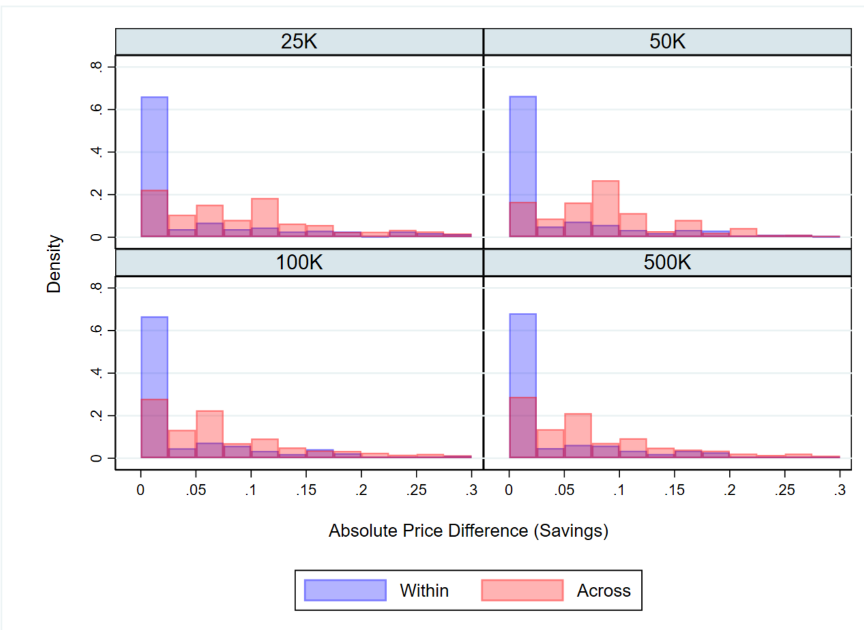


Figure E-4: Within and Across Price Dispersion (MM & Savings)

For the within difference, we only use banks which operate branches at least more than two metropolitan statistical areas (MSA) during our sample period. For each bank and each product in CD, we choose a pair of MSAs and then calculate the absolute difference and take the average over time. We repeat this process 10,000 times for each bank and for each deposit product. Finally, we take the average of these 10,000 values to get the within difference for each bank. Therefore, the unit observation of blue histograms is a bank. For the across difference, we randomly choose a pair of branches of two different banks at two different MSAs. For example, JP Morgan Chase in Chicago MSA and Bank of America in Charlotte MSA. Then, we calculate the absolute difference and take the average over time. This mean is the unit observation for red histogram representing the across difference. We repeat this process 25,000 times to select different banks and different MSAs for each deposit product in CD. The data is from RateWatch from S&P Global Market Intelligence.

