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Essays in Financial Intermediation and Household Finance

Author
ZHANG, DAYIN

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Essays in Financial Intermediation and Household Finance

by

Dayin Zhang

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Committee in charge:

Professor Nancy Wallace, Chair
Professor Ross Levine
Professor Amir Mohsenzadeh Kermani
Professor Matteo Benetton
Professor Christina Romer

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Abstract

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Finance is a significant part of any individual's life. The accessibility and quality of finance is an outcome of the financial intermediating infrastructure, and largely influences household welfare. This dissertation aims to understand how the detailed architecture of financial intermediation affects household finance in their real estate investment.

Mortgage finance plays a crucial role in the US economy and there is significant government intervention. What are the consequences of different types of government intervention in the US housing market is a central question, especially after the Great Recession. While much effort has been devoted to understanding government guarantee programs which aim to facilitate the secondary market of mortgage loans, the first chapter **"Government-Sponsored Wholesale Funding and the Industrial Organization of Bank Lending"** evaluates a less-studied government-sponsored wholesale funding program in support of the primary mortgage lending market—Federal Home Loan Banks (FHLB). I exploit quasi-natural variation in access to low-cost wholesale funding from the FHLB arising from bank mergers, and show that access to this funding source is associated with an 18-basis-point reduction in a bank's mortgage rates and a 16.3% increase in mortgage lending. This effect is 25% stronger for small community banks. At the market level, a census tract experiences an increase in local competition after a local bank joins the FHLB, with the market concentration index (HHI) falling by 1.5 percentage points. This intensified local competition pushes other lenders to lower their mortgage rates by 7.4 basis points, and overall market lending grows by 5%. Estimates of a structural model of the US mortgage market imply that the FHLB increases annual mortgage lending in the US by $50 billion, and saves borrowers $4.7 billion in interest payments every year, mainly through changing the competitive landscape of the mortgage market.

Another feature of the US mortgage market is its well-developed secondary market, full of various structured finance products. Among these structured finance products, credit derivatives such as credit default swaps (CDS) are largely viewed as redundant securities or side

bets that do not have any influence on the underlying mortgage lending activities and household access to mortgage credit. Contrary to this view, the second chapter **"Match-Fixing in the Mortgage Finance Field: Credit Default Swaps and Moral Hazard"** explores the ex post moral hazard problems in the subprime mortgage backed security market, and empirically demonstrates that the existence of CDS protection alters the incentives of market participants, which affects the performance of the underlying mortgages. Specifically, CDS sellers encourage borrowers in their mortgage pool to refinance, in order to unload the CDS sellers' obligation to cover the loss of the underlying mortgages. Consequently, the mortgages in CDS referencing pools are 3.6% more likely to be refinanced and 2.1% less likely to default. To mitigate the endogeneity concern that CDS sellers choose to write CDSs on better mortgages, this paper further explores the local randomization due to the discontinuous sale of mortgages by their originators, to establish a causal relationship between CDS coverage and mortgage refinance and default performance. This paper provides the first direct evidence that credit derivatives can affect fundamental assets through the ex-post actions of derivative traders.

The third chapter **"Residential Investment and the Business Cycle"** focuses on the connection between household investment in housing and the macro economy. To achieve a smooth path of consumption, consumption surplus can be stored either in the form of manufacturing capital through business investment, or in the form of housing structures through residential investment. The return of business investment is exposed to the corporate bankruptcy risk, since potential bankruptcy of the holding firms would incur huge displacement cost to the specialized assets. The residential investment, however, is free from such risk due to the generic function of housing service. Therefore, the investors would shift more resource from the residential side to the business side in response to the low bankruptcy rate in economic booms. This mechanism could explain why the share of residential investment in GDP decreases before the advent of the crisis while the business investment acts in the opposite way.

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Chapter 1

Government-Sponsored Wholesale Funding and the Industrial Organization of Bank Lending

1.1 Introduction

Banks in the US currently rely heavily on wholesale funding to resolve the mismatch between their deposits and their lending. In fact, more than 25% of banks' total liabilities came from wholesale funding sources during the period 2002–2018.[1] In the wholesale funding market, many government agencies are intensively involved to help support mortgage lending, agriculture-related lending, and credit for other areas of the economy. In 2018, for example, the government-sponsored Federal Home Loan Banks provided $729 billion of mortgage collateralized wholesale funding to mortgage lenders, accounting for 65% of all mortgage collateralized wholesale lending.[2]

Despite the central role of government-sponsored wholesale funding, the effects of this support on lending markets are not fully understood. On the one hand, the extension of credit by government-sponsored wholesale funding facilities to banks of all sizes could increase market efficiency by reducing large banks' market power, but on the other hand, government intervention could encourage excessive risk taking (Stojanovic, Vaughan, and Yeager, 2008) and destabilizing liquidity transformation (Sundaresan and Xiao, 2018). This ambiguity has led to fierce debates, and has caused contradictory shifts in policy in regards to extending public wholesale funding to non-depository lenders, which have grown dramatically in many

[1]According to Federal Deposit Insurance Corporation (FDIC), wholesale funds include brokered deposits, public funds, federal funds purchased, FHLB advances, correspondent line of credit advances, and other borrowings. After 2002, the historical average share of wholesale funding in all banks' liabilities is 25.95%, according to Federal Reserve call reports.

[2]The other primary source of mortgage origination funding is through warehouse lending. According the Mortgage Bankers Association, the outstanding warehouse lending was $392B in 2018. Source: MBA's Warehouse Lending Survey.

lending markets.[3]

To fill in this knowledge gap, this paper (1) empirically evaluates the impact of government-sponsored wholesale funding on mortgage lending, mortgage interest rates, and local bank concentration, and (2) builds and estimates a quantitative model of local bank lending systems to explore how access to government-sponsored credit shapes the structure, efficiency, and performance of bank lending markets.

The empirical analysis focuses on a specific government-sponsored enterprise—Federal Home Loan Banks (FHLB), whose primary business is to provide collateralized funding (FHLB advances) exclusively to their member banks to support their mortgage lending.[4] The funding cost is close to the risk free rate, and is kept the same for all member banks regardless of their size. The exclusiveness of member funding provides a natural laboratory to evaluate this public funding facility.

The empirical challenge in estimating the impact of access to government-sponsored wholesale funding through FHLB membership is that the FHLB application decision is endogenous to the banks' economic conditions. Banks that are on an expanding trajectory tend to apply for FHLB membership to secure more funding sources, and a naïve event study would produce a biased estimate of the effect of accessing FHLB funding. To solve this endogeneity problem, I take a novel approach and explore the exogenous changes in access to FHLB funding that arise from bank mergers. If an FHLB member bank acquires a non-FHLB member target, the branches of the target bank will operate under the acquiring bank and automatically get access to FHLB advances after the merger. However the change of target bank branches mixes two effects: a merger effect (managerial change and access to funding sources other than the FHLB) and an FHLB effect. To achieve identification, I further consider multiple-target mergers, where the acquiring bank simultaneously acquires multiple target banks, and the target banks differ in their FHLB membership status. I rely on within-merger comparisons between target bank branches that have access to FHLB advances prior to the merger and those that do not, to difference out the merger effect. The identification assumption is that the target banks in multiple-target mergers share comparable trends regardless of their FHLB membership.

With the multiple-target merger identification strategy, I start my empirical analysis by examining the effect of public external funding access to the recipient banks themselves. The difference-in-differences estimates show that the treated banks reduce their mortgage interest rates by 18 basis points and increase origination by 16.3% after gaining access to external funding through the FHLB. This effect persists for at least 5 years. Compositionally, I find that banks issue mortgages with very similar credit score and loan-to-value (LTV) ratio profiles throughout the period, contrary to the view that public funding encourages banks'

[3] Buchak, Matvos, Piskorski, and Seru (2018a) and Buchak, Matvos, Piskorski, and Seru (2018b) document that shadow banks' market share in mortgage lending has dramatically increased in the recent years.

[4] There are 11 regional FHLBs, locating across the country. Each Federal Home Loan Bank is a government-sponsored enterprise, federally chartered, but mutually owned by its member institutions. Commercial banks, thrifts, credit unions, community development financial institutions, as well as insurance companies could apply to the FHLB that serves the state where their home office is located.

risk taking. The only striking change is that the treated banks increase their fixed-rate mortgage positions by 5% due to the structural feature of FHLB funding. Furthermore, I find that small community banks react 5% more strongly to this external source of funding, consistent with the well-documented fact that small banks have more funding challenges (Kroszner, 2016; Jacewitz and Pogach, 2018).

I then investigate the effect on the industrial organization of the local mortgage market after extending FHLB funding to the treated local banks. The results show that market competition in the local census tract improves significantly. The market concentration index (HHI) drops by 1.5 percentage points, from a baseline of 15%. The intensified local competition affects several market outcomes. First, competing lenders reduce their mortgage rates by 7.4 basis points following the treated banks' 18-basis-point reduction. As a result, the market-level interest rate falls by 8 basis points. Second, the local market experiences a growth in mortgage lending of 5%. A closer investigation suggests that roughly two-thirds of the mortgage growth comes from the treated banks, and the remaining third is from their competitors, through a competition channel. Finally, mortgage interest rates become more responsive to local economic conditions. I find that small (community or regional) banks actively price the local economic risk into their mortgage rates, while the national banks apply a uniform pricing strategy. After small banks gain more market share due to FHLB funding access, they incorporate their superior knowledge of local economic conditions into more mortgages' pricing.

Overall, this evidence suggests that government-sponsored wholesale funding has a substantial positive effect on both individual banks and the local lending market. But this inference is restricted to my multiple-target merger sample for identification purposes, and the shock to the local market is relatively small—one lender gaining access to FHLB funding. It remains unclear how government-sponsored wholesale funding affects banks out of my sample (i.e., national banks), and more importantly, how it affects bank lending through changing the industrial organization beyond simply reducing the funding cost. To tackle this question, I develop and estimate an equilibrium model of the mortgage market to uncover the cost heterogeneity for all banks, with which I am able to quantify the effect of FHLB funding to the full range of banks, as well as the market structure and outcomes. I then carry out a counterfactual exercise to decompose the FHLB effect, and isolate the impact of the reduction in market concentration. I address these questions and concerns by employing a structural strategy.

In my quantitative model, heterogeneous borrowers choose mortgages among different lenders who offer different interest rates and service quality. To capture the realistic borrower substitution pattern for demand, the model allows both observed and unobserved heterogeneity among borrowers following Berry, Levinsohn, and Pakes (1995).[5] On the supply side, banks offer differentiated mortgage products and set optimal interest rates to maximize

[5]Similar structural techniques have been recently applied to study markets of different financial products, including mortgages (Buchak et al., 2018a,b; Benetton, 2018), deposits (Egan, Hortaçsu, and Matvos, 2017), insurance (Koijen and Yogo, 2016), corporate lending (Crawford, Pavanini, and Schivardi, 2018) and pensions (Hastings, Hortaçsu, and Syverson, 2017).

their profit. If a bank is exposed to funding shocks (e.g. deposit withdraws), temporarily pushing up its marginal cost, the FHLB can serve as a stable alternative funding source for its member banks. Banks of different sizes (national, regional and community) have different cost parameters, and different pricing flexibility to react to local economic conditions.

I estimate the demand and supply parameters separately. On the demand side, two types of instruments are used to alleviate price endogeneity. First, I exploit the fact that the national banks apply a uniform pricing strategy across different regions and use the large banks' national mortgage rates to instrument for their mortgage rates in different markets.[6] Second, I use other lenders' product characteristics (LTVs and proportion of fixed rate mortgage), which would affect the lender's price but are not correlated with local demand, following Berry et al. (1995). In estimating supply parameters, I leverage the well-identified FHLB effect on mortgage rates in my reduced form exercise to discipline my model, and identify the cost parameters for different banks and the effective cost of FHLB advances. My model effectively captures the mortgage rate distribution and the FHLB effect on different groups of banks illustrated in my reduced form analysis.

With this quantitative model, I consider two counterfactuals to fully characterize the effect of public funding facilities. First, I simulate an economy without the FHLB. Market concentration (HHI) increases by 2.4 percentage points, average mortgage rates rise by 11 basis points, aggregate mortgage lending shrinks by 7%, and the borrowers experience welfare loss of 10.3%. Such a large impact is due to the two roles that the FHLB plays in addressing market imperfections: shielding banks from liquidity shocks (the direct effect) and providing equal external funding access (the competition effect). Since the direct effect could also be achieved by the private market (e.g., warehouse lending), the competition effect is more informative for the value of public provision of wholesale funding.

To isolate the competition effect of the FHLB, I consider a second counterfactual where the FHLB still exists, but chooses to offer different advance prices to different banks. The advance prices are made so that the average funding cost of FHLB member banks is the same as in the current equilibrium, but the market structure is the same as in the first counterfactual (with no FHLB). Therefore, this counterfactual has the same direct effect as in the current equilibrium. The only difference is the market structure in the mortgage lending, so this exercise would capture the effect of government-sponsored wholesale funding due to the shift of the industrial organization of the lending market (the competition effect). The simulation shows that if the FHLB were to apply this price schedule, aggregate mortgage origination would drop by 2.46%, banks' markup would rise by 3 basis points, and borrowers' welfare would drop by 3.76%. A simple back-of-the-envelope calculation implies that the FHLB's impact on the industrial organization of the mortgage market increases mortgage lending by $50 billion and saves borrowers $4.7 billion in interest payments every year.

Literature review. This paper contributes to four main lines of research. First, this

[6] The national banks' uniform pricing behavior echoes similar "puzzles" for GSE mortgages (Hurst, Keys, Seru, and Vavra, 2016), grocery products (DellaVigna and Gentzkow, 2018), rental cars (Cho and Rust, 2010), and movie tickets (Orbach and Einav, 2007).

paper contributes to the literature that evaluates government intervention in the credit market. There has been extensive study of government guarantee programs, which finds that the Fannie Mae and Freddie Mac mortgage guarantee distorts the banks' incentive (Frame and Wall, 2002) and the housing market (Elenev, Landvoigt, and Van Nieuwerburgh, 2016; Jeske, Krueger, and Mitman, 2013). Similar results are also found for the Small Business Administration guarantee program (Craig, Jackson, and Thomson, 2008; Cowling and Mitchell, 2003). This paper complements this literature by investigating another form of government intervention in the primary lending market.

Second, my paper contributes to the bank lending channel literature, which emphasizes the role of banks' financial constraints on their credit supply. Campello (2002), Gan (2007), Paravisini (2008) and Gilje, Loutskina, and Strahan (2016), have shown banks are generally financially constrained, and external funding has a positive effect on their lending. This paper further illustrates that the financial frictions are heterogeneous among banks of different sizes (Kashyap and Stein, 2000; Williams, 2017; Kroszner, 2016), which is a potential source of market power. The empirical analysis suggests that public provision of external funding could reduce the uneven distribution of banks' funding cost and intensify the competition of bank lending, which would increase the pass-through of shocks in aggregate credit supply (Scharfstein and Sunderam, 2016; Wang, Whited, Wu, and Xiao, 2018).[7]

Third, this paper adds to the literature on the role of the FHLB in the economy. Bennett, Vaughan, and Yeager (2005), Stojanovic et al. (2008) and Frame, Hancock, and Passmore (2007) study how the FHLB affects the member banks' risk taking and portfolio composition, and find mixed results. Ashcraft, Bech, and Frame (2010) highlights the FHLB's role as a liquidity backstop in the 2008 financial crisis. Sundaresan and Xiao (2018) and Narajabad and Gissler (2018) investigate how the FHLB interacts with the Basel III liquidity requirements and the recent money market reform, and find that FHLB advances are extracted for compliance purposes and unintentionally create potential liquidity fragility. This paper emphasizes the FHLB's unique role in providing equal funding access to banks of different sizes, and improving bank lending through reducing market concentration.

Finally, extensive research argues that small banks have a unique role in the economy by providing soft information and relationship banking. Their low cost of soft information communication (Liberti and Mian, 2009; Levine, Lin, Peng, and Xie, 2019) give them a comparative advantage in small business lending (Berger, Saunders, Scalise, and Udell, 1998; Canales and Nanda, 2012; Berger, Bouwman, and Kim, 2017), where relationship banking is key to overcoming information frictions (Petersen and Rajan, 1994; Berger and Udell, 1995; Cole, 1998; Elsas and Krahnen, 1998; Harhoff and Körting, 1998; Kysucky and Norden, 2015). This paper finds that small banks are also important due to their organizational flexibility to react to economic conditions and set risk-adjusted prices. Thus, this paper

[7]An extensive literature also shows the industrial organization of banking has an profound influence on bank lending quality (Liebersohn, 2017), credit access and price (Rice and Strahan, 2010), economic growth (Jayaratne and Strahan, 1996), entrepreneurship (Black and Strahan, 2002; Kerr and Nanda, 2009) and income equality (Beck, Levine, and Levkov, 2010).

provides a novel source of small banks' comparative advantage beyond their low cost of soft information communication.

Overview. The paper proceeds as follows. Section 1.2 discusses the data and the institutional setting for the FHLB. Section 1.3 outlines the empirical strategy and describes the characteristics of the sample banks. Section 1.4 illustrates public funding access's effect on individual banks' mortgage lending, and section 1.5 demonstrates the effect on market structure and outcomes. Section 1.6 tests the robustness of the reduced form results. In section 1.7, I develop a model of mortgage lending, and section 1.8 estimates it. In section 1.9, I carry out two counterfactual exercises to quantify the effects of the FHLB in a general equilibrium setting. Section 1.10 concludes.

1.2 Institutional Setting and Data Description

The institutional details of the Federal Home Loan Bank are important in understanding why this source of government-sponsored wholesale funding would be expected to affect both the recipient banks and the local credit markets more broadly. In this section, I discuss the institutional details about the FHLB, and the data that I use for the empirical analysis.

Federal Home Loan Banks

The Federal Home Loan Bank system was chartered by Congress in 1932, as a government-sponsored enterprise (GSE) to support mortgage lending and related community investment. It is composed of 11 regional Federal Home Loan Banks[8], which are collectively owned by more than 7,300 member financial institutions. Equity in the FHLB is held by these members and is not publicly traded. Institutions must purchase stock in order to become a member, and in return, members obtain access to low-cost funding (FHLB advances) and also receive dividends based on their stock ownership.

Initially, the FHLB only accepted members from savings and loan associations and insurance companies, and provided funding support to these members. But after the savings and loan crisis of the 1980s, the FHLB system was dramatically reformed by the Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA) of 1989, and opened membership to all federally insured depository institutions, including commercial banks and credit unions. As shown in Figure B.1, 90% of all FDIC insured banks have joined the FHLB as of 2017.

As an FHLB member, the primary benefit is to have access to long- and short-term advances (collaterized lending). Advances are primarily collateralized by residential mortgage

[8]The regional FHLBs are located in: Atlanta, Boston, Chicago, Cincinnati, Dallas, Des Moines, Indianapolis, New York, Pittsburgh, San Francisco, and Topeka. Historically, there was another regional Federal Home Loan Bank in Seattle, which was merged into Federal Home Loan of Des Moines in 2015. District details can be found at https://www.fhfa.gov/SupervisionRegulation/FederalHomeLoanBanks/Pages/FHLBank-Districts.aspx.

loans, and government and agency securities.[9] The interest rates of advances are at the level of the treasury rates with comparable maturity plus a very tiny margin. Figure B.2 illustrates the historical advance rates of various maturities from an FHLB (Des Moines), and they follow the benchmark rate closely. More importantly, the FHLB is mandated to give the best price daily to all members, regardless of their size or business model. Therefore, the access to such a low-cost funding source is disproportionally more beneficial for small banks, who either have no other wholesale funding opportunities, or have to pay higher premiums for their higher counterparty risk. In addition to the cost benefit, the member can borrow in various structures. The borrowing interest rates can be either fixed or floating, and the maturity ranges from overnight to as long as 30 years.

To fund advance borrowing, the FHLB issues consolidated obligations of the system in the public capital markets, and all regional FHLBs are jointly liable for all system-consolidated obligation debt. Although FHLB obligations are not explicitly guaranteed or insured by the federal government, their status as a government-sponsored enterprise accords certain privileges and enables the FHLB to raise funds at rates slightly above comparable obligations issued by the US Department of the Treasury. As of 2018, the total outstanding FHLB advances amount to $729 billion, which makes the FHLB a fundamental part of the US mortgage market.

Data

The primary unit of observation in this paper is the bank *branch*, instead of the bank (a group of branches). This is mainly because the boundary of banks changes after mergers, while the boundary of individual branches is stable across time. FDIC Summary of Deposits (SOD) provides an annual survey of all branches for each FDIC-insured institution since 1994, including the ownership of each branch. In addition, SOD records each branch's street address, which I map to its census tract using GIS software. I will focus on the sample period between 1994 and 2016.

The Federal Housing Finance Agency website publishes the roster of all FHLB member institutions every quarter, from which we can find the membership status for a bank in a certain year. Bank merger activities are from the FDIC Report of Changes. In section 1.3, I will elaborate how I construct the multiple-target merger sample.

To measure the mortgage lending outcome for each branch, I combine three loan-level data sources: Home Mortgage Disclosure Act (HMDA) data, ATTOM and McDash. HMDA surveys cover 90% of mortgage origination in the US, and provide information on the lender and the census tract where the collateral is located. ATTOM data provide transaction and assessor information including loan performance data (i.e., prepayment and default), lender names and exact location. McDash data provide comprehensive information on the metrics of the mortgage (including interest rates, credit scores, loan-to-value ratios, product types and

[9] Community financial institutions may pledge small business, small farm, and small agri-business loans as collateral for advances.

ex post performance). However, there is no unique identifier of mortgages across the three difference datasets. To connect them, I follow Bartlett, Morse, Stanton, and Wallace (2018) and exploit overlapping variables within these datasets to construct a merged data set of mortgages with lender identifiers, borrower characteristics, product metrics, and performance information, with a statistical-learning algorithm.

However, to measure the mortgage lending outcomes of a bank branch, we need to know the originating bank branch. Unfortunately, HMDA does not record the originating branch within each bank, which is crucial for this paper's purpose. I instead geocode each mortgage's property address using GIS software, and assign it to the closest branch of its lender, assuming each mortgage is originated by the nearest branch of the lender.

To explore the spillover effect of public funding access, I define the local market as the census tract where the bank branch is located, as in Nguyen (2019). These are defined by the US Census Bureau to be small, relatively permanent statistical subdivisions of a county. Specifically, census tracts are defined to optimally contain 4,000 inhabitants and therefore vary in size across urban and rural areas.[10] The mortgage-branch matching results show the median distance from a branch to the mortgage borrowers is around three miles, which indicates that the tract captures most of the effect of a structural change to a bank branch. In the robustness part in section 1.6, I look at the spillover effect at various distances, and find most of the effect is kept within ten miles from the treated branch.

1.3 Empirical Strategy

The empirical challenge in estimating the effect of accessing wholesale funding through FHLB membership is that the FHLB application decision is endogenous to the banks' economic conditions. Banks that are on an expanding trajectory tend to apply for FHLB membership to secure more funding sources, and thus a naïve event study would overestimate the effect of joining the FHLB. As a solution to this endogeneity problem, I explore the exogenous FHLB funding access change caused by bank mergers. Specifically, if FHLB member bank A acquires non-FHLB member target B, then the branches of the target bank B will operate under bank A and automatically get access to FHLB advances after the merger. But the change of bank B's branches mixes two effects: a merger effect (managerial change and access to other funding sources) and an FHLB effect. To achieve identification, I further consider multiple-target mergers, where the acquirer bank simultaneously acquires multiple target banks, and the target banks differ in their FHLB membership status. I rely on within-merger comparisons between target banks (branches) that have access to FHLB advances prior to the merger and those that do not, to difference out the merger effect. The identification assumption is that the target banks in multiple-target mergers share comparable trends regardless of their FHLB membership.

[10]Since the population would change across different years, the boundaries of tracts are revised every 10 years in the decennial census. This paper uses the tract system in the 2000 Census, since the majority of the events are in 2000-2010, and crosswalk variables in other systems to the 2000 census tract.

Figure 1.1 illustrates the identification strategy with a sample merger. The acquirer bank (dots) was seeking to expand its geographic footprint into the suburban areas by acquiring two small banks. The treated bank branch (cross) was not able to tap into FHLB advances before the merger, but could do so thereafter, while the control bank branch (triangle) already had FHLB access. Additionally, both target branches experience similar organizational change due to the merger. Therefore, the within-merge difference-in-differences strategy could identify the effect of getting access to wholesale funding provided by the FHLB.

Multiple-Target Merger Construction

To construct multiple-target mergers, I first use the change of branches' ownership from FDIC Summary of Deposits to identify all the mergers in the sample period. Noting that this period experienced a wave of substantial bank consolidation within the same bank holding company due to the relaxation of interstate branching restrictions, I drop all mergers whose target and acquirer belong to the same bank holding company, so that what remains are bank mergers that involve a change of the ultimate owners.

I then define a multiple-target merger if the same acquirer bank merges with more than one target bank in the same year.[11] All targets that are established less than four years before the merger, or closed less than four yeas after the mergers are dropped, to guarantee I have a balanced panel four years around the mergers. I further focus on all multiple-target mergers in which the acquirer is an FHLB member, and there is at least one FHLB member and at least one non-FHLB member in the target banks. The final sample contains 174 multiple-target merger events, which span the full sample period. Figure 1.2 plots the counts of multiple-target mergers in the sample period. The events are evenly distributed with slightly more happening before 2005, since there were still many small banks in the potential target pool that had not joined the FHLB in the earlier period.

Summary Statistics

Table 1.1 tabulates the characteristics of the sample banks, as well as their census tracts. The sample contains 174 multiple-target mergers. 250 target banks are not FHLB members before they are acquired, and 254 target banks are. The non-FHLB targets have 2051 local branches operating, while the FHLB targets have 1170 branches.

Panel B of Table 1.1 exhibits the bank characteristics of the two groups of targets. From the results, we can see the targets are mostly of small to medium size, with about \$13 billion in total assets and \$9 billion in deposits on average. The non-FHLB targets have 60% of their lending in real estate, of which 31% are mortgages. The FHLB members'

[11]Due to the data feature, I define the year to match the reporting cycle of FDIC summary of deposits, from the mid (June 30th) of last year, to the mid of this year. For example, mergers happening from July of 2002 to June of 2003 are considered to be in the same year 2003. This is to cater to the fact that FDIC report the detailed branch level information as of June 30th of each year, which would be the key for my mortgage assignment algorithm.

position in real estate is slightly higher, at the 65% level, of which 32% are mortgages. This is consistent with the story that banks with a larger real estate position have a higher propensity to join the FHLB. But the difference in our sample is much smaller than the general case, and statistically insignificant, since the acquirers tend to acquire banks with similar characteristics. As another important component, non-FHLB targets have 16% of their investment in commercial and industrial lending (C&I), while the FHLB targets invest 14%. Both groups of targets have a very low non-performing loan ratio (1-2%) and loan loss rate (2%).

Column (3) calculates the difference of columns (1) and (2) within each merger event. Column (4) reports the p-value of the hypothesis test that this difference is zero. Since my identification assumption is that the non-FHLB and FHLB target banks are comparable along all dimensions except for FHLB membership within each merger, we should focus on the within-event differences. The results in columns (3) and (4) indicate that the treated and control groups have similar characteristics. Although we cannot exploit all possible features, especially for unobserved information, this is a reassuring sign that we are using a quite balanced sample for our exercise.

Now let us examine the markets in which the two groups of banks are located. Figure 1.3 plots the geographical footprints of the target banks, where the crosses are the branches of non-FHLB members before the mergers, and the triangles are those of FHLB members. We can see they spread out across the nation, and represent the bank population well.

Panel C of Table 1.1 presents the socio-economic features for the locating census tracts in 2000. Again columns (3) and (4) show that the treated targets are located in similar markets as the control targets. The median income for the both groups is around $45k. Both groups of tracts have 62–64% home owners, 18–20% minorities, 69% mortgagers, and 64–65% educated population, defined as people with at least some college education. I also compare the median income of the locating county and the relative ratio of income to this county benchmark. The control bank branches tend to be located in higher income tracts relative to the county, but the difference is not statistically significant. In terms of bank penetration, the tracts in our sample have four to five local bank branches.

Empirical Specification

I use a generalized difference-in-differences framework to compare the mortgage lending of the target banks in the treated and control groups before and after mergers, and allow for time-varying trends based on premerger tract characteristics. In such a framework, the identification assumption is that the two groups of target banks share parallel trends: absent the FHLB membership difference, outcomes of the treated and control banks would have evolved along the same path. To facilitate transparent examination of any pre-trends in the data, I estimate a year-by-year difference-in-differences and present all my results as event study plots. The primary specification is

$$y_{it} = \left(\delta_{E(i)} \times \lambda_t\right) + \left(\delta_{E(i)} \times \gamma_i\right) + \left(\beta + \sum_{\tau} \beta_\tau D_{it}^\tau\right) FHLB_i + \gamma X_{iz(i)} + e_{it}, \tag{1.1}$$

where y_{it} measures the outcome variable for bank branch i in year t; $\left(\delta_{E(i)} \times \lambda_t\right)$ are event-by-year fixed effects; $\left(\delta_{E(i)} \times \gamma_t\right)$ are event-by-branch fixed effects; D_{it}^τ is a dummy equal to one if year t is τ years after merger $E(i)$ is completed; $FHLB_i = 1$, if branch i belongs to a bank that is not an FHLB member before the merger; $X_{iz(i)}$ include all control variables for branch i and its locating tract $z(i)$, including fraction of minority, fraction of college-educated, median income, the number of branches as of the year preceding the merger, as well as county-year fixed effect. Here, τ ranges from -6 to 8, and standard errors are clustered at the event level. The coefficient of interest is β_τ, which measures the difference, conditional on controls, in outcome y between treated and control banks τ years after the merger.

1.4 Effects of Public Funding on Individual Banks

The next two sections illustrate the reduced form results of banks getting access to public funding. This section will focus on the effect on the treated bank, while the next section discusses the effect to the local market structure and outcomes.

Bank Mortgage Lending

This section presents evidence for the effect of the access to external wholesale funding (FHLB advances) to the mortgage lending of the target banks. Figure 1.4 provides the template used for the event study results. It plots the β_τ estimated from Equation (1.1), where the dependent variable is the number of mortgage originations. The bars show the 90 percent confidence intervals. Notice, $\beta_\tau > 0$ indicates that more mortgages are originated by the treated banks relative to controls τ years after a merger. The coefficients in the shaded area are estimated from a balanced panel, while the data outside are not balanced because the target banks are not yet established, or closed.

Figure 1.4 shows that up to six years prior to the merger, the non-FHLB member banks share the same trend with FHLB members in the number of mortgage originations. However, the relative origination counts dramatically increase in the year of the merger, and this origination increase persists over the following years. On average, each branch of the treated banks originates 9.8 more mortgages, off a baseline of 60 mortgages, after they get access to FHLB advances. In another word, access to FHLB funding leads to a 16.3% increase of mortgage originations.

This indicates that the treated banks are indeed financially constrained before getting support from external funding. In theory, financial frictions would force banks to scale back from profitable projects for three reasons. First, financial constraints would impose a shadow cost on top of the direct funding cost, and make the banks' mortgages less attractive. Such a price effect will be shown in the next subsection. Beyond this, having inadequate funding sources prevents the banks funding all good investment opportunities that they can find. A more subtle reason is that inadequate funding sources also make it hard for banks to maintain their relationship with customers, so the banks have to incur more effort or cost to find qualified borrowers. After this friction is relaxed by external funding sources, the mortgage origination increases substantially.

While the effect on mortgage originations is substantial, we need to be aware of a caveat, that the banks in my sample are small, and tend to have a small mortgage lending base. Thus their growth potential in mortgage lending tends to be higher than a typical bank in the general population, so we need to be more conservative about the result in terms of external validity. In subsection 1.4, I will demonstrate this heterogeneous effect within my sample. And in the structural model, the effect to the full range of banks will be quantified after imposing structural assumptions on their cost functions.

The total mortgage origination measure includes securitized mortgages which the banks would sell to the securitization pipeline (most of the time, GSEs) shortly after origination, and those which the banks would hold on their balance sheet. I also investigate the effect of FHLB funding on both business models of mortgage origination in Figure 1.5. Panel (a) depicts the effect on securitized mortgages. Banks issue 5 more securitized mortgages, which corresponds to a 20% increase. Panel (b) focuses on the mortgages that are held on banks' balance sheet, and they increase by around 15% (or 5 in absolute counts) in the first five years after the banks join the FHLB. While both business models benefit from public funding access, the growth on securitized mortgages is slightly higher. This is consistent with the fact that mortgage securitization is more exposed to liquidity shocks (Stanton, Walden, and Wallace, 2014), and FHLB advances are a ready solution for the shortage of short-term funding.

Mortgage Interest Rates

This subsection looks at the effect of FHLB funding to mortgage interest rates. The same event study for mortgage interest rates is shown in Figure 1.6. After mergers, the treated banks lower their interest rates by about 18 basis points.

There are two contributing factors that drive the results. First, the easing of financial friction increases small banks' lending capacity, and reduces the shadow cost of the finance constraints. For example, when the small banks are short of funding due to deposit deficiency, they have to raise the interest rates to drive down the potential demand of mortgages. Second, the external funding is itself cheaper than at least some banks' marginal cost of deposits. FHLB advances have rates comparable to risk-free rates, which greatly lowers the cost of funding for the those banks. As a result, the recipient banks lower their mortgage interest rate and pass this benefit to their borrowers.

Effect on Mortgage Profile

This subsection explores the composition change of mortgage profiles after a bank gets access to FHLB funding.

Figure 1.7 plots the effect of FHLB funding access to the composition change of lenders' mortgage profiles. To interpret the magnitude of the effect more easily, the estimates in Figure 1.7 are from a less flexible version of the difference-in-differences regression:

$$y_{it} = \left(\delta_{E(i)} \times \lambda_t\right) + \left(\delta_{E(i)} \times \gamma_i\right) + \left(\beta + \beta_{POST} POST_{it}\right) FHLB_i + \gamma X_{iz(i)} + e_{it}, \tag{1.2}$$

where $POST_{it}$ is a dummy equal to one if year t occurs after merger $E(i)$, and all other variables are as previously defined.

The upper panel reports the change in the distribution of mortgages of different interest types. The outcome variables are the shares of mortgage originations for each interest rate type. One striking pattern is that the banks tilt more toward fixed-rate mortgages after they get access to FHLB advances. The position increases by 5% off the baseline of 83%. Correspondingly, their position in adjustable-rate and other types of mortgages drops significantly.

We know that fixed-rate mortgages are predominately preferred by US mortgage borrowers, since they shield the borrowers from the risk of interest rate increases. Such interest rate risk is instead shifted to the lenders, especially for the lenders who want to hold the mortgages on their balance sheet. And such risk is one-sided, since the borrowers have an embedded option to refinance if the interest rate drops. If the banks use floating-rate deposits to fund such mortgage lending, they have to face substantial risk due to interest rate fluctuation. What is worse, limited access to derivative markets and lack of economies of scales make many smaller lenders even less capable of managing their exposure to this interest rate risk. As a result, these banks that heavily rely on deposit funding are either less likely to offer fixed-rate mortgages, or have to charge higher interest rates to compensate for their risk exposure.

After the banks get access to FHLB funding, they can directly fund their fixed-rate mortgages with fixed-rate funding. In other words, the flexible structure of wholesale funding helps banks manage their interest rate risk, and issue more products with the consumer-preferred interest type. This explains why we see a spike in the fixed-rate mortgage position. In fact, FHLB advances give banks a chance to outsource their risk management burden. For many banks, the availability of various structures of external funding is as important as the availability itself.

The middle panel of Figure 1.7 presents the composition change across different buckets of credit scores. The FICO profile of the borrowers seems quite stable before and after the mergers. This refutes the hypothesis that banks would expand to low-risk borrowers after getting access to low-cost funding. On the contrary, if anything, banks tend to lend more to borrowers with very high FICO scores.

The lower panel explores the change of LTV profile. While there is not much change for the loans that have LTVs above 80%, there is a strong shift from low LTV to high LTV for loans below 80% LTV. The 80% threshold is important here because it is one of the many requirements for a loan to be qualified for a GSE (Fannie Mae or Freddie Mac) guarantee. Conditional on these loans being GSE-guarantee eligible, the treated banks would grant more credit to the same borrowers after they get access to the wholesale funding. Again, this is consistent with the financial friction story, and such evidence suggests that the lenders do not only ration credit on the extensive margin, but also do so on the intensive margin.

Heterogeneous Effect on Banks of Different Sizes

How do banks of different sizes react to the access to FHLB funding? I split my sample banks into two groups: regional banks with total assets above $1 billion at the year before merger, and community banks with total assets below $1 billion.[12] I then run the same regression as specified by Equation (1.2), but interact $FHLB_i$ with the indicator of the size category that the bank belongs to. The results are displayed in Table 1.2. Column (1) and (3) report the average effect for the full sample (same as in Figure 1.4 and 1.6), while columns (2) and (4) report the effect for regional banks and community banks, respectively. Below each point estimate, the row "relative to baseline" reports the size of the effect relative to the baseline of each outcome variable at the year before merger.

The results show community banks originate 12 more mortgages off the baseline of 57, while regional banks originate 9 more mortgages off the baseline of 61. Thus, lending grows more for smaller community banks both in absolute counts and relative to the baseline. The same heterogeneous pattern can be found in the effect to mortgage interest rates. Community banks reduce their interest rates by 29 basis points, while the regional banks' rates go down by 16 basis points.

This heterogeneous effect pattern is consistent with the well documented fact that smaller banks have more funding challenges in general. They usually have to pay higher interest to the depositors for the following reasons. First, small banks have a limited branch network, which makes it less convenient for the customers to withdraw cash. Second, the perception that big banks have an implicit government guarantee puts small banks in a difficult position for attracting depositors, especially for those deposit products that are not insured by FDIC (Jacewitz and Pogach, 2018; GAO, 2014). In addition, small banks have to confront higher costs or are completely excluded from external financing, due to their limited scope for diversification (Kroszner, 2016).

A very similar funding structure also exists in the private market, and is commonly referred to as warehouse lines of credit. The small banks can alternatively turn to warehouse lenders and do collateralized borrowing as they do with the FHLB. However, the warehouse lenders would charge a higher cost for the small banks for their greater counterparty risk.

[12]In a later section, I will group the banks into three size categories: national, regional and community. The national banks are those who belong to a bank holding company that ranks top four in combined total assets. So the strict definition of regional banks should be all non-national banks with total assets above $1 billion. But in my sample, all target banks are non-national, and thus only fall into the other two size categories.

In this sense, FHLB levels the playing field for small banks' wholesale funding by offering low-cost and non-discriminatory funding to all its member institutions.

Why does the FHLB not do risk pricing, as the private lenders do? In fact, the Federal Home Loan Bank Act requires the FHLB to give fair and non-discriminatory rates to all its members.[13] This is a crucial feature of the government-sponsored funding facilities, that has a profound effect on the industrial organization of mortgage lending as we will see in section 1.5.

1.5 Effects of Public Funding on Local Mortgage Markets

This section will further explore the spillover effect of banks after getting access to FHLB funding. Specifically, I will focus on the effect on market competition, and illustrate how strengthened local banks propel market competition.

Market Concentration

I look at the effect of FHLB membership to the local market concentration measure (Herfindahl-Hirschman Index[14]). Here the market is defined as the census tract where the bank branch is located. In the example merge sample, the markets are the colored tracts as shown in Figure 1.1. I choose this small geographical unit to make sure I will have enough statistical power to identify the spillover effect from my natural experiment. After a local bank gets FHLB funding, it is able to better compete with its competitors in the local market. For example, it could lower its mortgage interest rates or closing fees, or run more advertising campaigns to market their mortgage products. As shown in Figure 1.8, the concentration measure in the market falls by around 1.5 percentage points, from the baseline of 15%. Since the treated bank tends to be a small lender in the local census tract, its expansion due to better funding structure intensifies the market competition significantly.

Here I need to clarify that the market effect I present here considers all types of mortgage lenders. Table 1.1 shows there are on average 4–5 bank branches in the sample census tracts, which might lead to a misconception that there are only 4–5 lenders in the local mortgage markets. Actually, there are potentially more lenders, for the following reasons. First, even though distance is important for mortgage lending, it is still often the case that

[13] The term 7(j) in Federal Home Loan Bank Act requires the board of directors shall administer the affairs of the bank fairly and impartially and without discrimination in favor of or against any member, and shall, subject to the provisions hereof, extend to each institution authorized to secure advances such advances as may be made safely and reasonably with due regard for the claims and demands of other institutions, and with due regard to the maintenance of adequate credit standing for the Federal Home Loan Bank and its obligations.

[14] The local HHI is constructed from the share of each lender's mortgage originations. And it ranges from 0 to 100% (monology).

banks lend across census tracts, since a census tract is quite a small geographic subdivision. Second, there might be lenders that are not commercial banks, such as credit unions and non-depository mortgage companies (or shadow banks). Especially after the crisis, non-depository mortgage companies' market share grows very fast due to a regulatory environment favorable for these lenders. HMDA data survey almost all mortgage lenders, so the market effect that I present in this paper involves all market participants.

Competitors' Reaction in Mortgage Rates

The competition can take different forms, such as price competition or advertising campaigns. Table 1.3 illustrates the evidence consistent with price competition, by exploring how the market competitors react in their pricing strategy after one local bank gets access to FHLB funding.

Column (2) illustrates that the treated banks lower their mortgage rates by 18 basis points after joining the FHLB. Their competitors react to the change by lowering their interest rates by 7 basis points on average, as in shown in column (3). As a result, the market level mortgage rates fall by 8 basis points.

Aggregate Mortgage Credit Supply

Figure 1.9 shows the effect on mortgage origination in the local market. If a local bank branch gets access to FHLB advances, the locating census tract will see 10 more mortgage originations, or a 5% increase, in the later years. This suggests the treated bank is not just crowding out the business from its competitors. It is able to extend credit to otherwise unsatisfied borrowers through its relationship network. This is consistent with the relationship banking literature, that emphasizes that it is costly and slow for banks to build relationships with their borrowers. So if a financially constrained bank is not able to satisfy the demand of its clients, and the unfilled demand cannot be easily filled by other non-constrained lenders.

Market Structure

To dig into the interaction between the treated banks and the local market, I look at the effect on lenders of different sizes. I first categorize all competing lenders into three groups: national banks, other small banks, and non-banks. The national banks are those who belong to a bank holding company that ranks top four in terms of combined total assets. Small banks are all non-national banks, including both regional and community banks. Here I exclude the treated banks to focus on the competition effect. Non-banks are all other lenders, among which most are shadow banks.[15] I then normalize the mortgage originations for each group of lenders by the baseline market mortgage originations at the year before mergers, and regress these normalized mortgage originations with estimating Equation (1.2).

[15]Here non-banks also include credit unions. But they have very small market share.

The results are reported in Figure 1.10, where the three panels (upper, middle and lower) correspond to different mortgage products. The upper panel plots the effect for all mortgages. We can see the entire market grows by around 5%, in which two-thirds of the credit expansion directly comes from the bank that gets access to FHLB advances through mergers. This measures the direct effect caused by the better funding structure of the treated banks. The remaining third comes from the competing lenders through a competition effect. Specifically, the competing lenders are pushed to lower their mortgage rates, which increases their credit provision. This suggests that FHLB funding does not only benefit the treated banks, but also exhibits a positive spillover effect to the local market. If we look into the competitors, we can see other small banks are driving most of the competition effect. Their mortgage originations grow by almost 2% relative to the baseline market lending, which contributes 40% of the aggregate market growth. The national banks instead lose a significant share (1%) of the market.

As I will illustrate more extensively in the next subsection, national banks tend to apply a uniform pricing strategy across different markets. Their mortgage rates involve a centralized decision market process, so are less responsive to the change in local market structure. Other small banks, on the other hand, are more vigilant to the changing market conditions, so we can see the small banks are gaining market share, while national banks' market share is eaten by other lenders. Shadow banks also seem to react to the intensified market competition and gain some market share, but the effect is not statistically significant.

I then carry out the same exercise for mortgages of different types. The middle panel of Figure 1.10 plots the effect for refinance mortgages, where the borrowers seek to replace their existing mortgages with new ones. Issuing this type of mortgage usually involves less information acquisition, so the service is quite standard, and different lenders are more homogeneous from the borrowers' point of view. In this sense, the price competition is more important for refinance mortgages. And indeed, we see that only about half of the market growth is driven by the treated banks, and the competition effect plays a more important role. Again, other small banks account for most of the competition effect.

The lower panel plots the effect for the other mortgage type—purchase mortgages, where the borrowers seek financing to purchase their houses. To issue such mortgages, the lenders need to collect more information from the borrowers and go through a lengthy screening process. For this reason, the service is more customized and thus less homogeneous across different lenders, so the lender-borrower relationship is key to this process while price plays a less important role. The regressions show that almost all market growth of purchase mortgages comes from the treated banks. The price competition is not as salient in this case.

Market Responsive to Local Economic Shocks

This subsection aims to test the effect on pricing efficiency. This is based on the premise that small banks are more flexible in making decisions and tend to be more responsive to local economics shocks. If a small bank in the local market is strengthened by external funding and takes more market share, then their regional adjustment of interest rates based on local economic conditions is more relevant for the borrowers. Therefore, market pricing efficiency will improve. This section first verifies the premise that small banks are indeed more responsive to such information on regional risks. After that, I will illustrate how extending external funding to these small banks affects the pricing responsiveness of the local economic conditions.