F Counterfactual Analysis and Extension

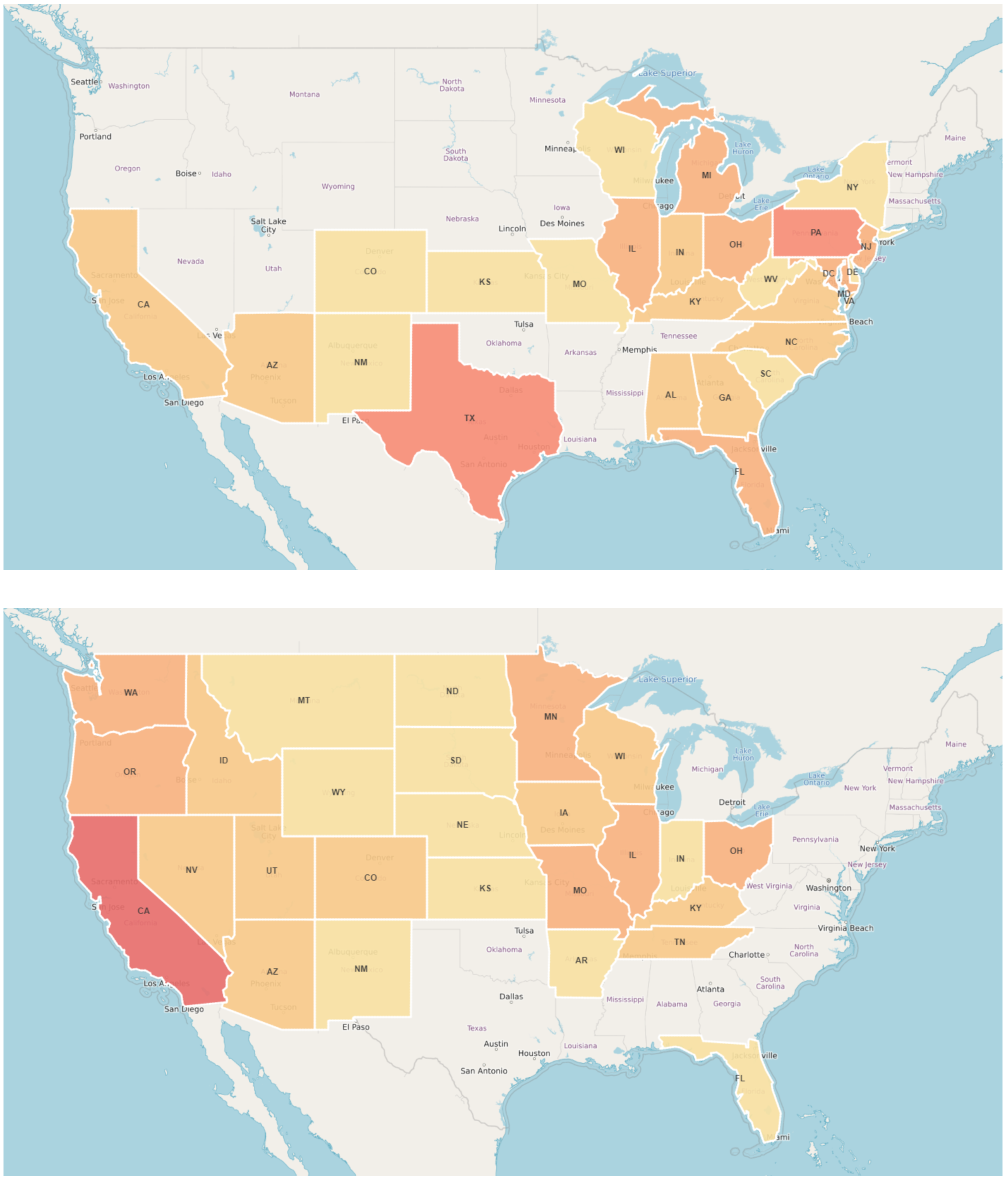


Figure F-1: Branch Locations of PNC (above) and US Bank (below) in the United States

A darker shade of red means more bank branches. PNC Bank operates with 2,495 branches located in 26 states. The financial institution has most branches in Texas, Pennsylvania, Ohio, New Jersey and Florida. PNC Bank is the fourth largest bank in the United States by branch count. Regionally, PNC Bank is the fourth largest bank in Texas with 297 branches, the first in Pennsylvania with 286 branches, the third in Ohio with 228 branches, the third in New Jersey with 227 branches and sixth in Florida with 189 branches. On the other hand, US Bank operates with 2,223 branches located in 26 states. The financial institution has most branches in California, Ohio, Illinois, Missouri and Washington. US Bank is the fifth largest bank in the United States by branch count. Regionally, US Bank is the fourth largest bank in California with 460 branches, the fifth in Ohio with 195 branches, the third in Illinois with 166 branches,the first in Missouri with 152 branches and the third in Washington with 136 branches. The data is based on 2022:2Q and from Bank Branch Locator.