A Measure of Local Default Information. In order to examine whether mortgage rates vary with local economic conditions, we need to define measures of local economic activity observable to lenders that could potentially be used in their pricing decisions. I follow Hurst, Keys, Seru, and Vavra (2016) and use default rate in the past two years in the locating county to proxy for local economic conditions. First, a mortgage is defined as defaulted if the borrower is 60 days delinquent at least once, which is one of the best predictors of repayment distress. Specifically, within each county c in year t, I measure the fraction of loans originated during the prior two-year period that defaulted at some time between their origination and the beginning of the current period t. I refer to this measure as $d_{c,t}$. This lagged delinquency is a good measure of local economic activity both because it is a summary statistic for many economic factors that could predict future default (e.g., weak local labor markets, declining house prices) and because it is easily observable by lenders.[16] This measure of local default information has great predictive power of the realized local default, as elaborated in appendix A.1.

Residualized Interest Rates. I want to illustrate spatial variation in mortgage rates and show how this variation correlates with spatial variation in predicted future mortgage default rates for lenders of different sizes. However, interest rates and default rates could potentially differ spatially just because borrower or loan characteristics such as FICO score or date of origination vary spatially.[17] To formally control for these factors, I purge the variation in mortgage rates and subsequent default rates of spatial differences in borrower and loan characteristics. To do so, I fit the mortgage rates into the following equation with the loan-level micro data:

$$r_{it} = \lambda_t + \sum_{\tau} \beta_\tau Z_{it}^{\text{FICO}\in\tau} + \sum_{\tau} \delta_\tau Z_{it}^{\text{LTV}\in\tau} + \sum_{\tau} \psi_\tau Z_{it}^{\text{Lien}\in\tau} + \sum_{\tau} \phi_\tau Z_{it}^{\text{Interest Type}\in\tau} + \tilde{r}_{it}, \quad (1.3)$$

[16] Here I use a county level measure to capture the economic condition in the regional market. Although there are still idiosyncrasies within a county, the county is generally viewed as a connected market that has a shared labor force base and a common house price trend. The results are robust to alternative choices, such as MSA.

[17] For example, borrowers with lower credit scores empirically face higher interest rates and are more likely to later default. If borrower creditworthiness varies spatially, this could explain some spatial variation in observed mortgage rates and default rates. What I am after, however, is whether interest rates and the predictable component of default rates vary spatially after conditioning on borrower and loan characteristics. A borrower with a given characteristic may be more likely to default in one region relative to another because overall economic conditions differ across regions. This paper seeks to explore whether a given borrower would pay a higher interest rate when taking out an otherwise identical loan in a high risk rather than a low risk location.

where r_{it} is the loan-level mortgage rate for a loan made to borrower i in quarter t. And I discretize the FICO distribution with a bin width of 20, and $Z_{it}^{FICO \in \tau}$ is a dummy equal to one when the borrower i's FICO score falls in bin τ. This would give the fitting structure great flexibility to allow for the non-linear relationship between interest rates and credit scores. Similarly, I discretize the LTV distribution with a bin width of 20%, and $Z_{it}^{LTV \in \tau}$ is a dummy equal to one when the loan-to-value ratio falls in bin τ. In addition, I also control interest rate type and lien status. λ_t is the month fixed effect.

Table C.1 in the appendix reports the results of the these regressions. We can see that this flexible structure explains as much as 71% of the variation in the mortgage interest rates. After controlling for these loan and borrower characteristics, the following analysis will use the residualized interest rate $\tilde{r}_{it}$ to explore the spatial variation.

Are Small Banks More Responsive to Local Economic Shocks? To show this empirically, Figure 1.11 plots the relationship between the residualized interest rates $\tilde{r}_{it}$ and the local lagged default rates $d_{c(i),t}$, for three groups of banks : national, regional, and community banks. The slope of the fitted line indicates the degree of regional pricing. I divide the mortgages into two subsamples: GSE mortgages that are not securitized by the two housing GSEs (Fannie Mae and Freddie Mac), and non-GSE mortgages, since banks do not have full control or great incentives to set optimal rates for GSE mortgages (Kulkarni, 2019).

For non-GSE mortgages in panel (a), we can clearly see that national banks barely have regional shocks priced into their products, but the regional and community banks are much more responsive to local default rates.[18] I also find that GSE mortgages do not price regional risks for each size category, as shown in panel (b). This is consistent with Hurst et al. (2016).

Although the underlying rationale for this data pattern is not the focus of this paper, Gan and Riddiough (2008) provides a rational framework where the insights could apply in this scenario. In their model, the lenders that have information monopoly are reluctant to reveal their information through risk based pricing, to prevent potential entries. In addition, I provide more analysis in appendix A.2 to show that regional pricing could improve price efficiency, so a profit-maximizing lender should implement regional pricing if the cost of doing so is not very high.

FHLB effect on market responsiveness to local economic shocks. Table 1.4 reports the change of interest rates at the market level across heterogeneous markets. The markets are grouped into safe and risky markets, according to their local default rate at the county level in the past two years. Markets are defined as safe if located in a county where the mortgage default rates in the past two years are below the national median, or defined as risky otherwise. Column (1) and (2) still use the difference-in-differences specification as in Equation (1.2), and report the effect for safe and risky markets, respectively. We can see that the market interest rate in the safe market drops more than in risky areas. Column (3)

[18] In terms of magnitude, if the lagged default rate of a local county is 1% higher than other places, the local national banks would not raise its mortgage rates, while the regional banks would raise their rates by as much as 16 basis points, and community banks would their rates by 18 basis points.

further interacts Post$\times FHLB$ with the indicator of safe markets (triple diff), and confirms that the reaction difference between safe and risky markets is significantly different. Since small banks are gaining more market share in the safe markets, their representation in safe markets increases more, and thus their influence on the market interest rate is higher. This will make the mortgage interest rate more reflective of the local default risk, and pricing efficiency is increased.

Columns (4) and (5) apply the triple diff regression to GSE securitized mortgages, and non-GSE securitized mortgages respectively. The effect is entirely driven by the non-GSE mortgages.

1.6 Robustness Checks

This section carries out a series of robustness checks to rule out identification concerns.

Placebo Test: Small Business Loan Lending

This subsection exploits the effect of FHLB funding on small business loans of less than 1 million dollars, as a placebo test. Since FHLB advances require mortgages as collateral, we could expect that the effect on the mortgage lending is the most salient, and the effect on small business lending would be minimal. Using Community Reinvestment Act (CRA) public data, I apply the same assigning algorithm to link each small business loan to its originating bank branch. Figure 1.14 shows that FHLB advances seem not to affect the lending of small business loans.

There are two offsetting forces that are driving the effect on small business loans. On the one hand, a dampening force arises because FHLB funding is better tailored for mortgage lending, which might make the recipient banks more willing to switch to the mortgage business. On the other hand, commercial lending could also benefit from the relaxation of financial constraints. The insignificant effect on small business lending indicates that the two forces are completely offsetting.

Spillover Test

One might be concerned that the effect of FHLB funding access to the local market comes from the selection of bank locations, instead of treated banks joining the FHLB. In this subsection, I implement the spillover effect to verify that the effect is really coming from the structural change to the target banks, to rule out the concern of selection of different markets. The spillover test could also illustrate how far the target bank's effect reaches, which can justify my choice of census tract as the market definition.

Specifically, I draw a series of concentric rings around the target banks, as illustrated in Figure 1.12. Each ring has a band width of two miles. To measure the outcomes in each ring, I crosswalk the overlapping census tracts to the featured rings.

For each ring, I estimate Equation (1.1) where the dependent variable is mortgage originations per square mile. Figure 1.13 plots the results for different rings, and shows that the effect is very localized. The impact is most severe in the tract where the branch is located, and strikingly, the magnitude of the effect decreases nearly monotonically as the distance from the target branch increases. This pattern is remarkably consistent, both qualitatively and quantitatively, with existing evidence on the local nature of mortgage lending markets.

1.7 A Structural Model of Mortgage Lending

I develop and estimate an equilibrium model of the local mortgage markets, with three objectives. First, due to my identification strategy, the markets I have studied in the reduced form exercise are just a limited and non-representative sample. By developing a model framework, I am able to uncover the cost heterogeneity for all banks, and apply counterfactual exercises to the full sample of banks across the nation. Second, the model allows me to study unobserved policy counterfactuals (e.g., shutting down the FHLB, or the FHLB charging different prices for different banks), from which we can comprehensively analyze the FHLB's impact. Third, the structural model helps me to evaluate many unobserved outcomes, including borrowers' welfare and the pass-through of the cost reduction from the FHLB.

Model Setup

Geography and Market Participants

The economy has M segregated markets. In each market m, I_m heterogeneous households indexed by $i \in \mathcal{I}_m$ look for mortgage financing from the K_m lenders, denoted by $k \in \mathcal{K}_m$. At each period t and market m, a regional shock $\delta_{m,t}$ is realized, and determines the local economic performance. In the empirical estimation, the market is defined at the CBSA-loan purpose level. For example, the borrowers who live in the city of San Francisco and look for mortgage refinancing (in a certain year) are considered to be in the same market and face the same set of banks supplying credit. The lenders include both banks and shadow banks. I group banks into three categories according to their size. Therefore, this model has four lender categories: national banks (nb), regional banks (rb), community banks (cb) and shadow banks (s). Let $g(k) \in \{nb, rb, cb, s\}$ denote the category that lender k belongs to.

Here my defined the geographical span of the market is CBSA, which is different but not inconsistent with my choice of census tract in the empirical part. Please note that I am not assuming that in the reduced form framework the effective market for a local bank branch is the census tract. It can be larger than census tract. But the effect on the locating census tract should be the most salient from an empirical point of view. In the structural model, since I do not model the effect of distance on lending, every census tract within the CBSA will have the same competition structure with the CBSA because they are just homogeneous subdivisions. So the structural model will predict that the competition effect is the same across all the census tracts within a CBSA. The only subtle problem is that distance is a feature of reality, and that is why I choose to look at the locating census tract in the reduced form exercise. But my structural model does not include it (to avoid complexity). This would only be a problem if I use census tract level reduced form results to calibrate my model, which I do not. I will just use the bank-level reduced form results to calibrate the model.

Mortgage Demand

In each market m, each household i chooses which lender to borrow from among all lenders in the market. The indirect utility that household i derives from lender k at period t depends on the interest rate the lender offers $r_{k,m,t}$, and the service it provides $q_{k,m} + \xi_{k,m,t} + \epsilon_{i,k,m,t}$. In this model, the lender offered interest rate $r_{k,m,t}$ is risk- and product-adjusted, so it does not depend on the borrower and mortgage characteristics. In other words, I am modeling the baseline interest rate for each lender, on which they can add premiums according to borrower and mortgage characteristics (e.g. FICO scores, LTV, interest rate types). $q_{k,m}$ is the time-invariant component of the service quality for lender k's operation in market m (e.g. lender k's proximity to borrowers). $\xi_{k,m,t}$ captures the time-varying component of the service quality (e.g. processing time and screening efficiency). $\epsilon_{i,k,m,t}$ is borrower's i idiosyncratic preference of lender k (e.g. relationship between borrowers and the lender), and is assumed to be distributed *i.i.d.* Type I extreme value, which leads to the standard logit market share.

$$v_{i,k,m,t} = -\alpha_i r_{k,m,t} + \underbrace{q_{k,m} + \xi_{k,m,t} + \epsilon_{i,k,m,t}}_{\text{service}} \tag{1.4}$$

To characterize the extensive margin of the equilibrium credit, I assume each household has a reservation utility of $v_{0,m,t}+\epsilon_{i,0,m,t}$ with a standard normalization assumption $v_{0,m,t} = 0$, and they only choose to finance when $v_{i,k,m,t} > \epsilon_{i,0,m,t}$.

The borrowers' disutility coefficients α_i vary across the population. For example, a low-income household might have a higher elasticity to interest rates. Here I assume the coefficient α_i is random and has the following structure:

$$\alpha_i = \bar{\alpha} + \gamma(D_i - \bar{D}) + \sigma_\alpha \zeta_i \tag{1.5}$$

where D_i are the borrower's observed demographics, including their income and house prices. $\sigma_\alpha \zeta_i$ captures borrowers' unobserved characteristics (e.g. assets, risk-aversion, housing preferences), and ζ_i is assumed to follow *i.i.d.* standard normal distribution. This random coefficient assumption would allow a rich substitution pattern between different lenders, and enable me to match the data more flexibly. The demand parameters to be estimated are then $(\bar{\alpha}, \gamma_\alpha, \sigma_\alpha)$.

Mortgage Supply

In each market m, K_m lenders maximize their (expected) profits by setting the optimal price conditional on their marginal cost and perception of the borrowers' default risk. The (unconditional) net profit for each lender can be written as:

$$\max_{r_{k,m,t}} \pi_{k,m,t} = I_m S_{k,m,t} \bar{Q} \bar{T} \left[(r_{k,m,t} - c_{k,m,t} - \bar{l} E_k[d_{m,t}]) \right] \tag{1.6}$$

where $S_{k,m,t}$ is lender k's market share mortgage origination in market m and year t. For simplicity, I assume all mortgages have the same size $\bar{Q}$, and the same average life $\bar{T}$. The average life $\bar{T}$ maps one-period net interest income to the total value of all future net income.[19] $\bar{l}$ is the annualized loss rate conditional on default, which is normalized by $\bar{T}$.[20] This loss includes both interest loss and principal loss.

Marginal cost. $c_{k,m,t}$ captures the marginal cost lender j incurs when originating the mortgage in market m during year t. It can be decomposed into three components:

$$c_{k,m,t} = f_t + c^F_{k,t} + c^O_{k,m,t}. \tag{1.7}$$

where f_t is the risk free rate that captures the time cost of the funding, $c^F_{k,t}$ is the lender-specific funding cost, and $c^O_{k,m,t}$ captures the market level variation in operating mortgage origination.

The funding cost of lender k depends on lender k's category and its access to the FHLB

$$c_{k,t} = \begin{cases} \mu_{g(k)} + \sigma_{g(k)}\omega_t & \text{if } k \notin FHLB \\ \min\{\mu_{g(k)} + \sigma_{g(k)}\omega_t, c^{FHLB}\} & \text{if } k \in FHLB \end{cases}. \tag{1.8}$$

If lender k does not have access to the alternative funding source (FHLB advances), its funding cost is drawn from a log-normal distribution ($\omega_t \sim logN(0,1)$). The two size-related parameters shift the cost distribution from a standard log normal distribution, where $\mu_{g(k)}$ controls the level of average funding cost (e.g. deposit interest), and $\sigma_{g(k)}$ governs its dispersion (e.g. exposure to funding shocks, such as deposit withdraws).[21]

If lender k is an FHLB member, its funding cost will be capped by the cost of FHLB advances c^{FHLB}. Here the FHLB is a steady wholesale funding source, and their advances

[19] Equation (1.6) strictly applies to the cases where the mortgage's principal amortizes according to a schedule that does not depend on the contractual interest rate. For example, let T be the contractual maturity of a mortgage product, $\{P_t\}_0^{T-1}$ be the beginning principal fraction for each period, and r_f be the risk-free rate, then

$$\bar{T} = \sum_{t=0}^{T-1} \frac{P_t}{(1+r_f)^t}.$$

But the real-life fixed-rate mortgages are amortized to guarantee a fixed payment for each month, which makes the principal schedule depend on the contractual interest rate. In this case, such representation is a close approximation.

[20] $\bar{l} = E[\mathcal{L}]/\bar{T}$, where $E[\mathcal{L}]$ is the expected loss rate conditional on default. For example, if the loss rate is 50% upon default, and the average life of a mortgage is 5 years, the annualized loss rate conditional on default $\bar{l} = 10\%$.

[21] Strictly speaking, $E[\mu_{g(k)} + \sigma_{g(k)}\omega_t] = \mu_{g(k)} + \sigma_{g(k)}e^{0.5}$, and $Var[\mu_{g(k)} + \sigma_{g(k)}\omega_t] = \sigma^2_{g(k)}(e-1)e$.

are a substitute for lenders' deposit funding when they suffer bad deposit shocks. c^{FHLB} is the spread that the FHLB charges over the risk free rate that includes term premium, operational expenses, and the cost of posting collateral. In this sense, it is the effective cost of FHLB funding. For FHLB member lenders, FHLB advances cap their funding cost at the level of $f_t + c^{FHLB}$. They will fund their mortgages with FHLB advances when their instantaneous deposit cost is higher than the cost of FHLB advances.

Default rate. $d_{m,t}$ is the default rate of borrowers in market m, which depends on local economic conditions. Here, we are not considering borrowers' idiosyncratic risk (e.g. FICO and LTV) in pricing market specific baseline interest rates.

Motivated by the fact that different lenders respond to local economic shocks differently, as shown in Figure 1.11, this model assumes in a very parsimonious way that a lender's perception of local economic conditions is a function of the lender's size.

$$E_k[d_{m,t}] = \phi_{g(k)}\rho(d_{m,t-1} - \bar{\delta}) + \bar{\delta}, \tag{1.9}$$

where ρ measures the persistence of the local default rate. $\bar{\delta}$ is the national average level of default rate. $\phi(\cdot)$ is a monotonically decreasing function bounded by $[0, 1]$. It governs a lender's perception of the local economic conditions, thus its responsiveness in pricing mortgages. We can see that if $\phi(\cdot) = 0$ (e.g., the big four national banks), the lender just prices their mortgage at the national default rate. On the other extreme where $\phi_{g(k)} = 1$, the lender fully adjust its interest rate to account for local economic conditions.

This is a very parsimonious way to model lenders' heterogeneous reaction to local shocks, but this representation can be well micro-founded. In appendix section A.3, I provide a micro foundation, which builds on the agency frictions between the lender management and local branch managers, a la Stein (2002), and attributes national banks' low responsiveness to local shocks to their great cost in verifying local branch managers' report on local default prediction.

Equilibrium

In equilibrium, mortgage demand is characterized by borrowers' choice of mortgage lenders, given the mortgage rates and lender service quality. Supply is characterized by the lenders' optimal decision on their offered interest rates. FHLB funding would affect the equilibrium interest rates by capping the funding cost of the member banks. The lenders are heterogeneous in two key dimensions: the cost structure (average cost and volatility), and the perception of the local default rate.

Mortgage Demand. Household i in market m maximizes its utility by choosing between all lenders available in the market. It also has the option not to borrow if its reservation value is higher than that offered by any lender. The distributional assumption of the idiosyncratic preference $\epsilon_{i,k,m,t}$ implies that the (conditional) probability that borrower i in market m at year t chooses lender k follows the standard logit form, as the integrand in Equation (1.10).

Integrating out the unobserved heterogeneity ζ_i gives us the market share of each lender:

$$S_{k,m,t} = \int_{\zeta_i} \frac{\exp(-\alpha_i r_{k,m,t} + q_{k,m} + \xi_{k,m,t})}{1 + \sum_{\iota=1}^{K_m} \exp(-\alpha_i r_{\iota,m,t} + q_{\iota,m} + \xi_{\iota,m,t})} dF(\zeta_i). \tag{1.10}$$

Mortgage Supply. The lender would set the optimal interest rate to maximize its expected profit in Equation (1.6). Solving the first order condition, we get the optimal interest rate

$$\begin{aligned} r^*_{k,m,t} = &\underbrace{c_{k,m,t}}_{\text{Marginal cost}} + \underbrace{\bar{l}E_k[d_{m,t}]}_{\text{Risk premium}} \\ &+ \underbrace{\frac{S_{k,m,t}}{\int_{\zeta_i} \frac{\alpha_i \exp(-\alpha_i r_{k,m,t} + q_{k,m} + \xi_{k,m,t})(1 + \sum_{\iota \neq k} \exp(-\alpha_i r_{\iota,m,t} + q_{\iota,m} + \xi_{\iota,m,t}))}{(1 + \sum_{\iota=1}^{K_m} \exp(-\alpha_i r_{\iota,m,t} + q_{\iota,m} + \xi_{\iota,m,t}))^2} dF(\zeta_i)}}_{\text{Markup}}. \end{aligned} \tag{1.11}$$

The optimal interest rate has three components: lenders' marginal cost, risk premium and markup. The marginal cost varies within year t due to deposit fluctuations. The markup depends on the lenders' market power.

1.8 Estimation and Results

The model is summarized by Equation (1.8), (1.11) and (1.10), and characterized by a set of demand parameters $(\bar{\alpha}, \gamma, \sigma_\alpha, q_{k,m})$, parameters in default prediction $(\rho, \phi_{g(k)})$, lenders' funding cost structures $(\mu_{g(k)}, \sigma_{g(k)})$, and the cost of FHLB advances (c^{FHLB}). In this section, I discuss the estimation procedures and identification strategies.

Estimation and Identification

Estimation proceeds in two steps. In the first step, I estimate demand parameters using data on mortgages originated across the US. In the second step, I estimate the supply parameters by targeting the FHLB effect in the reduced-form exercise, as well as other necessary moments.

Demand Estimation

I use mortgages originated between 2000 and 2015 from my HMDA-Attom-McDash merged sample to estimate the demand parameters. Since I only have the baseline interest rates for each lender in my structural model, I first residualize the mortgage rates using Equation (1.3), where I factor out borrower and product characteristics, including credit scores, LTV, lien status and interest type. I then aggregate the mortgage level data to lender-market observations. A market is defined at the level of CBSA-loan purpose, e.g., mortgage refinances in the city of San Francisco. Following Buchak et al. (2018b), this paper also separates markets into mortgages originated for new purchases and mortgage refinances since a borrower looking for one type of mortgage financing is not looking for the other type. Borrowers can choose between all lenders in the market. In each CBSA-year, I include two demographic variables: log incomes and log house prices. Both variables are from the American Community Survey (ACS).

To capture the extensive margin of mortgage lending, I define market size in the same way as Buchak et al. (2018b). One tenth of the total number of households are looking for purchase mortgages, and all mortgagors are in the market of mortgage refinance.

I estimate the demand parameters in two steps. In the first step, I rewrite the Equation (1.10) as

$$S_{k,m,t} = \int_{\zeta_i} \frac{\exp(-\gamma(D_i - \bar{D})r_{k,m,t} - \sigma_\alpha \zeta_i r_{k,m,t} + \lambda_{k,m,t})}{1 + \sum_{\iota=1}^{K_m} \exp(-\gamma(D_i - \bar{D})r_{\iota,m,t} - \sigma_\alpha \zeta_i r_{\iota,m,t} + \lambda_{\iota,m,t})} dF(\zeta_i). \tag{1.12}$$

With a generalized method of moments (GMM), I search over the (γ, σ_α) parameter space to minimize the predicted and the observed market shares of lenders. Here $\lambda_{k,m,t}$ is the market-year-lender fixed effects. In each GMM iteration, they are recovered by the contraction mapping method following Berry et al. (1995) and Nevo (2001). In the second step, we can recover $\bar{\alpha}$ and $q_{k,m}$ by running the regression:

$$\lambda_{k,m,t} = -\bar{\alpha} r_{k,m,t} + q_{k,m} + \xi_{k,m,t}. \tag{1.13}$$

Identification strategy. The interest rates offered by lenders might be reacting to some unobserved factors, which might bias the estimation in both steps of the estimation. To resolve this endogeneity problem, I construct a list of instrumental variables to instrument for the interest rates in both steps. First, I use the big four national banks' national interest rate to instrument for their mortgage rates in the local markets, by noting the fact that national banks apply the uniform pricing strategy across the nation. For example, JP Morgan's local interest rates in San Francisco are not reacting to the local demand factors, but are dictated by JP Morgan's national pricing strategy. I also use other lenders' mortgage characteristics to instrument for the lender's own interest rates following Berry et al. (1995). Specifically, I use other lenders' average proportion of fixed rate mortgages, and average LTV.