Table F-1: Counterfactual Analysis 2: M&A Situation (Joint Entry)

	Average Between Two Banks			PNC Acquiring US Bank			US Bank Acquiring PNC		
	Chase	**BoA**	**Wells Fargo**	**Chase**	**BoA**	**Wells Fargo**	**Chase**	**BoA**	**Wells Fargo**
Game I: Entry Decision									
$\Delta P(\text{Entry})$	0.01%	0.01%	0.02%	0.01%	0.01%	0.02%	0.01%	0.01%	0.02%
	(0.25%)	(0.26%)	(0.38%)	(0.25%)	(0.26%)	(0.38%)	(0.25%)	(0.26%)	(0.38%)
Game II: Menu Choice Decision									
Joint Probability: $\Delta P(\mathbb{1}\{\text{TD}\}, \mathbb{1}\{\text{DD}\}, \mathbb{1}\{\text{IRA}\})$									
$\Delta P(1,1,1)$	−0.21%	−11.12%	−1.42%	−0.12%	−10.37%	−1.65%	−0.25%	−11.13%	−1.56%
	(−0.27%)	(−19.20%)	(−8.65%)	(−0.15%)	(−17.91%)	(−10.07%)	(−0.31%)	(−19.34%)	(−9.55%)
$\Delta P(1,1,0)$	0.22%	1.54%	−0.25%	0.16%	1.41%	−0.36%	0.30%	1.58%	−0.27%
	(3.75%)	(14.24%)	(−1.85%)	(2.68%)	(13.06%)	(−2.67%)	(5.08%)	(14.49%)	(−1.99%)
$\Delta P(1,0,1)$	0.24%	1.54%	−0.22%	0.16%	1.41%	−0.33%	0.33%	1.59%	−0.23%
	(4.04%)	(14.44%)	(−1.67%)	(2.67%)	(13.24%)	(−2.45%)	(5.72%)	(14.84%)	(−1.72%)
$\Delta P(0,1,1)$	0.24%	1.56%	−0.21%	0.18%	1.43%	−0.29%	0.30%	1.58%	−0.26%
	(4.04%)	(14.42%)	(−1.61%)	(2.96%)	(13.27%)	(−2.19%)	(5.17%)	(14.53%)	(−1.93%)
$\Delta P(1,0,0)$	0.42%	2.08%	0.62%	0.44%	1.92%	0.66%	0.50%	2.13%	0.72%
	(95.36%)	(70.76%)	(5.45%)	(100.24%)	(65.52%)	(5.84%)	(115.57%)	(71.48%)	(6.30%)
$\Delta P(0,1,0)$	0.40%	2.10%	0.62%	0.44%	1.96%	0.69%	0.46%	2.13%	0.68%
	(90.43%)	(70.82%)	(5.52%)	(97.36%)	(65.98%)	(6.11%)	(105.03%)	(70.43%)	(6.06%)
$\Delta P(0,0,1)$	0.43%	2.07%	0.64%	0.45%	1.92%	0.71%	0.50%	2.12%	0.72%
	(97.04%)	(70.79%)	(5.72%)	(102.46%)	(65.68%)	(6.36%)	(114.90%)	(71.00%)	(6.38%)
Marginal Probability									
$\Delta P(\mathbb{1}\{\text{TD}\}=1)$	0.67%	−5.97%	−1.27%	0.64%	−5.63%	−1.68%	0.89%	−5.82%	−1.34%
	(0.72%)	(−7.24%)	(−2.34%)	(0.68%)	(−6.83%)	(−3.08%)	(0.95%)	(−7.09%)	(−2.47%)
$\Delta P(\mathbb{1}\{\text{DD}\}=1)$	0.65%	−5.92%	−1.26%	0.65%	−5.57%	−1.62%	0.82%	−5.84%	−1.40%
	(0.70%)	(−7.17%)	(−2.32%)	(0.70%)	(−6.74%)	(−2.98%)	(0.88%)	(−7.09%)	(−2.58%)
$\Delta P(\mathbb{1}\{\text{IRA}\}=1)$	0.69%	−5.95%	−1.21%	0.67%	−5.61%	−1.56%	0.89%	−5.84%	−1.33%
	(0.74%)	(−7.23%)	(−2.24%)	(0.72%)	(−6.81%)	(−2.87%)	(0.96%)	(−7.12%)	(−2.45%)
Game III: Price-Setting Decision									
ΔMarket Share	−0.18%	−0.15%	−0.25%	−0.06%	−0.08%	0.36%	−0.26%	−0.21%	−0.90%
	(−0.71%)	(−0.32%)	(−0.73%)	(−0.25%)	(−0.16%)	(1.08%)	(−1.03%)	(−0.44%)	(−2.69%)
ΔDeposit Rate	−0.01 bps	−4.18 bps	2.32 bps	−0.01 bps	−4.43 bps	1.91 bps	−0.02 bps	−4.58 bps	1.78 bps
	(−6.44%)	(−60.33%)	(35.46%)	(−6.09%)	(−62.58%)	(28.97%)	(−7.06%)	(−65.03%)	(25.88%)

The unit for ΔP at the first two games and ΔMarket Share is a percent point. The unit for ΔDeposit Rate is bps ($1\% = 100$bps). The numbers in parentheses are percent changes.

Table F-2: Entry Game Estimates: Top 10 Banks

	Top 10 Banks									
	Chase	**BoA**	**Wells Fargo**	**PNC**	**US Bank**	**M&T**	**Associated**	**Fifth Third**	**Regions**	**Key Corp**
Covariates										
Income	− 0.0592	− 0.0731	− 0.0655	− 0.0578	− 0.0593	− 0.0678	− 0.0859	− 0.0854	− 0.0952	− 0.0675
	(0.0344)	(0.0332)	(0.0296)	(0.0204)	(0.0230)	(0.0358)	(0.0335)	(0.0358)	(0.0273)	(0.0365)
Population	0.0722	0.0824	0.0747	0.0679	0.0695	0.0774	0.0863	0.0857	0.0868	0.0794
	(0.0350)	(0.0326)	(0.0313)	(0.0236)	(0.0255)	(0.0345)	(0.0330)	(0.0339)	(0.0288)	(0.0329)
HPI	− 0.0376	− 0.0455	− 0.0454	− 0.0431	− 0.0374	− 0.0369	− 0.0566	− 0.0573	− 0.0517	− 0.0398
	(0.0223)	(0.0217)	(0.0198)	(0.0148)	(0.0163)	(0.0223)	(0.0221)	(0.0228)	(0.0181)	(0.0230)
# Small Banks	− 0.0521	− 0.0522	− 0.0377	− 0.0367	− 0.0381	− 0.0451	− 0.0412	− 0.0500	− 0.0392	− 0.0513
	(0.0171)	(0.0168)	(0.0148)	(0.0150)	(0.0148)	(0.0168)	(0.0176)	(0.0173)	(0.0153)	(0.0162)
# Branches	0.1074	0.1176	0.1391	0.1106	0.1090	0.0814	0.0494	0.0774	0.0839	0.0909
	(0.0104)	(0.0117)	(0.0096)	(0.0153)	(0.0123)	(0.0130)	(0.0148)	(0.0283)	(0.0103)	(0.0124)
Constant	− 0.0429	− 0.0507	− 0.0454	− 0.0476	− 0.0488	− 0.0491	− 0.0604	− 0.0584	− 0.0675	− 0.0482
	(0.0207)	(0.0204)	(0.0191)	(0.0144)	(0.0156)	(0.0211)	(0.0206)	(0.0214)	(0.0174)	(0.0210)
Strategic Interactions										
Top 1-5 Entry	− 0.0164	− 0.0034	− 0.0090	− 0.0042	− 0.0195	− 0.0019	− 0.0184	− 0.0118	− 0.0117	− 0.0111
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0006)	(0.0000)	(0.0001)
Top 6-10 Entry	− 0.0034	− 0.0146	− 0.0060	− 0.0158	− 0.0196	− 0.0030	− 0.0074	− 0.0083	− 0.0163	− 0.0187
	(0.0000)	(0.0000)	(0.0001)	(0.0003)	(0.0005)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table shows entry game parameter estimates of the model extended to include the top 10 banks. Standard errors are calculated from bootstrapping 600 samples. The bank's pre-entry expected profit affects the entry decision, and the entry determinants include various covariates and the strategic interaction term. Consistent with our result in Section 2.4, the table reveals the statistically significant correlations between determinants and entry probabilities across counties in the United States. The strategic interaction parameter estimates how sensitively banks respond to the entry of rival banks. All interaction effects are negative values and statistically significant.