Supply Estimation

The estimation of supply side parameters is based on the optimal pricing equation. I assume lenders in the same category share the same cost and default perception parameters $(\mu_{g(k)}, \sigma_{g(k)}, \phi_{g(k)})$. This largely reduces the dimension of the parameter space, and increases the power of estimation. The tradeoff is that I ignore the heterogeneity of lenders within the same category, which is a second order issue in this paper.

The estimation uses the simulated method of moments (SMM). Specifically, the optimal pricing formula (1.11) allows me to simulate the interest rates charged by all categories of lenders, from which we can calculate the model implied moments. By minimizing the distance between the model implied and empirical moments, I am able to estimate the supply side parameters.

Identification strategy. The key parameter on the supply side is c^{FHLB}, which determines the effect of the FHLB on banks of different categories. My estimation procedure adds the FHLB effect on member banks' interest rates (for regional banks and community banks) in my reduced form into the targeting moments. The parameter c^{FHLB} will be mostly identified by these two moments (interest rate drops after joining the FHLB for regional banks, and community banks). I also add other moments from the data to discipline my structural model, including the mean and variance of the interest rates offered from lenders in each category and mortgage rate sensitivity to lagged local default rates. The former is mainly used to identify the distribution parameters of lenders' funding cost $(\mu_{g(k)}, \sigma_{g(k)})$, and the latter is mainly used to discipline the default perception parameters $(\rho, \phi_{g(k)})$.

Estimation Results

Figure 1.15 plots the estimated distribution of the funding cost for banks of different sizes, and the funding cost of FHLB advances. The black line represents the funding cost for the national banks, the blue line is for regional banks, and the red line is for community banks. We can see the national banks' funding cost is on average lower than the other two groups of banks. This is due to multiple reasons. First, the national banks have a large network of branches, which facilitates their deposit raising. Second, national banks are perceived to be "too big to fail", so the depositors are more willing to put deposits into them if they are concerned with the downside risk. This is especially important for their uninsured deposits (Jacewitz and Pogach, 2018; Egan et al., 2017). Other than the lower average funding cost, the national banks' cost distribution is also tight due to their well diversified deposit base, so they are less exposed to funding shocks. So the idiosyncratic deposit withdraws would net out in their branch network. This can also be due to their many private wholesale funding sources, including their many secondary market funding facilities (e.g. repo funding, asset backed commercial papers). The regional banks' cost distribution shifts towards the right, representing their higher funding costs, and the community banks' cost distribution shifts right even further.

Given this funding cost heterogeneity, the FHLB will have different effects on banks of different sizes, with a larger impact on community banks and less on national banks. The numerical simulation implies that the FHLB would effectively reduce the funding cost by 1 basis point for national banks, by 15 basis points for regional banks, and by 28 basis points for community banks. The effect looks smaller than what appears in the figure due to the competition in the market. In the market, lenders with higher funding costs would have smaller marker share, thus its effective weight in calculating the FHLB effect is smaller.

Here I want to point out that the cost of FHLB advances is mainly identified using the reduced form effect on regional banks and community banks. We actually cannot observe national banks in the reduced form sample. The structural model enables me to recover the funding cost for the banks of all sizes, with which we can extrapolate the FHLB effect on national banks.

Model Fit

Figure 1.16 compares the empirical and the simulated interest rate distribution for banks of different sizes. Overall the model fits the data well along the three dimensions: the mean, dispersion, and responsiveness to local defaults of the interest rates. The main limitation is that the model is not able to capture the non-linearity of interest rates in markets with very low default rates. This is due to the linear assumption of banks' perception of the local economic conditions.

1.9 Counterfactual Analysis

In this section, I use the estimated model to study two counterfactual policy changes regarding the FHLB. The baseline is the current equilibrium, where more than 90% of banks are FHLB members, and the FHLB offers the same funding rate for all members. In these counterfactual policy environments, I evaluate the effect on aggregate mortgage originations, interest rates, as well as the market structure. With the structural model, we can also draw conclusions on the empirically unobserved outcomes, including borrowers' welfare and the pass-through of the cost reduction due to government intervention.

Counterfactual 1: An Economy without the FHLB

To fully capture the impact of the FHLB in the economy, I first study the case where the FHLB does not exist. In the reduced form exercise, we are only able to observe a partial equilibrium exercise that one local bank joins the FHLB. Such a change would have a smaller effect on the aggregate outcomes, including mortgage originations and interest rate, since the affected bank is only a small part of the market. As for the effect on the market structure, the comparison can go in either direction. On the one hand, only one bank's funding structure is changed, so the effect on the market structure is smaller. On the other hand, the affected bank tends to be small, and it pushes the market to be more competitive without any offsetting forces. If we change the funding structure for both small and big lenders, there might be an offsetting force to push the market to become more concentrated since the big lender also benefits from the FHLB. In this section, I am going to employ my structural model to quantify the effect of the FHLB in a general equilibrium setting.

The simulation implies that if the FHLB is removed from the economy, the average market interest rate would increase by 11 basis points, and aggregate mortgage originations will fall by 7.05%. A simple back-of-the-envelope calculation suggests that national mortgage originations will decrease by \$129.28 billion, and borrowers will have to pay \$13.55 billion more in interest payments.[22]

The impact of removing the FHLB is different for banks of different sizes, as shown in Figure 1.17. Community banks will be hurt the most, their interest rates will increase by 29 basis points, and they will therefore lose market share of 4%. The regional banks' mortgage rates will increase by 16 basis points, which would lead to a market share loss of 2%. The national banks, on the other hand, will benefit from the removal of the FHLB. Their interest rates will rise by 1 basis point, and they will have a market share increase of 2%. The lack of the low-cost wholesale funding gives the national banks' an advantageous position in the market since there is less competition. The measure of market concentration, HHI, will increase by 2.38 percentage points.

Figure 1.18 plots average market-level interest rates across markets with different local economic conditions. The x-axis is the local default rate in the past two years, and the y-axis is the average baseline mortgage rates for all lenders.[23] The solid line plots the pricing schedule for the current equilibrium with the FHLB, which is upward sloping, indicating the lenders are actively responding to the local economic conditions. The dashed line represents the same relation in the counterfactual without the FHLB. In this case, the responsive lenders (community and regional banks) lose some market share, and the uniform pricers (national banks) are more dominating. As a result, the market responsiveness to local economic conditions falls, so we see a flatter slope. This would have negative consequences. A decreased price responsiveness raises the degree of cross-subsidization from the safer markets to the riskier markets. This would increase the high-default markets' representation in the lending landscape, and raise the default rate at the aggregate level. Such a price distortion would suppress the aggregate credit supply.

My structural model also allows me to directly calculate borrowers' welfare, and it shows the borrower will lose 10.28% of welfare. The is due to a higher level of interest rates, and a constrained credit supply.

Counterfactual 2: The FHLB Offers Member Banks Different Prices

The large effect of the FHLB suggested by the first counterfactual exercise is due to the two roles that the FHLB plays in addressing market imperfections: shielding banks from liquidity shocks (the direct effect) and providing equal external funding access (the competition effect). Since the direct effect could also be achieved by the private market (e.g., warehouse lending), the competition effect is more informative for the value of public provision of wholesale funding.

[22]The back-of-the-envelope takes the aggregate statistics in 2018 as the baseline. In 2018, the aggregate residential mortgage origination is \$1833.79 billion, and the total outstanding balance of the residential mortgage is \$12.32 trillion.

[23]The interest rate does not include borrower- and product-characteristic rate premiums.

To isolate the competition effect of the FHLB, I consider a second counterfactual where the FHLB still exists, but chooses to offer different prices to different banks. The prices for different banks are made so that the average funding cost of FHLB member banks is the same as in the current equilibrium, but the market structure is the same as if there was no FHLB in the first counterfactual (orange bars in Figure 1.17). Therefore, this counterfactual has the same cost reduction as in the current equilibrium. The only difference is the market structure in the mortgage lending, so this exercise would capture the effect of government-sponsored wholesale funding due to the shift of the industrial organization of the lending market. Figure 1.19 plots the offered price of FHLB advances for the three groups of banks: C_N^{FHLB} is for national banks, C_R^{FHLB} is for regional banks, and C_C^{FHLB} is for community banks.

The results show that if the FHLB were to apply this price schedule, aggregate mortgage origination would drop by 2.46%, banks' markup would rise by 3 basis points, and borrowers' welfare would drop by 3.76%. A simple back-of-the-envelope calculation implies that the FHLB's impact on the industrial organization of the mortgage market increases mortgage lending by \$50 billion and saves borrowers \$4.7 billion in interest payments every year.

1.10 Conclusion

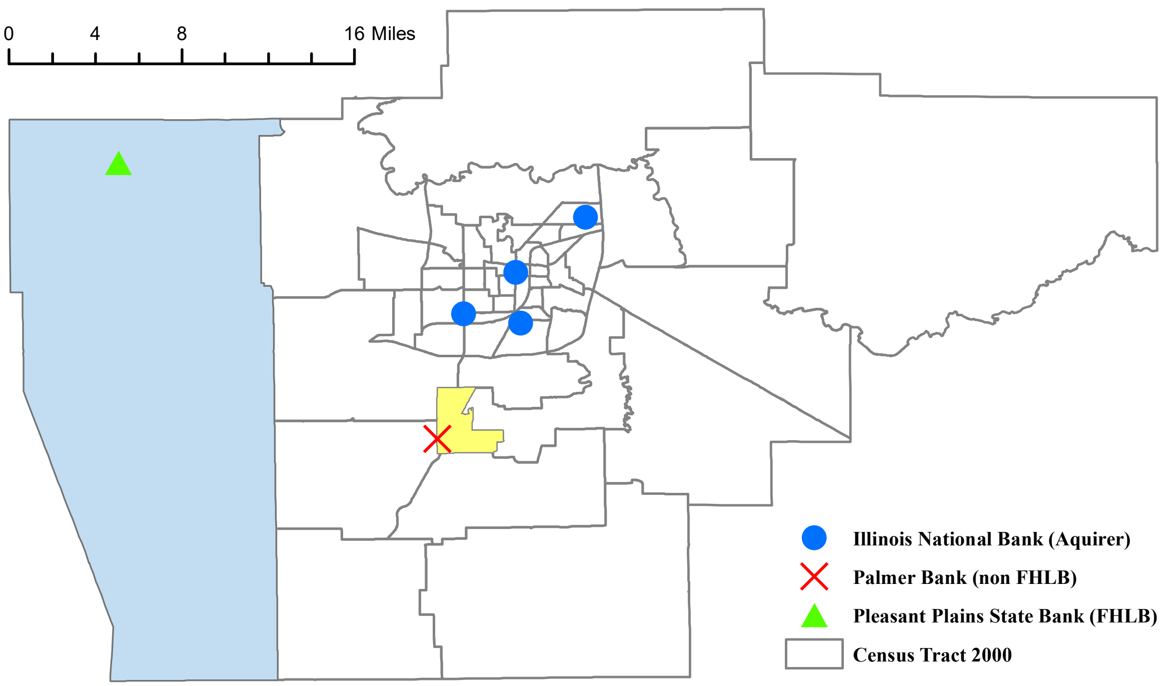
In testimony before Congress, Mike Menzies, the vice chairman of the Independent Community Bankers of America (ICBA), said "the FHLBanks provide members advances for liquidity and asset/liability management... This access allows our members to offer the same home mortgage products to our customers that the largest firms offer to theirs." This paper takes an empirical approach, and illustrates that Federal Home Loan Banks are indeed playing a crucial role in supporting banks' mortgage lending. Specifically, the FHLB provides banks with low-cost wholesale funding, which eases their financial constraints, thus enabling them to lower interest rates and issue more mortgages. What is more, the flexible structure of wholesale funding improves their ability to manage interest rate risk, and enables them to offer more fixed-rate products.

More interestingly, FHLB-funded small banks have substantial spillover effects on credit markets. First, the FHLB funding shifts the market structure and makes it more competitive. As a result, the market level interest rates fall, and the aggregate mortgage lending increases significantly. The second spillover effect is on pricing efficiency. Since the small banks are better at processing local information, they are very responsive to local economic shocks. After the FHLB increases the representation of small banks, more regional risk factors are incorporated into mortgage pricing, which makes credit more efficiently allocated.

I use a structural model to quantify the macro effect of the FHLB, and find that the FHLB increases mortgage originations by \$130 billion and saves the borrower \$13 billion in interest payments every year. The FHLB plays two roles in the economy. First, as an alternative funding source, the FHLB protects the individual banks from idiosyncratic funding shocks, and thus reduces their funding cost (the direct effect). Second, the FHLB levels the playing field for small banks, which improves market competition and facilitates the pass-through of cost reduction (the competition effect). My model enables me to quantify both effects, and show that the competition effect alone accounts for a substantial part of the overall effect. The shift of the competitive landscape of the mortgage market alone leads to an annual increase of mortgage originations of \$50 billion, and an annual decrease of \$4.7 billion in interest payments.

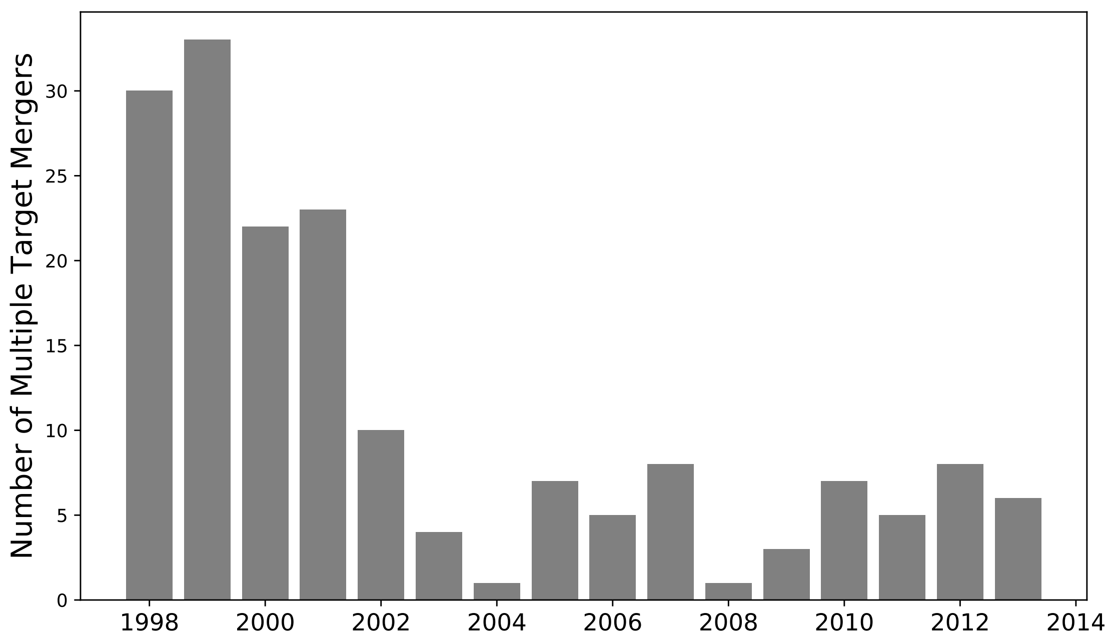
Figures

Figure 1.1 Illustration of Treated and Control Banks in an Example Merger



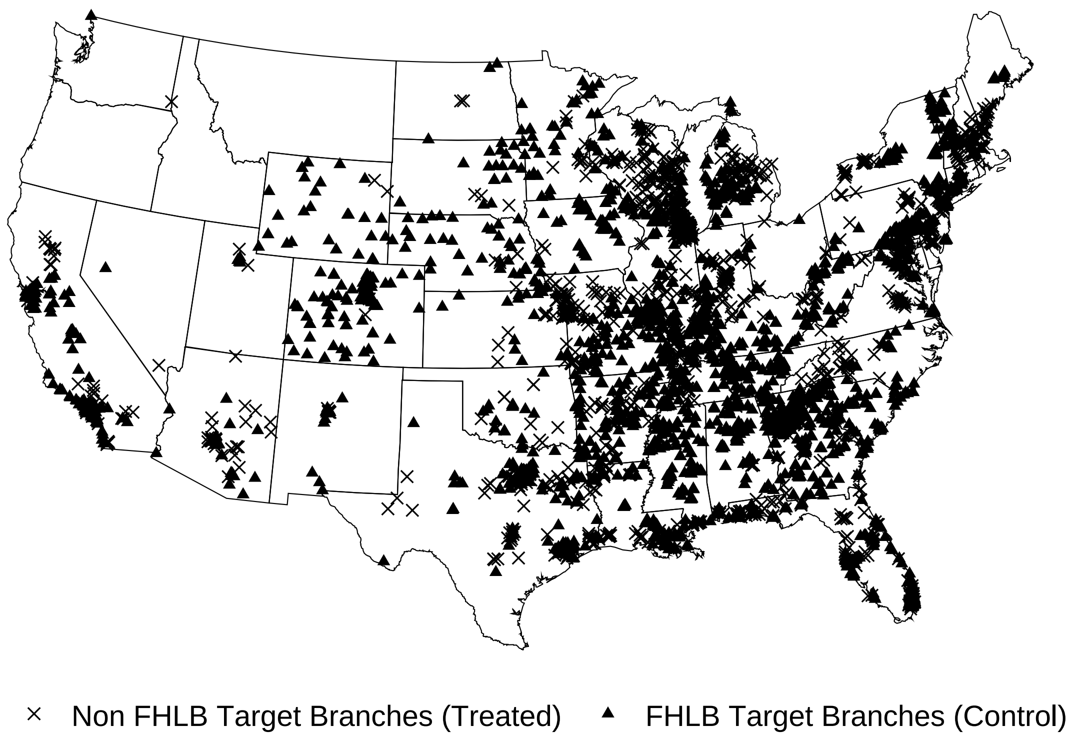
Note: This is a multiple-target merger from my sample, that serves as an example to illustrate the intuition of the identification strategy. This merger happened in 2003. The acquirer (blue dots) Illinois National Bank simultaneously merged two target banks: Palmer Bank and Pleasant Plains State Bank in the suburban area of Springfield, Illinois. The treated bank branch (cross) was not able to tap into FHLB advances before the merger, but could do so thereafter, while the control bank branch (triangle) already had FHLB access. Aside from this, both target branches experience similar organizational change due to the merger. Therefore, the within-merge difference-in-differences strategy could identify the effect of getting access to wholesale funding provided by FHLB.
Source: FDIC, FHFA, GIS.

Figure 1.2 The Time Distribution of the Sample Multiple-Target Mergers



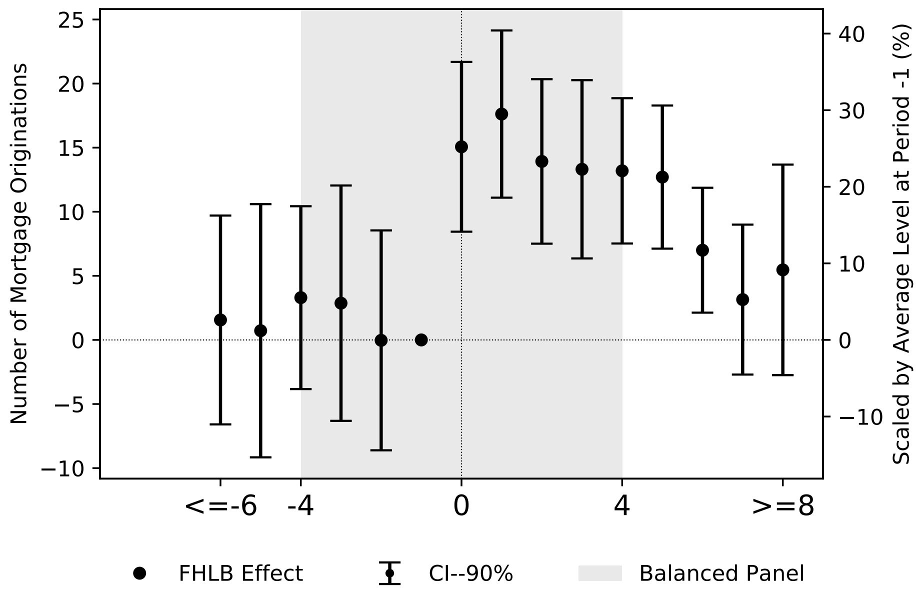
Note: This figure plots the number of sample multiple-target mergers over different years. All sample mergers satisfy the following conditions: (1) the acquirer merges at least two effective targets in the same year; (2) the target is effective, if it does not belong to the same bank holding company with acquirer, and it has at least one branch that exists at least 4 years around the merger; (3) the acquirer is an FHLB member before mergers, and there is at least one FHLB member and at least one non-FHLB member in its effective target banks.
Source: FDIC, FHFA.

Figure 1.3 The Geographical Distribution of Target Branches



Note: This figure plots the branch locations of the target banks in the treated (cross) and control (triangle) groups.
Source: FDIC, FHFA, GIS.