Table F-3: Menu Choice Game Estimates: Top 10 Banks

	Top 10 Banks									
	Chase	**BoA**	**Wells Fargo**	**PNC**	**US Bank**	**M&T**	**Associated**	**Fifth Third**	**Regions**	**Key Corp**
Covariates										
Income	0.0297	0.0313	− 0.0007	0.0054	0.0176	− 0.0117	− 0.0061	0.0281	0.0092	0.0346
	(0.0158)	(0.0158)	(0.0168)	(0.0148)	(0.0197)	(0.0145)	(0.0145)	(0.0148)	(0.0179)	(0.0155)
Population	− 0.0017	− 0.0134	0.0304	0.0104	− 0.0047	0.0211	0.0136	− 0.0129	0.0002	− 0.0007
	(0.0151)	(0.0149)	(0.0158)	(0.0146)	(0.0186)	(0.0136)	(0.0136)	(0.0140)	(0.0182)	(0.0145)
HPI	0.0182	0.0291	− 0.0061	0.0043	0.0237	− 0.0061	0.0030	0.0287	0.0106	0.0170
	(0.0118)	(0.0117)	(0.0124)	(0.0102)	(0.0131)	(0.0109)	(0.0109)	(0.0113)	(0.0126)	(0.0115)
Active County	0.0740	0.0454	0.0078	− 0.0069	0.0094	− 0.0190	− 0.0205	0.0428	0.0003	0.0421
	(0.0268)	(0.0234)	(0.0157)	(0.0317)	(0.0185)	(0.0170)	(0.0175)	(0.0197)	(0.0192)	(0.0161)
# Small Banks	0.0281	0.0449	0.0090	0.0076	0.0446	− 0.0152	0.0068	0.0292	0.0046	0.0394
	(0.0172)	(0.0177)	(0.0192)	(0.0228)	(0.0237)	(0.0152)	(0.0154)	(0.0156)	(0.0209)	(0.0166)
# Branches	0.2612	0.0295	− 0.0040	− 0.0035	0.0293	− 0.0258	− 0.0104	0.0127	0.0194	0.0352
	(0.0200)	(0.0189)	(0.0201)	(0.0310)	(0.0254)	(0.0169)	(0.0171)	(0.0173)	(0.0229)	(0.0185)
TD Ratio	0.0090	0.0083	− 0.0041	0.0029	0.0045	0.0059	0.0025	0.0035	0.0135	− 0.0018
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0004)	(0.0004)	(0.0005)	(0.0006)	(0.0005)
DD Ratio	0.0161	0.0112	− 0.0049	0.0081	0.0090	0.0015	0.0018	0.0111	0.0263	0.0148
	(0.0051)	(0.0050)	(0.0055)	(0.0048)	(0.0054)	(0.0045)	(0.0045)	(0.0048)	(0.0053)	(0.0049)
Constant	0.0083	0.0149	− 0.0131	− 0.0062	0.0090	− 0.0121	− 0.0078	0.0165	0.0017	0.0019
	(0.0105)	(0.0104)	(0.0111)	(0.0091)	(0.0116)	(0.0096)	(0.0096)	(0.0100)	(0.0112)	(0.0102)
Strategic Interactions										
Top 1-5 TD	− 0.0033	− 0.0152	− 0.0111	− 0.0077	− 0.0153	− 0.0132	− 0.0169	− 0.0146	− 0.0104	− 0.0039
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Top 6-10 TD	− 0.0182	− 0.0070	− 0.0033	− 0.0188	− 0.0053	− 0.0193	− 0.0039	− 0.0133	− 0.0103	− 0.0048
	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Top 1-5 DD	− 0.0017	− 0.0193	− 0.0027	− 0.0153	− 0.0154	− 0.0032	− 0.0108	− 0.0006	− 0.0093	− 0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Top 6-10 DD	− 0.0188	− 0.0017	− 0.0157	− 0.0180	− 0.0103	− 0.0083	− 0.0098	− 0.0185	− 0.0100	− 0.0010
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Top 1-5 IRA	− 0.0191	− 0.0134	− 0.0084	− 0.0098	− 0.0189	− 0.0082	− 0.0061	− 0.0149	− 0.0050	− 0.0163
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Top 6-10 IRA	− 0.0189	− 0.0079	− 0.0063	− 0.0072	− 0.0096	− 0.0026	− 0.0189	− 0.0121	− 0.0168	− 0.0027
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)

This table shows menu choice game parameter estimates of the model extended to include the top 10 banks. Standard errors are calculated from bootstrapping 600 samples. The menu choice game's utility function contains more covariates since more information reveals after the entry decisions are over. The menu choice game estimates show that income and housing prices positively affect selling new products. The interaction coefficients are all statistically significant, implying that the menu choice is strategic across banks, which confirms our result in Section 2.4.

Table F-4: Demand and Cost Estimates: Top 10 Banks

	Demand Estimates		**Cost Estimates**	
	(1)		(1)	(2)
Deposit rate	0.0711	TD	– 0.5913	– 0.8451
	(0.2175)		(0.2572)	(0.3382)
		DD	0.2300	0.0988
			(0.2772)	(0.2731)
		IRA	– 0.7431	– 0.1378
			(0.2169)	(0.2759)
Constant	– 2.1492	Constant	– 11.2245	– 11.4056
	(0.0275)		(0.1870)	(0.2346)
County FE	Yes		Yes	Yes
Year FE	Yes		Yes	Yes
Bank FE	Yes		No	Yes
Observations	4,557		4,557	4,557
R^2	0.6775		0.2938	0.3370

This table shows demand and cost parameter estimates of the model extended to include the top 10 banks. Depositors prefer to enjoy a higher deposit rate, thus the demand positively responds to the increase in deposit rate. The next columns discuss how the bank's cost structure correlates with the product choice. The next columns discuss how the bank's cost structure correlates with the product choice.

G Construction of Data and Fama-French Portfolios

Data Construction

A data set of bank stock returns is collected from the Center for Research in Security Prices (CRSP). We use monthly stock returns. For the balance sheet information, it is common to use the Compustat/CRSP merged data set among the studies on the stock returns of non-financial firms. However, we don't use the Compustat/CRSP merged data set for the balance sheet information (especially asset) in this paper since only some of commercial banks and bank holding companies have reported their balance sheet information to the Compustat. Instead, we use the Call Report from Federal Reserve Bank of Chicago to gather the balance sheet information of commercial banks and FR Y-9C (Consolidated Financial Statements for Holding Companies) from the Federal Reserve Board to collect the balance sheet information of bank holding companies. To merge the stock market data and the balance sheet data, we use the PERMCO/RSSD ID link provided by Federal Reserve Bank of New York.[28]

From the sample period (1986-2016) on a monthly basis, the number of unique commercial bank identities is about 100 although the total number of FDIC-insured commercial banks during the same period is more than 5,000. It means only a small portion of commercial banks were publicly listed in the stock market. On the other hand, a majority of bank holding companies are publicly listed in stock market and the number of unique bank holding companies during the sample period is more than 1,000. From this consolidation, our sample includes more financial institutions in the U.S. banking sector than other studies on bank stock returns (e.g. recently Gandhi and Lustig (2015) and Boualam and Cororaton (2020)). Furthermore, we can also well define top 8 banks from our sample. Table G-1 summarizes a list of top 8 financial institutions in the U.S. banking sector. The institutions in this list are the Globally Systematically Important Banks (G-SIBs) identified by Financial Stability Board.

From this merged date set, we exclude commercial banks or bank holding companies that are not incorporated in the United States. We identify these firms by looking share codes ending in 2 or 5, which are foreign firms. This is because these banks are not subject to the same regulatory policies as the financial institutions domestically operating and incorporated in the United States. Therefore, the remaining sample after checking this criterion includes only financial institutions doing business and founded inside the United

[28] This link is the key part of constructing the merged data set. This information links regulatory identification numbers (RSSD ID) from the National Information Center (NIC) to the permanent company number (PERMCO) used in CRSP. The RSSD ID is a unique identifier assigned to commercial banks or bank holding companies by the the FRB and is the primary identifier of entities in regulatory reports such as the Call Report and FR Y9-C. The PERMCO is a unique and permanent company identification number assigned to publicly traded institutions in CRSP database. While a company may change its name, ticker, exchange, or the Committee on Uniform Security Identification Procedures (CUSIP), the PERMCO will remain the same.