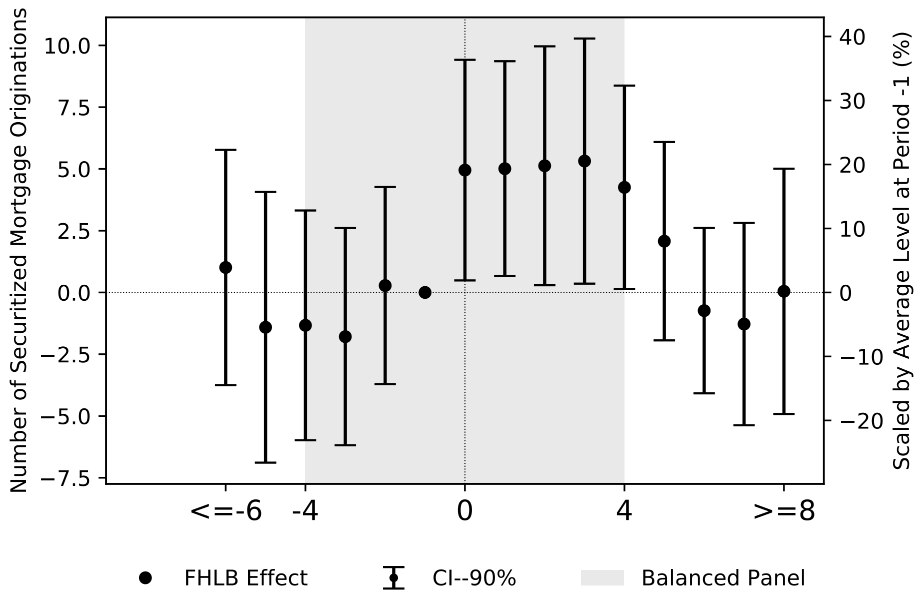
Figure 1.4 Effect of FHLB Funding on Mortgage Originations



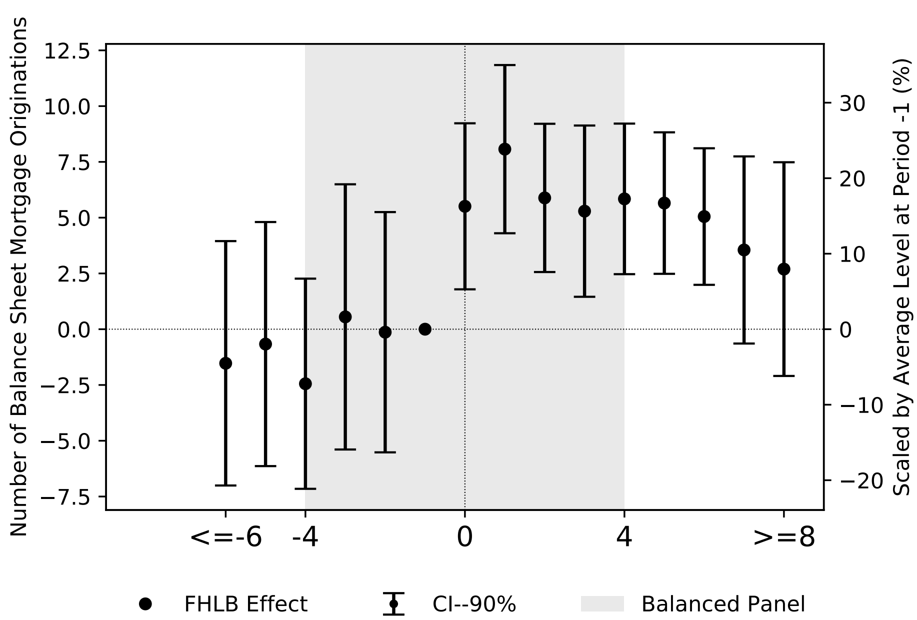
Note: This figure plots the effect of FHLB funding access to lenders' mortgage originations, obtained from estimating Equation (1.1). The left y-axis measures the effect in absolute mortgage originations, and the right y-axis rescales the effect by the baseline mortgage originations at event year -1. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. The bars plot 90% confidence intervals for each point estimate. Robust standard errors are clustered at the event level.
Source: FDIC, FHFA, HMDA, author's own calculations.

Figure 1.5 Effect of FHLB Funding on Mortgage Originations of Different Business Models

(a) Securitized Mortgages

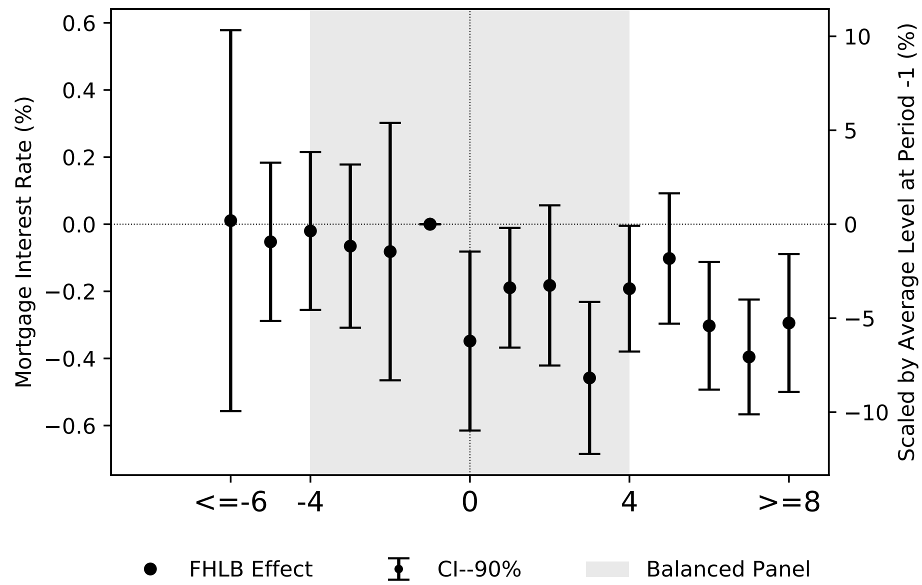


(b) Mortgages Held on Balance Sheet



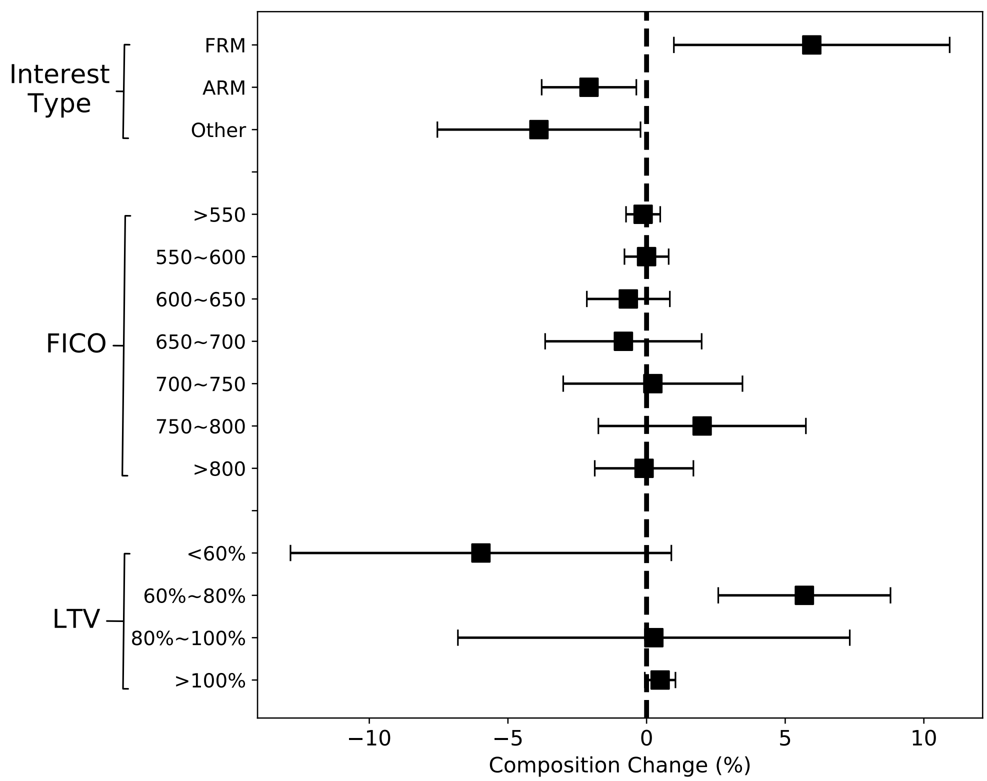
Note: This figure plots the effect of FHLB funding access to lenders' mortgage originations, obtained from estimating Equation (1.1). Panel (a) depicts securitized mortgages, and panel (b) illustrates the mortgages that are held on banks' balance sheet. The left y-axis measures the effect in absolute mortgage originations, and the right y-axis rescales the effect by the baseline mortgage originations at event year -1. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. The bars plot 90% confidence intervals for each point estimate. Robust standard errors are clustered at the event level.
Source: FDIC, FHFA, HMDA, author's own calculations.

Figure 1.6 Effect of FHLB Funding on Mortgage Interest Rate



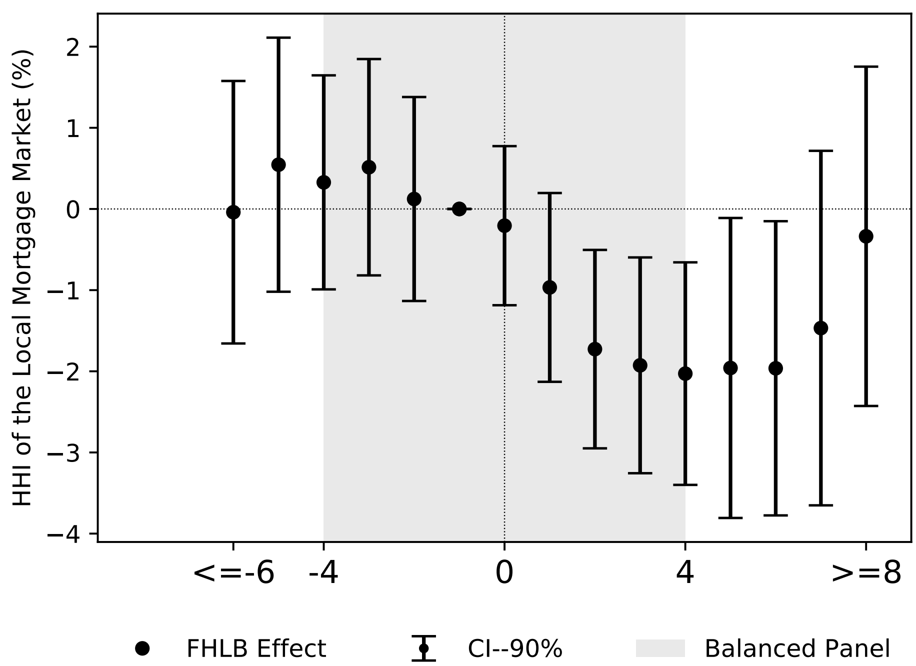
Note: This figure plots the effect of FHLB funding access to lenders' mortgage interest rates (%), obtained from estimating Equation (1.1). The left y-axis measures the effect in absolute mortgage rate, and the right y-axis rescales the effect by the baseline mortgage rate at event year -1. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. The bars plot 90% confidence intervals for each point estimate. Robust standard errors are clustered at the event level.
Source: FDIC, FHFA, HMDA, Attom, McDash, author's own calculations.

Figure 1.7 Effect of FHLB Funding on Mortgage Profile



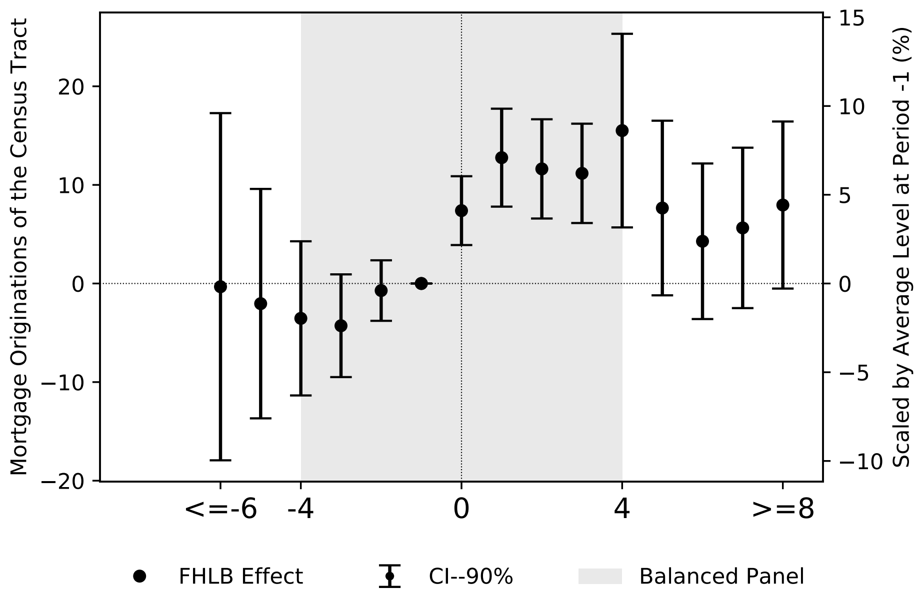
Note: This figure plots the effect of FHLB funding access to the composition change of mortgage profiles along interest type, FICO and LTV, obtained from estimating Equation (1.2). The dependent variable is the proportion of the originating mortgages in each category. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. The bars plot 90% confidence intervals for each point estimate. Robust standard errors are clustered at the event level.
Source: FDIC, FHFA, HMDA, Attom, McDash, author's own calculations.

Figure 1.8 Effect on Market Concentration in the Local Census Tract



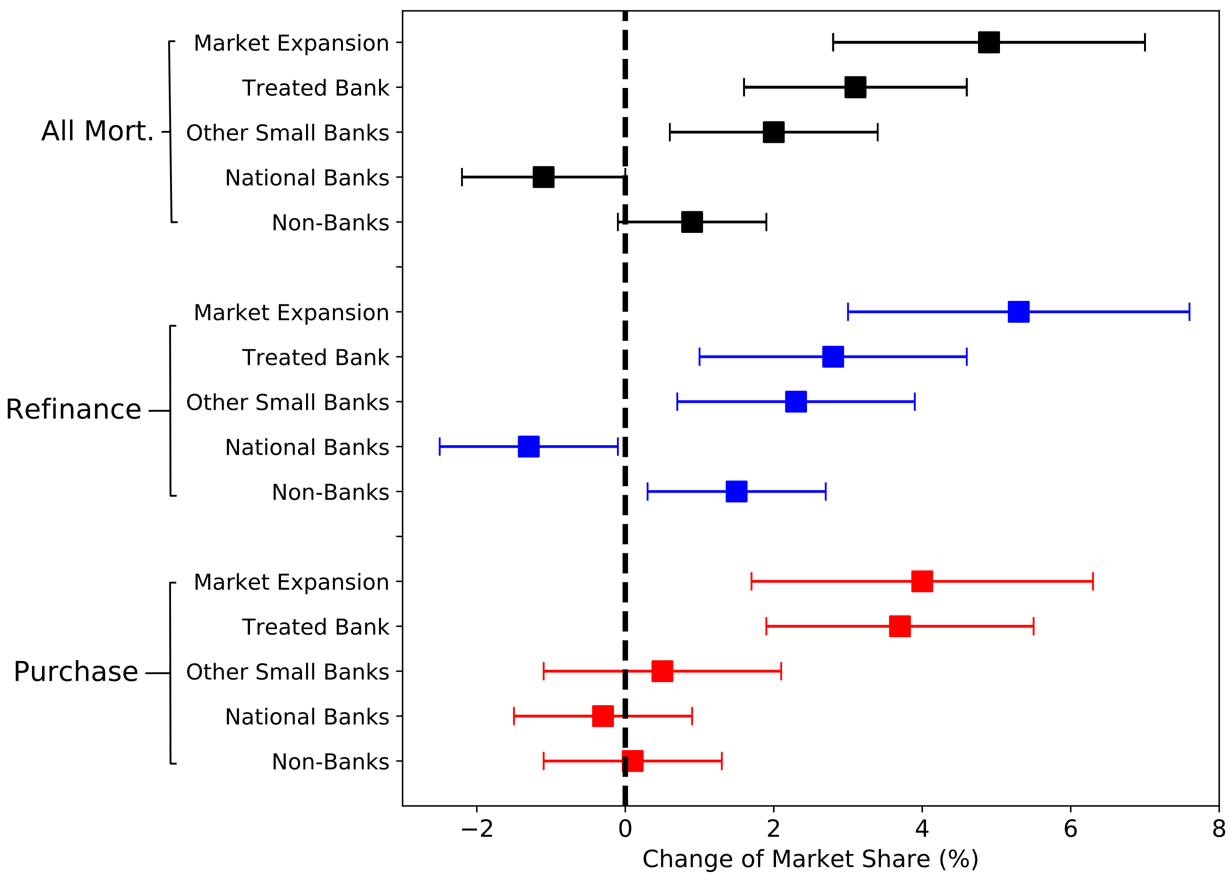
Note: This figure plots the effect to HHI of the local mortgage market after a local small bank joins FHLB, obtained from estimating Equation (1.1). The market is defined as the 2000 census tract where the bank branch is located. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. The bars plot 90% confidence intervals for each point estimate. Robust standard errors are clustered at the event level.
Source: FDIC, FHFA, HMDA, author's own calculations.

Figure 1.9 Effect on Aggregate Mortgage Originations in the Local Census Tract



Note: This figure plots the effect to market mortgage originations after a local small bank joins FHLB, obtained from estimating Equation (1.1). The market is defined as the 2000 census tract where the bank branch is located. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. The bars plot 90% confidence intervals for each point estimate. Robust standard errors are clustered at the event level.
Source: FDIC, FHFA, HMDA, author's own calculations.

Figure 1.10 Shift of Market Structure

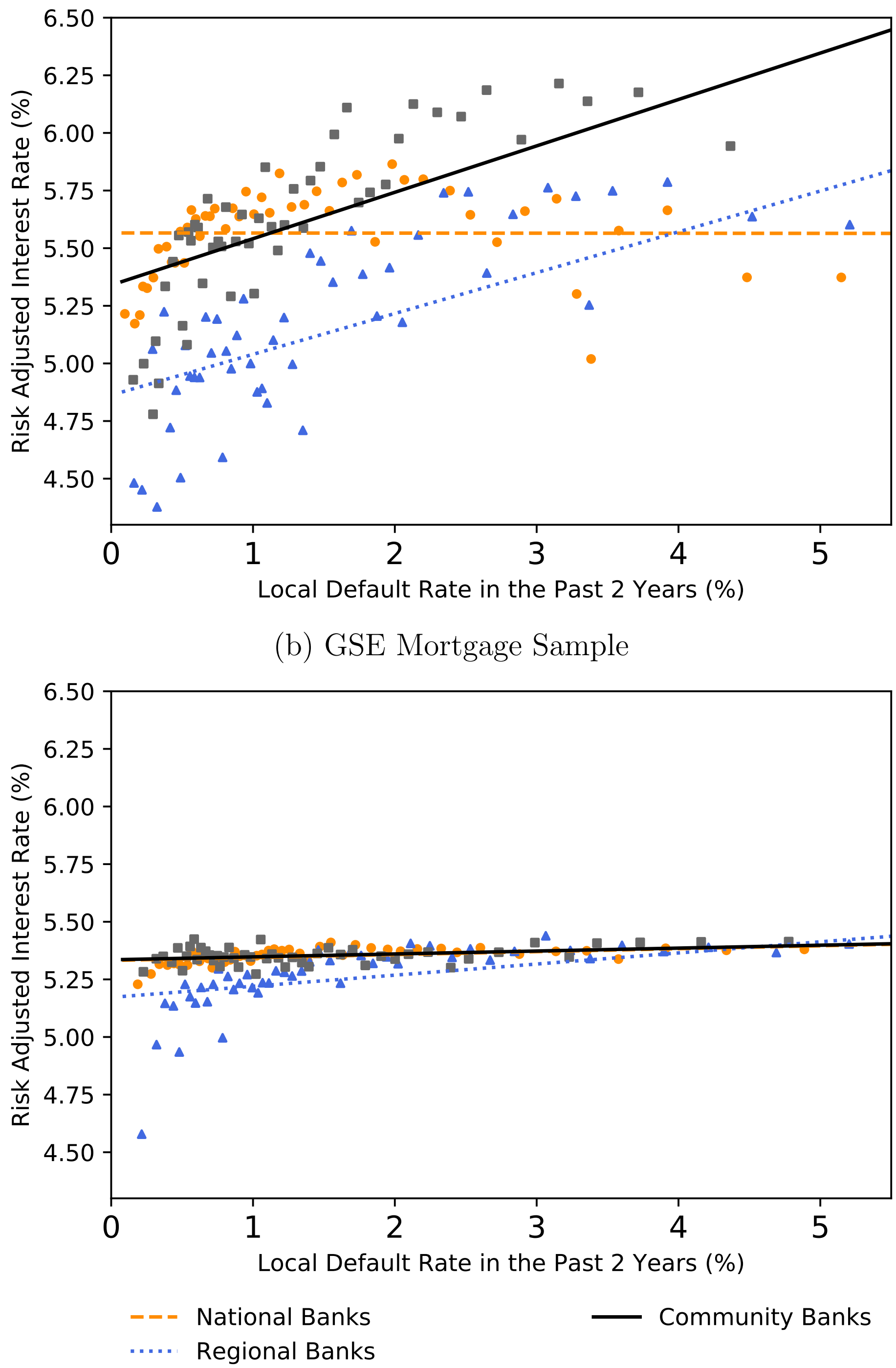


Note: This figure plots the effect of FHLB funding access to market share changes for different types of lender from estimating Equation (1.2). The upper panel plots the effect for all mortgages. The middle panel plots the effect for refinance mortgages, and the lower panel plots the effect for purchase mortgages. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. The bars plot 90% confidence intervals for each point estimate. Robust standard errors are clustered at the event level.
Source: FDIC, FHFA, HMDA, Attom, McDash, author's own calculations.