Table G-1: Top 8 Financial Institutions in the U.S. Banking Sector

Name	RSSD ID
JP Morgan Chase Corporation	1039502
Bank of America Corporation	1073757
Wells Fargo Corporate	1120754
Citi Bank Group	1042351 (before 1998/10) and 1951350 (after 1998/10)
US Bank	1119794
PNC Bank	1069778
State Street Corporate	1111435
Bank of New York Mellon	1068762 (up to 2006/12)

In 1998, the Travelers Group, an American insurance company, merged with Citi Corporation to form Citi Group, which led to a change in its RSSD ID. Bank of New York Mellon was formed in 2007, as a result of the merger of The Bank of New York and Mellon Financial Corporation. It became an investment and asset management company after the merger, so we only use data series before 2007.

States. This sample construction is consistent with Gandhi and Lustig (2015). We only use NYSE, Amex, and NASDAQ stocks.

Building Portfolios

We construct size-sorted portfolios from bank stocks by following Fama and French (1992, 1993). We only include bank stocks that are in the merged data set for more than 2 years to correct for survival bias. Also, we restrict to bank stocks that have the full 12-month information regarding both returns and balance sheet variables. If a monthly net return is greater than 100% or less than -100%, we do not include the bank stock for the specific year. For defining a size of banks, we use the book value of total assets, which is a common way in the literature. It is also reasonable to think that the government cares about the entire balance sheet of banks. We rank all bank stocks by this measure of size as of December of the previously year. We define size bins by using all NYSE, Amex, and NASDAQ stocks since there are a lot of bank stocks allocated to the smallest size portfolio if we use only NYSE stocks, which are mainly stocks of large financial institutions. Also, we design these size bins to include the similar number of bank stocks in each bin. Therefore, our size bins are not of equal size, but each portfolio can be interpreted in a percentile sense. Bank stocks are allocated to five portfolios based on their total assets. For the portfolio consisting of top 8 banks, we separate

Table G-2: Stock Return and Volatility of U.S. Commercial Banks

		2007 - 2009	2010 - 2016
Stock Return (%)	Bottom 20% Banks	- 7.35	5.17
	Top 20% Banks	-4.78	4.02
	Top 8 Banks	-1.71	3.57
Volatility (%)	Bottom 20% Banks	10.51	7.18
	Top 20% Banks	19.07	10.97
	Top 8 Banks	24.02	11.70

these bank stocks from the first sort (top 20% banks). Therefore, in fact, the portfolio including top 20% banks does not have top 8 banks. We calculate the equal-weighted returns for each portfolio for each month over the next quarter and consider the sum of net monthly returns for each quarter as quarterly returns. The result is summarized in Table G-2.

H Stock Returns of U.S. Commercial Banks and Non-Financial Firms

Figure H-1: Quarterly Stock Returns of U.S. Commercial Banks and Bank Holding Companies (1)

Figure H-2: Quarterly Stock Returns of U.S. Commercial Banks and Bank Holding Companies (2)

Figure H-3: Quarterly Stock Returns of Non-Financial Firms (1)

Figure H-4: Quarterly Stock Returns of Non-Financial Firms (2)