Figure 1.11 Regional Pricing Schedule for Banks of Different Sizes

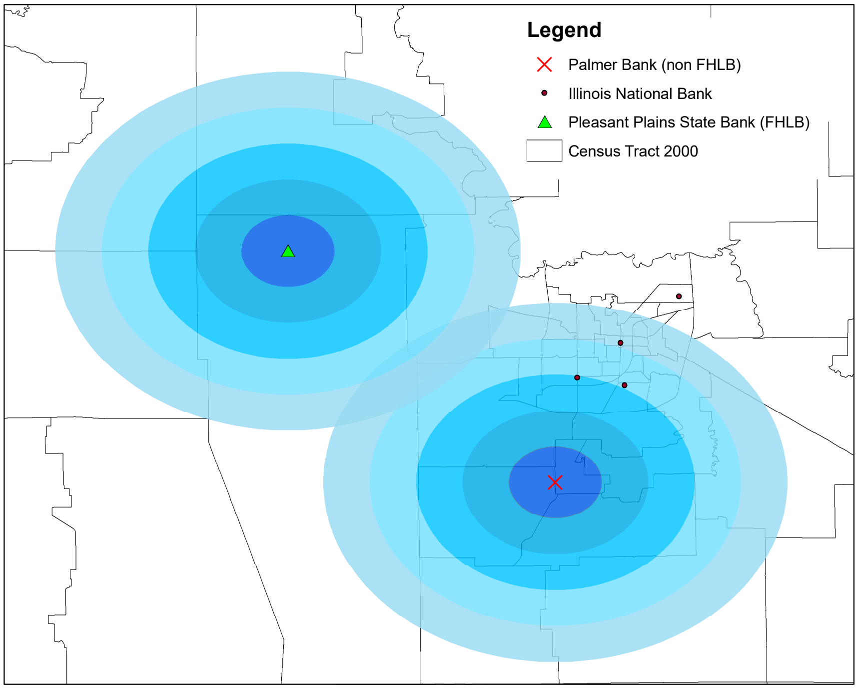
(a) Non-GSE Mortgage Sample

(b) GSE Mortgage Sample



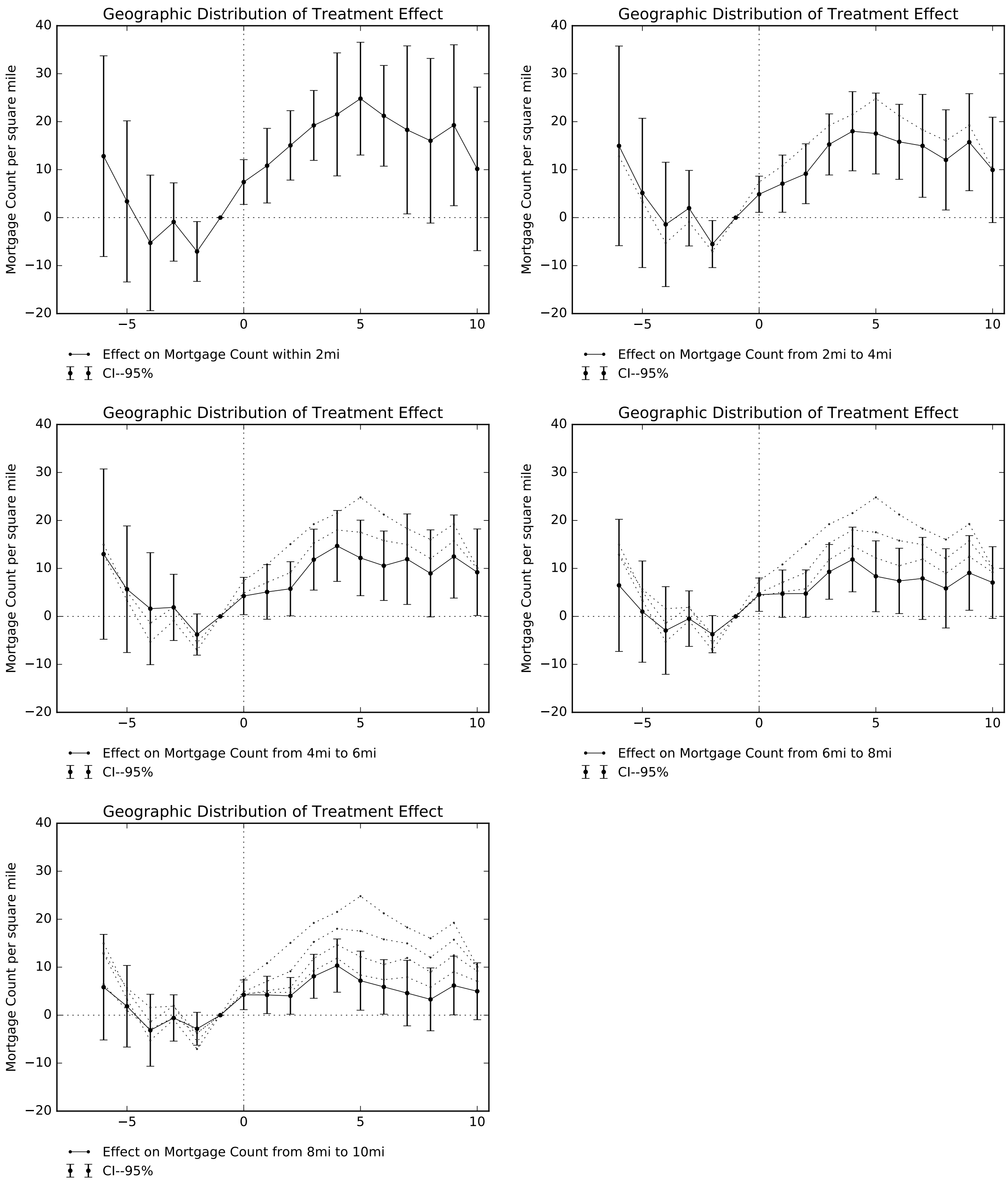
Note: This figure plots the relationship between the residualized interest rate $\tilde{r}_{it}$ (y-axis) and the local lagged default rates $d_{c(i),t}$ (x-axis) for both non-GSE mortgages (panel a) and GSE mortgages (panel b). The national banks are the top 4 bank holding companies by their combined total assets. The regional banks are all banks with total assets above $1 billion, except for the national banks. And the community banks are all banks with total assets below $1 billion. The scatters represent the average value for 50 percentiles for each group of banks.
Source: FDIC, FHFA, Attom, McDash, author's own calculations.

Figure 1.12 Concentric Rings from the Target Branch



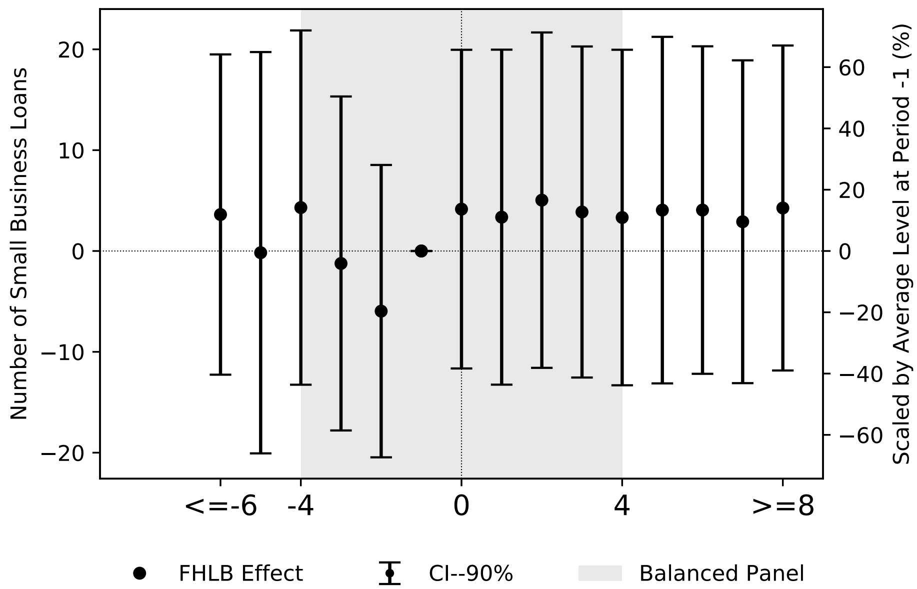
Note: This sample merger happened in 2003. The acquirer Illinois National Bank simultaneously merged two target banks: Palmer Bank and Pleasant Plains State Bank in the suburban area of Springfield, Illinois. The width of each ring belt is 2 miles.
Source: FDIC, FHFA, GIS.

Figure 1.13 FHLB Effect on Mortgage Lending Over Space



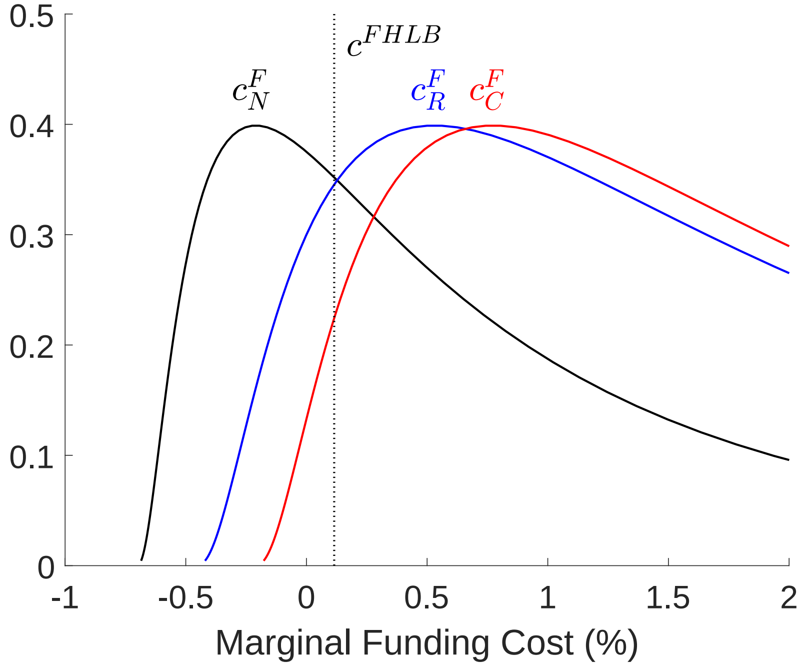
Note: This figure plots the effect on mortgage lending across different concentric rings. The results are obtained from estimating Equation (1.1). The bars plot 95% confidence intervals for each point estimate. Robust standard errors are clustered at the event level.
Source: FDIC, FHFA, HMDA, McDash, author's own calculations.

Figure 1.14 Effect of FHLB Funding on Small Business Loan Originations



Note: This figure plots the effect of FHLB funding access to lenders' small business loan originations, obtained from estimating Equation (1.1). The left y-axis measures the effect in absolute mortgage originations, and the right y-axis rescales the effect by the baseline mortgage originations at event year -1. The regression controls event-year fixed effect, event-branch fixed effect and county-year fixed effect. The bars plot 90% confidence intervals for each point estimate. Robust standard errors are clustered at the event level.
Source: FDIC, FHFA, CRA, author's own calculations.

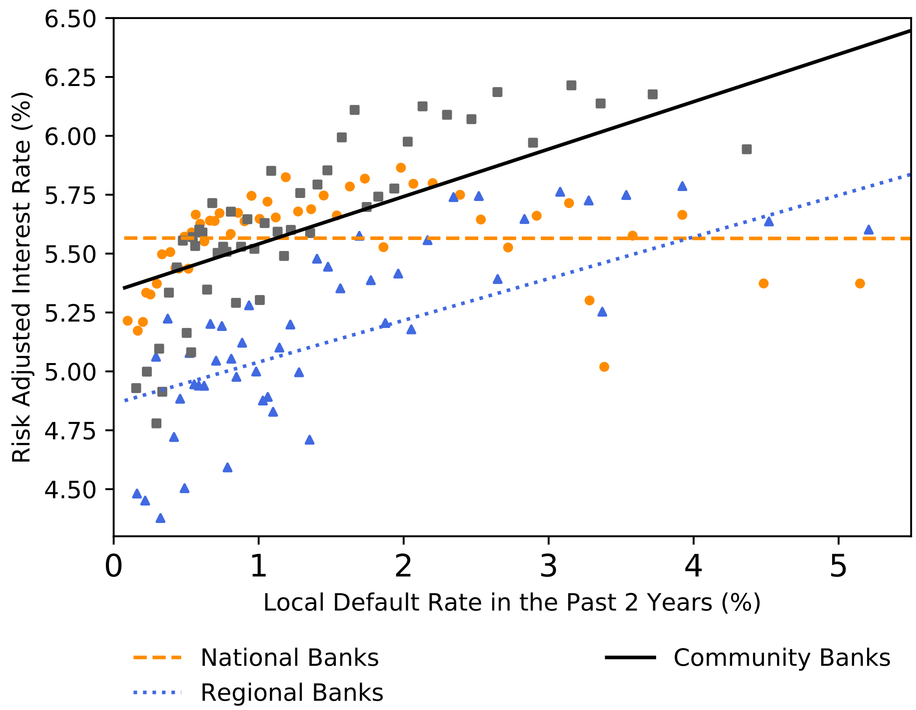
Figure 1.15 Estimates of Funding Cost



Note: This figure plots the offered price of FHLB advances for the three groups of banks: C_N^{FHLB} is for national banks, C_R^{FHLB} is for regional banks, and C_C^{FHLB} is for community banks.

Figure 1.16 Model Fit of Mortgage Interest Rates

(a) Empirical Interest Rates



(b) Simulated Interest Rates

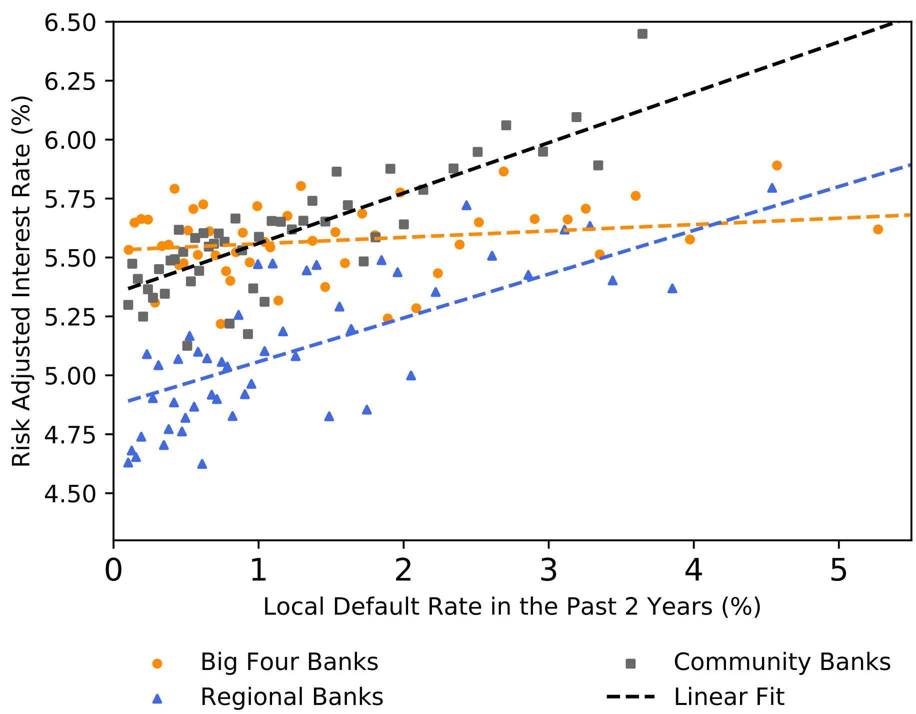
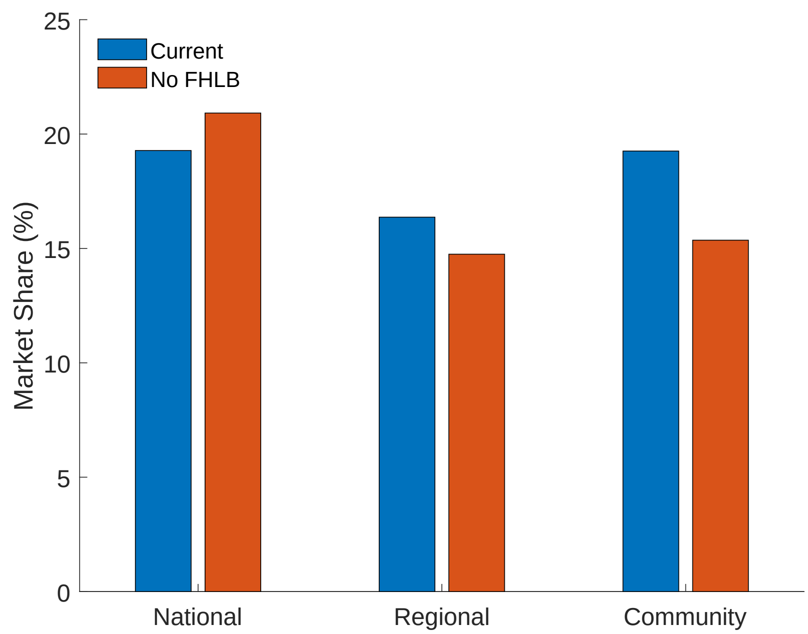
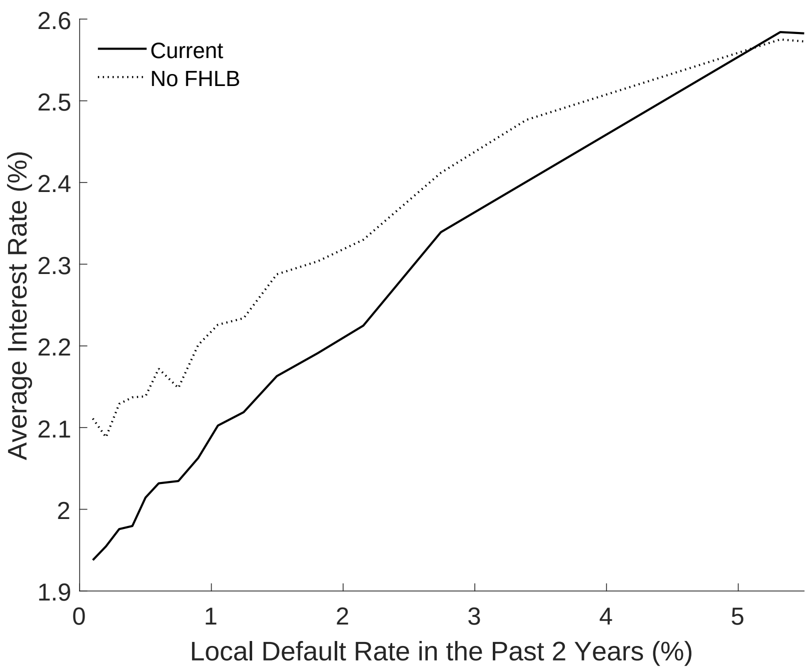


Figure 1.17 Counterfactual 1: Shift of Market Structure after Removing FHLB



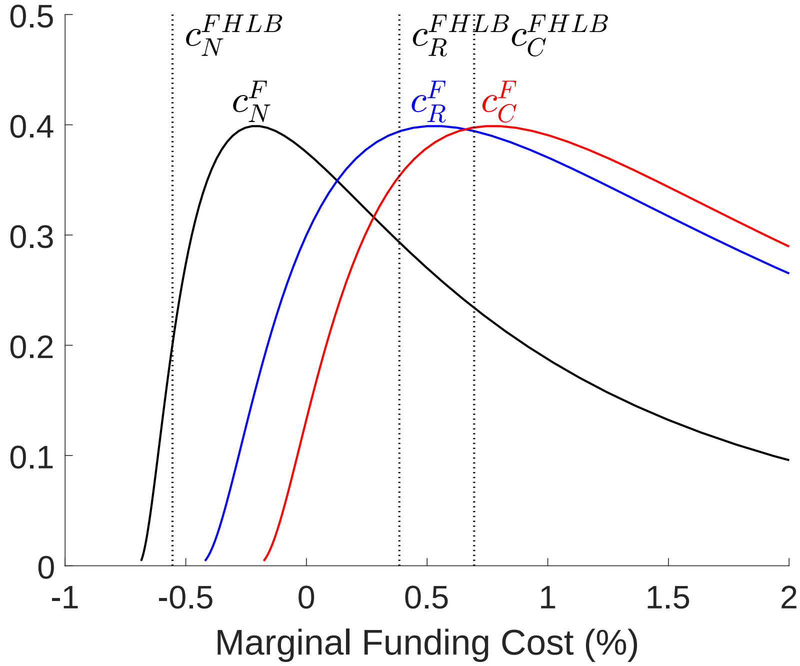
Note: This figure plots the market share of banks of different sizes for the simulated equilibrium with FHLB (blue) and the counterfactual without FHLB (orange).

Figure 1.18 Counterfactual 1: Average Mortgage Rates across Different Areas



Note: This figure plots market mortgage rates across markets with different local economic conditions for the simulated equilibrium with FHLB (solid line) and the counterfactual without FHLB (dash line).

Figure 1.19 Counterfactual 2: FHLB Advance Price Schedule



Note: This figure plots the cost of FHLB advances relative to the estimated funding cost for the three groups of banks. The black line and FHLB advance rate C_N^{FHLB} are for national banks, the blue line and C_R^{FHLB} are for regional banks, and the red line and C_C^{FHLB} are for community banks. The price schedule is made so that the average funding cost is the same as in the current equilibrium, but the market structure is the same as if there were no FHLB in the first counterfactual (orange bars in Figure 1.17).

Tables

Table 1.1 Sample Descriptive Statistics

	Non FHLB Target (1)	FHLB Target (2)	Difference within Merger (3)	p-value (4)
Panel A: Sample Size				
Multi-Target Mergers	174			
Target Banks	250	254		
Target Branches	2051	1170		
Panel B: Target Bank Characteristics Before Mergers (Unit: $Million)				
Total Asset	13,735	13,969	11,587	[0.19]
	(86,543)	(104,154)	(8,749)	
Total Deposit	9,068	9,452	5,662	[0.26]
	(58,849)	(69,608)	(5,009)	
Total Lending	7,890	8,468	5,959	[0.21]
	(47,297)	(57,534)	(4,743)	
Non-Performing Loan Ratio	0.01	0.02	-0.00	[0.86]
	(0.02)	(0.02)	(0.00)	
Loan Loss Ratio	0.02	0.02	0.00	[0.42]
	(0.01)	(0.01)	(0.00)	
Real Estate Ratio	0.60	0.65	-0.02	[0.15]
	(0.25)	(0.26)	(0.02)	
C&I Ratio	0.16	0.14	-0.00	[0.90]
	(0.11)	(0.10)	(0.01)	
Branch Count	112	114	39	[0.42]
	(589)	(602)	(49)	
Panel C: Census Tract Characteristics in 2000 Census				
Median Income	45,101	46,842	-731	[0.70]
	(20,327)	(21,454)	(1,864)	
House Unit	2,231	2,380	39	[0.64]
	(1,131)	(1,494)	(82)	
Home Ownership	0.62	0.64	-0.01	[0.36]
	(0.22)	(0.22)	(0.01)	
Minority Fraction	0.20	0.18	0.02	[0.11]
	(0.20)	(0.18)	(0.01)	
Educated Fraction	0.65	0.64	0.01	[0.58]
	(0.18)	(0.18)	(0.02)	
Mortgagor Fraction	0.69	0.69	-0.00	[0.99]
	(0.15)	(0.16)	(0.01)	
# of Bank Branches	4.32	5.02	-0.48	[0.14]
	(3.88)	(4.73)	(0.33)	

Note: This table summarizes the characteristics of the sample banks and their locating census tracts. Column (3) displays the difference within each merger event. Column (4) reports the p-value of the test that the corresponding difference is 0. Standard deviations/errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: FDIC, FHFA, GIS, FFIEC.

Table 1.2 FHLB Effect on Banks of Different Sizes

	Mortgage Originations		Mortgage Interest Rate (%)	
	(1)	(2)	(3)	(4)
FHLB	9.76***		-0.181**	
	(2.84)		(0.076)	
relative to baseline	16.3%		-3.2%	
FHLB×Regional		9.20**		-0.164**
		(3.72)		(0.079)
relative to baseline		15.2%		-2.7%
FHLB×Community		11.78***		-0.292***
		(4.23)		(0.095)
relative to baseline		20.7%		-4.3%
Event-Year FE	✓	✓	✓	✓
Event-Branch FE	✓	✓	✓	✓
County-Year FE	✓	✓	✓	✓
Obs.	62,260	62,260	56,099	56,099

Note: This table reports the effect of FHLB funding access to mortgage originations and rates, obtained from estimating Equation (1.2). Column (1) and (3) report the average effect for the full sample, while column (2) and (4) report effect for regional banks (total assets above $1 billion) and community banks (total assets below $1 billion), respectively. Below the point estimate, the row "relative to baseline" includes the size of the effect relative to the baseline of each outcome variable at event year -1. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. Standard errors in parentheses are clustered at the event level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: FDIC, FHFA, HMDA, Attom, McDash, author's own calculations.

Table 1.3 Effect of FHLB Funding on Market Interest Rates

Dependent Variable	Local Market	Treated Bank	Other Lenders	Other Lenders (National Banks)	Other Lenders (Small and Non-Banks)
	(1)	(2)	(3)	(4)	(5)
$FHLB$	-0.083**	-0.181**	-0.074*	-0.031	-0.093*
	(0.037)	(0.076)	(0.042)	(0.052)	(0.049)
Event-Year FE	✓	✓	✓	✓	✓
Event-Branch FE	✓	✓	✓	✓	✓
County-Year FE	✓	✓	✓	✓	✓
Cluster	Event	Event	Event	Event	Event
Obs.	152,658	56,099	96,329	29,830	66,499

Note: This table reports the effect to the market interest rates of the mortgages after a local bank joins FHLB, obtained from estimating Equation (1.2). Column (1) reports the effect for all lenders in the local market. Column (2) reports the effect for the treated banks, while column (3) reports the effect for lenders except for the treated banks. Column (4) illustrates the effect for national banks that are in the same market with the treated banks, column (5) focused on small banks (regional and community banks) and non-banks in the same market with the treated banks. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. Standard errors in parentheses are clustered at the event level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: FDIC, FHFA, HMDA, Attom, McDash, author's own calculations.

Table 1.4 Effect of FHLB Funding on Market Mortgage Rates (Triple Diff)

Dependent Variable	Market Mortgage Rates (%)				
	Safe Market	Risky Market	Full Sample	Non-GSE	GSE Loans
	(1)	(2)	(3)	(4)	(5)
Post×$FHLB$×Good Market			-0.037*	-0.048**	-0.021
			(0.019)	(0.024)	(0.016)
Post×$FHLB$	-0.096**	-0.065*	-0.061**	-0.097**	-0.028
	(0.045)	(0.038)	(0.030)	(0.041)	(0.023)
Event-Year FE	✓	✓	✓	✓	✓
Event-Branch FE	✓	✓	✓	✓	✓
County-Year FE	✓	✓	✓	✓	✓
Cluster	Event	Event	Event	Event	Event
Obs.	2,303,434	2,405,784	4,709,218	2,820,510	1,888,688

Note: This table reports the effect to the market interest rates of in both good and bad markets after a local bank joins FHLB, obtained from estimating Equation (1.2). Column (1) and (2) still use the difference-in-differences specification, and report the effect for safe and risky markets, receptively. Markets are defined as safe if it is located in a county where the mortgage default rates in the past two years are below the national median. Column (3) further interact Post×$FHLB$ with the indicator of safe markets (triple diff). Column (4) and (5) apply the triple diff regression to GSE securitized mortgages, and non-GSE securitized mortgages receptively. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. Standard errors in parentheses are clustered at the event level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: FDIC, FHFA, HMDA, Attom, McDash, author's own calculations.

Chapter 2

Match-Fixing in the Mortgage Finance Field: Credit Default Swaps and Moral Hazard

2.1 Introduction

The past few decades have witnessed a spectacular rise of the market for credit derivatives, such as credit default swaps (CDS). As the name suggests, these credit derivatives are largely viewed as redundant securities or side bets, that do not have any influence on the underlying assets. But in the public debates, it is not rare to hear that credit derivatives are blamed to cause trouble on the fundamental market. For example, mortgage CDS is still publicly referred to as one of the key drivers of the housing bubble in the early 2000.

In theory, the trading of credit derivatives would alter the incentives of market participants, and distort the fundamental outcomes (Bolton and Oehmke, 2011a; Parlour and Winton, 2013). Ex ante, the creditors might issue too much credit if they are able to insure against defaults through CDS trading. Mortgage CDS, in our example, swap out the default risk from the mortgage backed security (MBS) investors, thus drive up their demand, loosen their origination standards (Arentsen, Mauer, Rosenlund, Zhang, and Zhao, 2015), and exacerbate credit expansion to subprime borrowers. Ex post, given CDS participants' profit is a function of the underlying assets' performance, they would take actions to influence the fundamental outcomes. Similar moral hazard problems arise in the sports' games, and we could often see scandals where the gamblers bribe the referees or players to fix the matches. But whether this ex post distortion behavior is a significance phenomenon in the financial market remains unknown, to which an answer could contribute to the policy making process in the CDS market where different distortion behaviors have evoked close attention and preventative actions from the regulators.[1]

[1]Concurrently, the debate gets quite contentious whether "naked" credit derivatives are allowed to be traded between those who do not have any interest on the underlying assets. The concern that the speculative

To fill in this knowledge gap, this paper explores the ex post moral hazard problems in the subprime mortgage backed security (MBS) market, and empirically demonstrates the existence the CDS protection alters the incentives of market participants, which affects the performance of the underlying mortgages. Specifically, I find if there are CDS covering a mortgage pool, the CDS sellers would help the mortgage borrowers to refinance, which immediately unloads the CDS sellers' obligation to cover the loss of the underlying mortgages. Consequently, the mortgages in CDS referencing pools are more likely to be refinanced and less likely to default.

Using Moody's Lewtan ABSNet database, I collect a sample of subprime residential mortgages that were originated during 2003–2007, and securitized in the private label market. A mortgage is defined to be covered by CDS if it is securitized into a mortgage pool which is backing at least one bond (tranche) that are referenced by at least one CDS contract. In the final sample, roughly 1/3 of the 8,559,650 subprime mortgages are covered by CDS. An regression analysis with an exhaustive list of control characteristics demonstrates that CDC-covered mortgages are 3.6% more likely to refinanced, and 2.1% less likely to default. The differences sustain after controlling origination-year-by-CBSA fixed effect and mortgage servicer fixed effect.

An empirical challenge to the controlled regression analysis is that CDS sellers might endogenously write CDS on mortgages that have greater potential to refinance. This could be the case if CDS sellers are better informed about the unobserved mortgage characteristics, which are correlated with the mortgage borrowers' refinance behaviors. Then the observed differences between CDS-covered and non-CDS-covered mortgages are just driven by the CDS sellers' superior information instead of ex post actions. To mitigate this concern, this paper further explores the local randomization due to the discontinuous sale of mortgages by their originators. At the start of the mortgage securitizaion process, the originators issue mortgage loans for their daily business. They then stack many mortgages issued over a period and sell a whole chunk at a lower frequency (e.g. every one or two months). I assume the characteristics (both observed and unobserved) of the mortgages are slowly moving with time, and compare the mortgages originated just before and after the sale of a mortgage chunk. Mechanically, the mortgages that are originated before the sale will fall into a different mortgage pool from the ones originated right after. I then pick up the cases where the two mortgage pools have sharply different CDS coverage statuses and construct two balanced mortgage groups *a la* regression discontinuity design. Empirically, the treated and control groups are balanced across all different mortgage and borrower characteristics, but the CDS covered mortgages have significantly higher rate of refinance, and lower rate of default.

To better understand the mechanism of CDS seller's ex post distortion, I further look into the financial networks between CDS sellers and mortgage servicers. I hypothesize if the CDS seller and the mortgage servicer are in the same financial holding company, the

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use of credit derivatives might destabilize the market for the underlying asset motived EU to permanently ban "naked" CDS trading for European sovereign debt in 2011.

refinancing behavior of the mortgage borrowers can be more easily influenced through the servicer channel. Indeed, the affiliation of the CDS seller and mortgage servicer has a significantly positive interactive effect on mortgage refinance and negative interactive effect on the probability for loan default.

This paper provides the firsthand evidence to trace the outcome manipulation actions in the mortgage finance market. This evidence illustrates that credit derivative trading might give rise to crucial moral hazard problems, that motivate the derivative traders to influence the fundamental assets through ex post actions. For example, the change of the refinance and default rate for the underlying mortgages has huge price impact on the related securities. All the mortgage related securities are highly structured, thus any small change of the deep parameters will be largely amplified, and compromise the benefits of related market investors. Beyond the mortgage market, such outcome manipulation threatens market fairness, and distorts the hedging activities for other market participants. For example, if a pension fund wants to buy some mortgage CDS to hedge its overall exposure to housing market, it cannot achieve its goal. In particular, what it wants to hedge plummets, but what it uses as a hedge outperforms its hedged target because CDS seller has manipulated the performance of the underlying pools.

Literature review. This paper mainly relates to two lines of research. First, it contributes to the literature on CDS and their effect on underlying asset performance. Served as "side bets", credit derivatives including CDS should not affect the underlying assets in a frictionless world. However, many theoretical works have shown these credit derivatives could potentially play a role given the existence of various frictions. Duffee and Zhou (2001) and Arping (2014) show that they increase the credit supply from creditors given asymmetric information between creditors and debtors. Parlour and Winton (2013) incorporates contract incompleteness, and finds that CDS lead to inefficient monitors from the creditors. Bolton and Oehmke (2011b) considers renegotiation friction and shows that CDS can help to reduce the incidence of strategic default. However, lenders will "overinsure" in equilibrium, giving rise to an inefficiently high incidence of bankruptcy. In the empirical literature, Saretto and Tookes (2013) documents that firms with traded CDS can sustain higher leverage and borrow at longer debt maturities. Subrahmanyam, Tang, and Wang (2014) shows that the inception of CDS trading leads to higher credit risk of the referencing firm due to higher cost of creditor coordination. This paper complements this line of literature by focusing on the moral hazard friction ex post, and provides robust empirical evidence.

Second, this papers adds to the literature on the linkage between structured finance products and the housing market. Stulz (2010) provides a comprehensive discussion of the role of CDS in the recent financial crisis, and points out while many financial institutions incur huge losses in CDS trading, the primary drivers of the crisis are the financial institutions' misjudgment and misconduct. However, the prevalent securitization practice in the mortgage market has been shown to reduce the mortgage lenders' incentive to screen their borrowers (Keys, Mukherjee, Seru, and Vig, 2010; Purnanandam, 2011). Arentsen et al. (2015) directly investigates the CDS market, and argues that CDS coverage leads to higher default of subprime mortgages. This paper is the first in the literature to identify the outcome manipulation actions in the mortgage finance market, and shows that the CDS market participants directly influence the mortgage borrower behaviors after origination.

Overview. The paper proceeds as follows. Section 2.2 discusses the data and the institutional setting for the US mortgage market. Section 2.3 outlines the empirical strategy and documents the main results with a regression framework. Section 2.4 leverages a local randomization strategy to rule out the ex ante selection by the CDS sellers. In section 2.5, I employ interactive regressions to explore the mechanism of the CDS sellers' manipulation of mortgage performance. Section 2.6 concludes.

2.2 Institutional Background and Data Description

Institutional Background

The US mortgage market is characterized by the prevalence of securitization, which is seen as the most important financial innovation in the past few decades. After origination, mortgage loans are not usually held to maturity by the originators, which are usually banks, credit unions, or mortgage companies. Instead, a fast-growing share of mortgages are pooled and sold to financial intermediaries for securitization. During the securitization process, the cash flows from the mortgage pools will be structured into different bonds, or mortgage backed securities (MBS), and sold to final investors. Usually, different bonds have different seniorities and different degrees of risk according to their priority to receive cash flows. Typical final investors include pension funds, hedge funds, banks, and foreign financial institutions.

Before the financial crisis, there were two major mortgage securitization markets according to the types of financial intermediaries: agency MBS and private-label MBS. Agency MBS are securitized by three government or quasi-government agencies: Ginnie Mae, Fannie Mae, and Freddie Mac. These entities are either explicitly or implicitly backed by the full faith and credit of the US government,[2] and they provide guarantees to MBSs that they issue. Thus, agency MBSs are *de facto* free from credit risk. Private-label MBS are, instead, securitized by private financial institutions. Before the housing bust, large investment banks were very active in securitizing "subprime" mortgages, whose lenders either have very low credit scores or lack income documentation.[3]

As opposed to agency MBS investors, private-label MBS buyers must assume the credit risk of the underlying mortgages. However, they can choose to enter into a credit default

[2]Ginnie Mae bonds are backed by the full faith and credit of the US government. While Fannie Mae and Freddie Mac securities lack this same backing, a majority of the investors believe that these two agencies are backed by implied federal guarantee. This belief was realized when the government bailed them out in the mid of the financial crisis.

[3]These mortgages do not conform to government agency guidelines, thus cannot be securitized by the government agencies. Before the crisis, many scholars (Mian and Sufi, 2009) believe the growing demand for MBSs drive the expansion of credit to subprime borrowers and a boom of private-label MBS market.

swap (CDS) contract, which has been widely used in the corporate bond and sovereign bond market, to swap out the credit risk. A CDS contract works as an insurance on the underlying securities. In the case of underlying mortgage defaults, which lead to cash flow shortfall in their backed securities, the CDS seller, or the *de facto* insurer, will compensate the CDS buyer any cash flow shortfall, in exchange for a flow of fixed insurance premiums paid by the CDS buyer. Contrary to an ordinary insurance contract, the buyers do not have to hold insurable interests to enter into a CDS contract. CDS buyers can be the investors of the underlying MBS or some other investors that are betting on bad performance of the housing market. In some cases, the notional value of the CDS contracts can be multiple times as large as the underlying MBS because many CDS buyers do not hold any insurable interests. This actually increases CDS sellers' exposure to the default risks and elevates their incentive to improve the performance of the underlying mortgages, which exacerbates the match fixing phenomenon in the mortgage market.

An Anecdotal Match-Fixing Example

There is an anecdotal story in which a Texan brokerage firm, Amherst Holdings, managed to manipulate the mortgage payment to avoid default payments on CDS contracts it had sold to the investment banks (Zuckerman, Ng, and Rappaport, 2009). In 2009, Amherst Holdings sold CDS to the investors to guarantee the payment of a mortgage pool with a total balance of $27 million. The CDS contacts were sold to many investors, who did not have insurable interest, but wanted to short the housing market. The CDS buyers include JPMorgan Chase, Royal Bank of Scotland, and Bank of America. And the total bet (notional amount) reached $130 million, which was almost 5 times as high as the total balance of the underlying mortgage pool. Since it was deep in the financial crisis, the market was expecting that more than 90% of the underlying mortgage would default. Thus Amherst Holdings was able to collect premium payment worth more than $100 million, which was much more than the total balance of the mortgages it guaranteed.

In the end, Amherst Holdings took $27 million and paid back the principals for all the underlying borrowers, in which way all its insured obligation was immediately cleaned up.[4] And it still kept tens of millions dollars as its profit. While this case is quite extreme, it does exemplify that the CDS position might incentivize the CDS sellers to fix the mortgage performance ex post, given it directly affects their profit. And the goal of this paper is to test whether similar match-fixing behaviors are a significant phenomenon in the subprime mortgage market.

[4]Normally a third party cannot pay off loans directly for the mortgage borrowers. But if the amount of outstanding loans falls to less than 10% of the original pool, which was the case in this example, the mortgage servicer—or company that collects mortgage payments from homeowners and forwards them to investors who own the securities—can buy them and make bondholders whole.

Data

I use Moody's Lewtan ABSNet database to construct a sample of subprime[5] residential mortgages originated from 2003 to 2007.[6] Lewtan ABSnet is an industry leading data source that provides extensive performance metrics and origination information on almost all privately securitized mortgages. For each loan, we can observe the loan amount, securitization amount, combined loan-to-value (CLTV) ratio, credit score, prepayment penalty status, loan type, lien status, purchase purpose and documentation status, at the point of origination. Also, we can track each loan's payment history, and tell whether a loan is current, prepaid or defaulted at any month after origination.

To identify the reasons for prepayment, I supplement the Lewtan ABSnet data with ATTOM, which contains detailed property ownership and associated home loan information from the public records. At the property level, ATTOM records all ownership transfers and detailed information on the associated mortgages, including loan amount, interest rate type, and distress indicator.

Following Griffin and Maturana (2016) and Bartlett et al. (2018), I merge ABSnet with ATTOM through a matching algorithm.[7] Subprime mortgages from Lewtan ABSnet are matched with loan records in ATTOM if they agree with loan amount, origination date, termination date, default status and interest rate type. The algorithm successfully matches more than 63% of the prepaid mortgages, among which 60% are considered high quality matches.

For the purpose of this paper, I categorize the merged prepaid subprime mortgages (2.66 million) in Lewtan ABSnet into three groups according to their prepayment motivation. A prepaid mortgage is classified as moving (0.33 million) if there is at one real sale happening within 2 months around the prepayment date for the linked property in ATTOM. If the borrower is not moving and he or she takes out at least one new loan collateralized by the same property within 2 months around the prepayment date, the prepaid mortgage is classified as refinance (1.91 million). The rest of the prepaid mortgages are classified as normal pre-payoff (0.42 million).

Summary Statistics

Our final data sample contains 8,559,650 subprime mortgages in 4,756 mortgage pools that are originated during the 2003–2007 period. The number of the mortgage pools in this paper is very close to that in Arentsen et al. (2015), where they explore the LoanPerformance database from CoreLogic. Roughly 1/3 of the mortgage pools are covered by CDS protections, as can be seen from panel A of Table 2.1. The proportion of mortgage pools with

[5]Subprime mortgages are defined as those that back private-label mortgage-backed securities marketed as subprime, as in Mayer and Pence (2008) and Palmer (2015).

[6]This paper focuses on 2003 to 2007 period as in Arentsen et al. (2015), for it includes more than 90% (need to be verified) of the subprime mortgages that are ever issued

[7]I thank Justin Chiang and Paulo Issler for their tremendous help with the matching process.

CDS coverage is smaller than the level of 54.5% in Arentsen et al. (2015) since I do not observe the CDS contracts expiring or terminated before 2012. So I might misclassify some CDS-covered mortgage pools as non-CDS-covered in the case that the mortgage pools were covered by CDS, but the protection ended before 2012. This will mitigate the difference of the treated and control groups, and bias the observed effect of CDS coverage towards 0. On the other hand, the CDS-covered mortgage pools that I pick up tend to be longer positions, in which case the transaction participants have stronger incentives to influence the mortgage borrowers behaviors.

Panel B of Table 2.1 provides summary statistics for the borrowers and loans in our sample. Column (1) and (2) report the characteristics for non-CDS-covered and CDS-covered subsamples respectively. The CDS-covered mortgages are of similar size with those without CDS coverage. And the majority of the mortgage principal in the securitization pools are securitized for both subsamples. In the dimension of credit quality, the borrowers in the CDS-covered pools have slightly lower credit scores, since the investors in these mortgages are more concerned about credit risk, and are more likely to demand CDS protection on their MBS positions. On average, the mortgage borrowers in our sample have relatively low credit scores, with average FICO of 625. This is consistent with the common perception for the subprime mortgage borrowers. The borrowers in both subsamples have similar level of cumulative loan-to-value ratio, with 1.9 percentage points lower for the borrowers in the CDS-covered mortgage pools.

As to contract features, CDS sellers tend to pick mortgages with no prepayment penalty to underwrite protections on. The average proportion of the mortgages that have prepayment penalty in the CDS covered pools are 40.44%, 4.6 percentage points lower than those without CDS coverage. This strategic choice would reduce their cost to refinance these mortgages after origination. CDS investors also prefer adjustable rate mortgages (usually with lower teaser rate in the beginning few years), whose borrowers are more likely to refinance when the interest rate resets to its normal level. Noticeably, fewer of the CDS-covered mortgages have balloon payment features. Other than that, both categories have comparable levels of interest-only feature, first-lien status, investment purpose and documentation completeness. As consistent with other studies, the subprime mortgages in this paper have very low level of full documentation (53.58%), and high level of adjustable interest rate (66.31%). Other than that, the majority of the subprime mortgages are fist-lien mortgages and not for investment purposes, similar as in the prime mortgage market.

2.3 Main Results

In this part, I test the hypothesis that CDS sellers are encouraging the borrowers to refinance their mortgages after origination to reduce the default risk. Specifically, I demonstrate that mortgages with CDS coverage are more likely to be refinanced and less likely to default. This result survives a variety of different specifications.

Regression Specification

I test the treatment effect of CDS coverage with the following regression specification (2.1). Y_i is the outcome of the mortgages, and it can be mortgage prepayment, refinance, default, etc. D_i^{CDS} is a dummy variable, which equals 1 if a mortgage is in a pool that is backing at least one bond that some outstanding CDS are referencing, and 0 otherwise. Its coefficient β measures the effect of CDS coverage on the corresponding outcome Y_i. X_i incorporates an exhaustive list of control variables to make the mortgages comparable in the observable dimensions. They include CLTV, credit score, loan purpose, as well as indicators of prepayment penalty, interest only, balloon payment, ARM, first lien, investment house and full documentation.

$$Y_i = \alpha + \beta D_i^{CDS} + \gamma X_i + \epsilon_i \tag{2.1}$$

To make sure the difference is not coming from CDS sellers' strategic choice over geographies or market timing, I also include origination year by CBSA fixed effect in my main specification. I also include mortgage servicer fixed effect to make sure the difference performance of the two subsamples are not driven by the facts that they are serviced by different servicers. This paper chooses to cluster the standard errors at the mortgage pool level, since this is where the true variations come from.

Regression specification (2.1) applies the linear probability model to estimate the CDS coverage effect. In the implementation, I also apply the logit model as a robustness test. The results are very similar with the linear probability model, which indicates that the non-linearity at the tail distribution is not first order.

Mortgages with CDS Coverage Have Higher Prepayment Rate

Table 2.2 demonstrates the estimation of the CDS coverage effect on mortgage prepayment with different regression specifications. Column (1) controls observed borrower and loan characteristics and origination year fixed effects. To match geographical distribution of the mortgages, column (2) further includes core-based statistical area (CBSA) fixed effects. Column (3), instead, includes Origination Year $\times$ CBSA fixed effects to compare mortgages only originated in the same year and located in the same CBSA. I control servicer fixed effects in specification (4) and resort to a logit model in column (5).

Across all different specifications, CDS coverage has a significantly positive effect on mortgage prepayment. Specifically, if I control the observed borrower and mortgage characteristics, as well as the origination year fixed effects in column (1), the point estimate of the CDS coverage effect is 5.4%. Column (2) and (3) further control CBSA fixed effects in two different ways. But they barely change the result, which indicates that the CDS covered mortgages do not distribute very differently from those not covered by CDS geographically. But if I further add the servicer fixed effects into the regression, the CDS coverage effect shrinks a bit to 4.2%. This is my preferred specification, since it accounts for the fact that the servicers for the mortgage pools that are covered by CDS are different from those not covered by CDS. Column (4) shows that for two mortgage with similar characteristics, originated to similar borrowers in the same year and same CBSA, and that are served by the same servicer, the one with CDS coverage is 4.2% more likely to be prepaid in its life than the other that is not covered by CDS. For robustness, I also apply a logit model with the same set of control variables in column (5), the result is of the same magnitude with that the linear probability model suggests.