I Capital Ratios of U.S. Commercial Banks

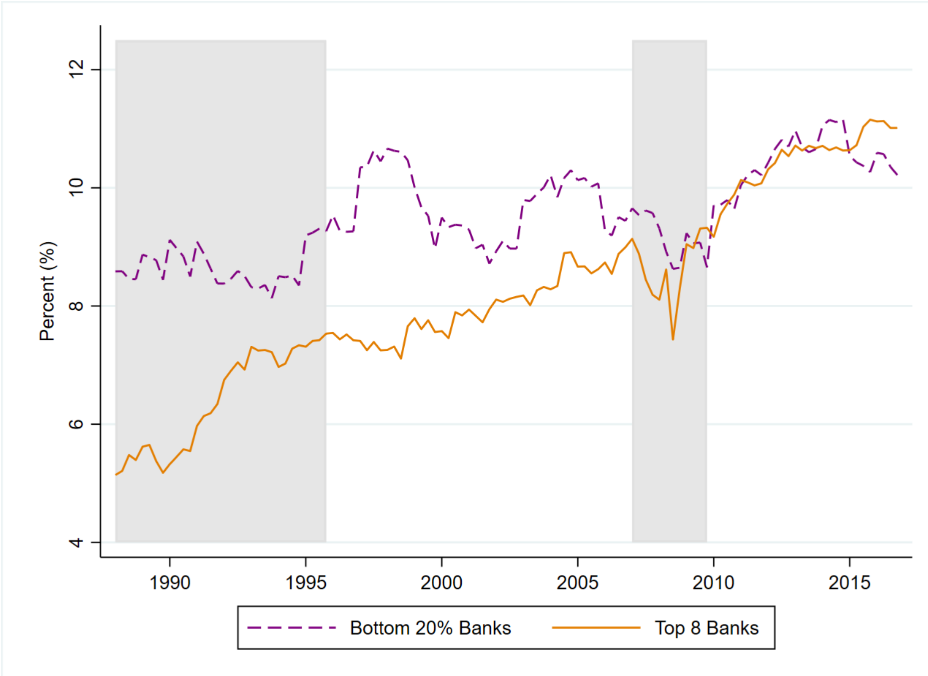


Figure I-1: Capital Ratios of U.S. Commercial Banks and Bank Holding Companies (1)

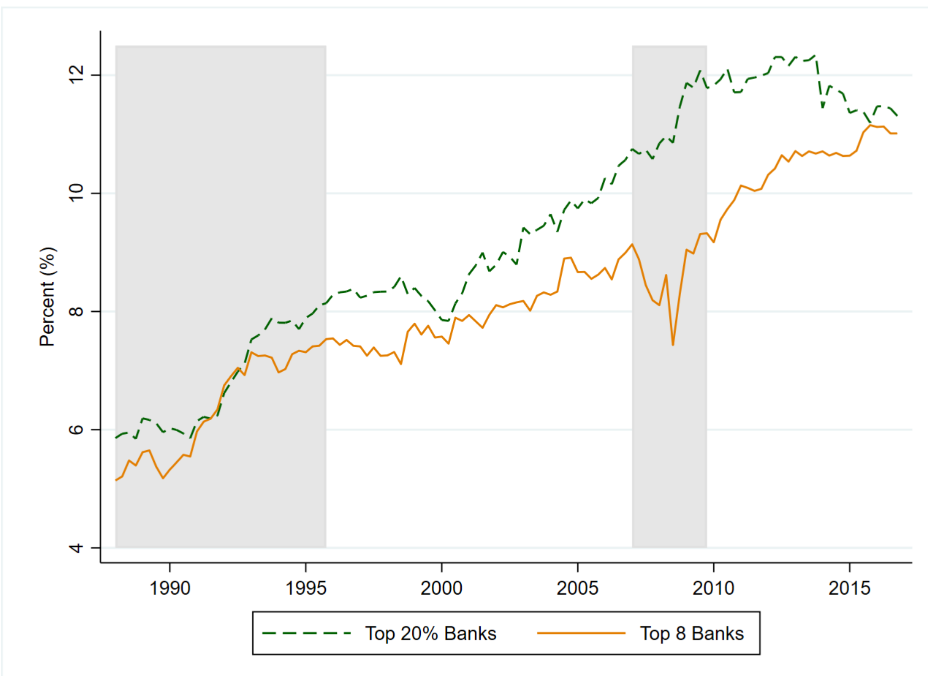


Figure I-2: Capital Ratios of U.S. Commercial Banks and Bank Holding Companies (2)

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