Here prepayment is a general form of mortgage termination if the balance of the mortgage is paid off ahead of the schedule in the mortgage contract. Due to the special arrangement of payment (equal installment, or with various types of small deviations) and long-term feature for mortgage contracts, the majority of the mortgages end up being prepaid if not defaulted.[8] Prepayment can be motivated by three reasons. First, the majority of the prepayment takes the form of refinancing. Refinancing can be for the purpose of lowering interest rates or cashing out from home equity. For borrowers who have adjusted-rate mortgages that offer low initial "teaser" rates, they might want to use a new loan to replace their outstanding mortgage if they can reduce their effective mortgage rate. As opposed to the general mortgage pools, the majority of the subprime mortgages are adjustable rate, of which most have low initial "teaser" rates. So refinancing is also important for the borrowers in the subprime sample. Another important reason for refinancing is to borrow more from the same collateral, which is often referred to as "cash-out refinance". Both types of refinancing are driven by cost reduction incentives. Second, a mortgage has to be prepaid if the borrowers choose to move out from the collateralized house. This type of prepayment is usually driven by non-economic incentives, including job changes or other exogenous life events. Finally, mortgage prepayment could take place if the borrowers choose to pay off the remaining balance without taking out a new loan or moving. In the next subsection, I will break down the mortgage prepayment according to different reasons to see which channel is driving the prepayment results.

Mortgages with CDS Protection Are More Likely to Be Refinanced

By merging the mortgages in Lewtan ABSnet into the property information in ATTOM, I am able to identify the reasons for mortgage prepayment. Precisely, if there is a ownership change of the property within 2 months around the mortgage prepayment date, I identify the mortgage prepayment to be driven by moving. If there is not an ownership change during this period, and there is at least one new loan originated during this period, we can infer the previous mortgage is replaced by new loans, and mark the prepayment as refinance. The rest of the prepayment activities are just normal pre-payoff by the borrowers.

[8]In my sample, 53% of the subprime mortgages are prepaid over their life. For prime mortgages, according Federal Housing Finance Agency (2018), 10–20% of the 30-year fixed-rate agency mortgages are prepaid every year.

In Table 2.3, I report the CDS coverage effect for each category of the mortgage prepayment. For each prepayment category, I apply both the linear probability model and logit model to estimate the CDS coverage effect, controlling borrower and loan characteristics, origination year by CBSA fixed effects, and servicer fixed effects.

We can see that almost all of the CDS coverage effect on prepayment is driven by mortgage refinance. Mortgage pools with CDS coverage have 3.6% more mortgage refinance rate than those without CDS coverage, given other characteristics are identical. This difference dwarfs other two types of prepayment, including moving and normal pre-payoff. As we notice, the effect of CDS coverage on moving-driven prepayment is marginally significant. The effect is very small, both statistically and economically. This effect is mainly due to property short-sale, which is a preferred process to liquidate the borrowers' properties (Zhang, 2018). In the case of mortgage distress, CDS sellers would also have an incentive to encourage the borrowers to short-sale his or her property to recover the most of collateral value. These short-sale transactions will show up in the moving prepayment if the sale of the property is enough to cover the mortgage remaining balance.

Normal pre-payoff, as a control group, is not affected by the CDS coverage. This is supportive to the ex post manipulation channel, as opposed to the selection channel. If the CDS sellers just pick up mortgages with unobservably good characteristics, instead of exerting ex post effort to refinance the borrowers, we would expect to see the same effect on normal payoff, which is not the case in the data.

Table 2.4 reports the CDS coverage effect on mortgage refinance using different regression specifications. Similar with mortgage prepayment, CDS coverage consistently contributes to mortgage refinance by about 4 to 6 percentage points. This result is robust across origination year, geographic area and servicer controls. With the preferred specification in column (4), a mortgage with CDS coverage is 3.6% more likely to be refinanced than those without CDS coverage.

Will the mortgage borrowers' decision influenced by a third party? To answer this question, we need to understand a little background about how refinance works in practice. As explained in the last subsection, mortgage borrowers choose to refinance to lower their effective interest rate, or to extract more debt from their home collateral. The literature has pointed out that the mortgage borrowers under-explore refinance opportunities to lower their effective interest rate, especially for the poorer and less educated borrowers. There are many reasons for the inertia for the borrowers to react to the rate-reducing incentives. An important one is that the decision to refinance a mortgage is challenging for many households, so the borrowers need to be financially literate enough to make the right decision. And the borrowers need to pay certain fee for the refinancing processing, which might be difficult for liquidity constrained borrowers. Campbell (2006) documents 12–14% of households were paying more than 2 percentage points above the prevailing mortgage interest rate in the late 1990s and early 2000s; this figure rose above 25% in 2003 after steep drops in interest rates made refinancing particularly advantageous. So in practice, many third parties, including mortgage originators, servicers, or other lending competitors, would nudge the borrowers to refinance, by marketing calls/emails, or other advertisement campaigns. Although costly, these refinance "reminders" are the mortgage originators' or servicers' fiduciary duty, as well as a good investment since refinancing could generate origination profit for the originators of new loans.

The intensity of the refinance reminders would be mortgage-dependent, and it will affect the likelihood of refinancing for the borrowers. The results in Table 2.4 show that if the mortgage is securitized into a mortgage pool whose performance determines the payout of some CDS contract, the CDS sellers will influence the refinance reminding intensity to increase the refinance rate for the borrowers in their pools. In the later sections, I will explore more on which parties would help them implement this strategy.

CDS-Covered Mortgages Default Less

Finally, let us look at how CDS coverage would affect mortgage default performance. Since greater proportion of mortgages are refinanced in the CDS covered pools, we can expect the mortgage default would be less. Table 2.5 verifies this premise.

Table 2.5 shows the mortgages with CDS coverage tend to have about 2% lower default rate than those without CDS. This result is robust after controlling mortgage and borrower characteristics, origination year, CBSA and mortgage servicers. Both linear probability and logit models suggest the same conclusion. The CDS sellers' strategy of refinancing is effective so that it indeed moves some risky borrowers out of the mortgage pools that they cover, and lower the corresponding default rate. The reduction of the default rate is statistically significant and economically meaningful.

Before I move to how the CDS sellers are able to implement this refinancing strategy, let me briefly discuss the efficiency of this refinance strategy. In a typical subprime mortgage pool from my data sample, 53% of the borrowers (prepayers) end up prepaying their mortgages, 29% (defaulters) choose to default, and the rest 18% (normal borrowers) pay back their mortgage as scheduled. If the CDS sellers were able to perfectly distinguish the borrowers and pinpoint the ones they prefer for refinancing, the most efficient strategy for them is to target all defaulters. With this first-best strategy, all incremental refinanced borrowers are defaulters, there should be a one-to-one relationship between refinance increase and default decrease. So the first-best strategy would lead to a 3.6% decrease of the mortgage default. But our observed default decrease is 2.1% with the preferred specification in column (4) of Table 2.5, which indicates the practical efficiency is lower than the first-best scenario. Actually, the first-best strategy does demand some unrealistic requirement on the CDS sellers. To implement this strategy, they need to acquire enough information to perfectly predict each borrower's performance. So the efficiency of the first-best strategy should be thought of as a upper bound on any practical implementation of the refinancing strategy.

Now let us consider another random-refinance strategy, where the compliant refinanced borrowers are a random sample from the mortgage pool. With this strategy, the incremental refinanced borrowers are a mix of defaulters and normal borrowers, and their relative distribution is the same as the mortgage pool (29:18). In this case, the incremental 3.6% refinancers consist of 62% defaulters and 38% normal borrowers. And the realized default decrease should be 2.2%, which is still larger than our observed level of default rate decrease. To interpret this result, let us think of under what circumstance the random-refinance strategy can be implemented. For example, if the CDS sellers do not have any information on the mortgage borrowers, but randomly mail refinance pamphlets and coupons to the mortgage borrowers, and all the borrowers have the same probability of compliance to use the coupons to refinance their mortgages. This would lead to a 2.2% decrease of the mortgage rate. The CDS sellers could increase their efficiency from this benchmark by targeting more likely defaulters based on their inside information. But there is the other force driving down the efficiency if the defaulters' compliance probability is lower than the normal borrowers, which is very likely since defaulters are more liquidity constrained and have more moral hazard problems. In an extreme case that the defaulter never comply to CDS sellers' refinancing promotions, the default rate would not change. The observed lower efficiency level suggests that the second unequal-compliance force slightly dominates the first targeting force. But a significant decrease of default rate tells us that some defaulters did comply to CDS sellers' actions.

2.4 Casual Analysis with Local Randomization

In section 2.3, I compare the mortgages with and without CDS coverage using a regression framework and controlling an exhaustive list of observed variables. The results show compelling patterns of strong CDS effects. Even if I have controlled many mortgage characteristics, as well as origination year, CBSA and servicers, there might be some unobserved characteristics that are observed and used by the CDS sellers. In that case, the observed difference in refinance and default performance is due to ex ante selection, instead of ex post actions.

To rule out the selection story, this part further explores the local randomization due to the discontinuous sale of mortgages by their originators to achieve more convincing identification. At the start of mortgage securitizaion process, the originators issue mortgage loans for their daily business. They then stack many mortgages issued over a period and sell a whole chunk at a lower frequency (e.g. every one or two months). I assume the characteristics (both observed and unobserved) of the mortgages are slowly moving with time, and compare the mortgages originated just before and after the sale of a mortgage bulk. Mechanically, the mortgages that are originated before the sale will fall into a different mortgage securitization pool from the ones originated right after. I then pick up the cases where the two mortgage pools have sharply different CDS coverage statuses and construct two balanced mortgage groups *a la* regression discontinuity design.

Local Randomization Around Mortgage Sales

Figure 2.1 depicts mortgage origination counts for a specific originator from the beginning of 2003 to the mid of 2004. It aims to serve as an example to illustrate how mortgage origination and sale works. The length of the bars marks the volume of mortgage origination for different dates. The bars with the same color represent the mortgages in the same securitization pool. And we can clearly see this originator focuses on one specific mortgage pool during one period. On average, this originator is issuing about 200 mortgages on a daily basis. But it does not sell the loans all the time. Instead, it stacks the originated mortgages in its inventory, and sells a whole bulk very 2 months. The date of the mortgage sale is called "cutoff date" by the practitioners. For this specific originator, we can tell from this figure that its cutoff date is on the first date of very odd month. As a result, we can roughly see the color is changing every 2 months.

The potential local randomization comes from the cutoff date, around which the two groups of mortgages are very much comparable, but fall into different mortgage pools, thus might have different CDS coverage statuses.

The black dash line plots the realized proportion of CDS coverage for the mortgages in each date. Here it is important to point out that the mortgages in the same pool have the same CDS coverage status by definition. In the case of this mortgage originator, the mortgages sold before October 31, 2003 were not covered by CDS, which the mortgage pools sold after that date happened to have CDS coverage.

We will compare the mortgages issued just before the cutoff date October 31, 2003 (control group), and those issued right after (treated group). And the local randomization comes from the discontinuous change of the CDS coverage at this cutoff date. Our identification assumption is that the characteristics of the issued mortgages are slowly moving with time. Under this assumption, the mortgages issued on October 30 or 31 do not significantly different from those issued on November 1 or 2. But the realized CDS coverage statuses are sharply different for the control and treated groups. The CDS coverage status of the control group is inherited from the whole black pool, and the treated group is inheriting CDS coverage from the teal pool. There might be many reasons that the black pool and the teal pool have different CDS coverage statuses. Maybe the investors of the teal pool were hit by some exogenous shocks that encouraged them to buy CDS protection. Or maybe the market knew the mortgages were getting worse with time due to the ever loosening origination standard, thus the later mortgage pools were perceived to be riskier, and need CDS protection. However, this would not harm our identification, since the pool level decisions were made based on the average mortgages in that pool, while I focus on a small window of origination dates overlapping the two mortgage pools. As long as the origination standard was slowly relaxed, the treated and control groups should be fairly comparable.

Detecting Cutoff Dates and Constructing the Local Randomization Sample

Mortgage originators sell a bulk of mortgages at sparsely distributed cutoff dates, which creates an opportunity for identification. But the exact cutoff dates are not observed. In practice, there is no industry standard set of cutoff dates. Instead, the cutoff dates are chosen by individual originators separately. Moreover, not every cutoff date is useful to identify the CDS coverage effect. If the mortgage pools on the two sides of the cutoff date are both covered by CDS, or either is covered, there would not be any variations that can be used to identify the CDS effect.

To detect useful cutoff dates, I develop a algorithm that aims to address both of above problems simultaneously. For each mortgage originator k at each day t, I compute the share of mortgages that ex post have CDS coverage s_{ct}^{CDS}. Then the useful cutoff dates will be the set of dates that have daily absolute changes of CDS coverage share above some threshold $\bar{s}$.

$$\mathcal{E}_k = \{(k,t) : |s_{kt}^{CDS} - s_{kt-1}^{CDS}| \geq \bar{s}\} \tag{2.2}$$

For a reasonably large $\bar{s}$, the dates that fall in $\mathcal{E}_k$ are extremely likely to be cutoff dates, since we would except a close to zero change of the CDS coverage share unless the mortgages originated on the two consecutive dates fall in different mortgage pools. For example, in Figure 2.1 I plot the s_{ct}^{CDS} for this specific originator with the black dash line. For any dates inside a bulk of colored area, the dash line never jumps sharply. If an originator does not have this "originate daily and sell bulks at cutoff dates" model, there would not be sharp pool switches, and the mortgage CDS coverage share should not jumps sharply either. This algorithm also rules out less useful cutoff dates by definition. Mechanically, the set of identified cutoff dates require the CDS coverage change larger than $\bar{s}$. In the example of Figure 2.1, only 2003-11-01 and 2004-05-01 will be included, while other clearly seen cutoff dates will not be included into $\mathcal{E}_k$ because of CDS coverage changes less than $\bar{s}$.

The choice of $\bar{s}$ involves some discretion. A small $\bar{s}$ would mistakenly include some undesired and less powerful dates, while a large $\bar{s}$ would restrict the size of the data sample. In this paper, I set $\bar{s} = 0.5$. With this choice, I am able to pick up 87 originator-cutoff-date pairs. I call each pair an event. So the event set is the union of identified cutoff dates from all originators.

$$\mathcal{E}(\bar{s}) = \cup_k \mathcal{E}_k(\bar{s}) \tag{2.3}$$

For each event (k,t), I collect all mortgages originated by k in the time window $[t-5,\ldots,t,\ldots,t+5]$. To facilitate the regression exercises in the later part, I reorder the calendar dates for a subset of the events. Actually, the identified events can be grouped into two categories according to the sign of the CDS coverage changes $(s_{kt}^{CDS} - s_{kt-1}^{CDS})$. A positive share difference means the mortgages after the cutoff dates have more CDS coverage ex post, while a negative share difference indicates the opposite. To make this more similar to a even study framework, I reverse the date order for the cutoff dates with negative share difference, so the treated group always falls on the right side of the cutoff dates.

Table 2.6 reports summary statistics for the 26,372 mortgages in the identified local randomization sample (the set of loans originated within 5 days of each of the detected cutoff dates) used in estimation. Panel A reports loan and borrower characteristics, which are very similar with those in the full sample as reported in Table 2.1. Panel B summarizes the outcome variables, including prepayment (refinance, moving, normal pre-payoff) and default. Different from the full sample, the overall prepayment rate in this sample is lower, and the default rate is slightly higher. Here we can see that the prepayment is broken down into three categories according to the reasons. But the sum of their means (25%) are not equal to the overall prepayment rate (36%). This is because the breakdown is done by merging ABSnet with ATTOM, but not all mortgages can be successfully merged. The missing 9% is due to the failed merges.

First-Stage Results

To validate my research design, I present a series of diagnostics designed to test whether my local randomization sample meets the two main identifying assumptions required for valid estimation. First, similar with the regression discontinuity design, the probability of treatment (i.e., CDS coverage) is discontinuous at detected cutoff dates. Second,a valid design requires that any borrower and loan characteristics (observed or unobserved) that could influence loan outcomes change only continuously at the cutoff dates. This smoothness condition requires that borrowers on either side of a cutoff date are otherwise similar, such that borrowing outcomes on either side of a cutoff date would be continuous absent the difference in treatment induced by the sale of a bulk of mortgages at the cutoff date.

Figure 2.2 plots the average CDS coverage share for mortgages in the short window around the identified cutoff dates, which demonstrates the time pattern of the CDS coverage. It illustrates the smoothness in the conditional expectation function except for the cutoff date, at which we can clearly see a sudden jump of the CDS coverage status. This figure confirms the slow moving feature of CDS coverage, and the sudden switch due to the bulk sale of mortgages at cutoff dates.

To formally estimate the average magnitude of the CDS coverage discontinuity across the cutoff dates, I resort to a regression discontinuity regression.

$$D^{CDS}_{ikt^*+\tau} = \beta_1\tau + \delta\mathbf{1}(\tau \geq 0) + \beta_2\tau\mathbf{1}(\tau \geq 0) + \alpha_{kt^*} + \gamma X_{ik} + \epsilon_{ikt^*+\tau} \tag{2.4}$$

for any originator-cutoff-date pair (k, t^*) in $\mathcal{E}(\bar{s})$. $D^{CDS}_{ikt^*+\tau}$ is the dummy variable equal to one if mortgage i originated by lender k at τ days after (or $-\tau$ days before) the cutoff date t^* is covered by CDS ex post. It will be replaced by other outcome variables (e.g. other mortgage characteristics and performance) in the reduced form regressions. $\mathbf{1}(\tau \geq 0)$ is an indicator variable equal one if the mortgage i is originated after the cutoff date ($\tau > 0$, or treated). α_{kt^*} controls the event fixed effect, and X_{ik} controls the loan and borrower characteristics, origination year by CBSA fixed effects and the servicer fixed effects, as in Equation (2.1). In this specification, δ is the key coefficient and quantifies the size of CDS coverage shock due to the fact that the mortgages on the two sides of the cutoff dates fall into different mortgage pools that happen to have different CDS coverage statuses, although they are otherwise similar mortgages.

Table 2.7 reports the results of this exercise. The mortgages that are originated right after the identified cutoff dates are 61.4% more likely to have CDS coverage than the mortgages originated just before. This is a very strong first stage result, mainly due to the fact that I restrict the cutoff dates to having CDS coverage differences above 50%. This would provide quasi-exogenous variations with great power to identify the effect of CDS coverage on mortgage performance.

Quasi-Randomness Test

To verify our identification assumption that other loan characteristics beside CDS coverage do not change discontinuously at the cutoff dates, Figure 2.3 plots the average value of a few loan-level characteristics that might affect mortgage performance by the origination dates around the cutoffs. I plot the sample means and associated 95% confidence intervals along with fourth-order polynomial robust functions estimated following Calonico, Cattaneo, and Titiunik (2014). From panel A to F, I display borrower credit score, cumulative loan-to-value ratio, loan balance at origination, prepayment penalty indicator, interest only indicator and full documentation indicator, respectively. These plots indicate smoothness in ex ante borrower and loan characteristics around the cutoff dates. Mortgages originated on both sides of the cutoff dates do not appear statistically different in terms of their credit quality, debt capacity or other contract features.

Table 2.8 uses the specification in Equation 2.4 replacing the outcome variables with the 6 loan characteristics in Figure 2.3 to report the magnitude and significance of the discontinuity coefficients on these variables using the loan-level data. The estimates in column (1) indicate no statistical difference in credit scores for borrowers on either side of the threshold. Column (2) shows that cumulative loan-to-value ratios of borrowers on either side of the thresholds are statistically indistinguishable. Column (3) looks at the loan amounts granted to the borrowers, and suggests that the sizes of the mortgages are not statistically different on either side of the cutoff dates. Column (4) suggests borrowers just before and after the cutoff dates have similar proportion of investment purpose. Column (5) investigates a detailed contract feature for the mortgages, and shows that mortgages originated across the cutoff dates have statistically indistinguishable level of interest-only feature. Also, they have indistinguishable proportion of full documentation.

While the CDS coverage proportion is sharply different across the identified cutoff dates, borrowers on either side of these cutoff dates are demographically similar and apply for similarly sized loans with similar characteristics, supporting the validity of the identification strategy.

Causal Effect of CDS Coverage on Mortgage Refinancing

By quasi-randomly assigning mortgages into different mortgage pools, the cutoff discontinuities represent exogenous variations in their CDS coverage. Next I document empirically that borrowers on the side with more CDS coverage will be influenced to refinance more than those on the other side.

Figure 2.4 provides visual evidence of the different prepayment performance for mortgages originated across the cutoff dates by plotting proportion of different types of prepaid mortgages for left- and right-of-threshold borrowers using the local randomization strategy. Panel A plots the proportion of the refinanced mortgages. As in the first-stage estimation, the gray dots represent the sample means for mortgages originated in each day around the cutoff dates, and the solid lines are the fitted forth-degree polynomial functions for either side. Refinance proportion is smooth leading up to the cutoff date, and then jumps up discontinuously at the cutoff date, which demonstrates a strong causal effect of CDS coverage on mortgage refinancing performance. Panel B plots the proportion of prepaid mortgages due to moving incentives, and panel C plots that of normal prepayment. Consistent with the results I have shown in section 2.3, the CDS coverage has at most weak influence on mortgages' prepayment due to moving and normal prepayment.

As before, I estimate Equation (2.4) by controlling for mortgage characteristics, origination year by CBSA fixed effects and servicer fixed effects using a bandwidth of 5 days around the mortgage sale cutoff dates with a triangle kernel. Column (1) of Table 2.9 presents the reduced form results. Mortgages originated right after the mortgage sale cutoff are 4.9% more likely to be refinanced after origination. Since the mortgages are otherwise similar across the cutoff dates, which has been shown extensively in the quasi-randomness test, the cause of the different refinancing performance can only be attributed to the fact that the mortgages originated right after the cutoff dates happen to be sold to mortgage pools with higher level of CDS coverage. To quantify the causal effect of the CDS coverage, I resort to two-stage least square estimation. Column (2) shows that CDS coverage will lead to an increase of refinance rate by 8%. This is statistically significant, and is slightly larger than the controlled regression estimates in section 2.3 with the full sample.

Column (3) and (4) report the reduced form and two-stage least square estimates for prepayment due to moving. The difference around the cutoff dates is not significant. So we can conclude that the CDS coverage has little effect on this type of prepayment. Intuitively, the CDS sellers' advertisement campaigns are effective to remind the mortgage borrowers to refinance, but turn out not very effective to push them to move to other houses. Column (5) and (6) report the results for normal prepayment, and the difference is statistically significant for the case with the bandwidth of 5 days. But this is not a robust result for different choices of bandwidth. As can been seen in panel C of Figure 2.4, the average proportion of normal prepayment right before the mortgage sale cutoff dates appears to be abnormally lower than that after the cutoff dates, as well as that originated a few days before. It bends the trend downward sharply, likely due to some idiosyncrasies in the data. If I se a larger bandwidth, the difference significance around the cutoff dates disappears.

Causal Effect of CDS Coverage on Mortgage Default

To further test my second hypothesis that CDS sellers are able to reduce the mortgage default rate by improving the refinance rate, Figure 2.5 displays the different default performance for mortgages originated across the cutoff dates using the same strategy. Similar as in the refinance performance, the average default rate is smoothly moving for mortgages originated on either side of the cutoff dates, but there is a striking jump at the mortgage sale cutoff dates. The quasi-random setup allows us to conclude this default rate difference is due to the different CDS coverage levels.

The precise estimates are presented in Table 2.10. The mortgages originated right after the cutoff dates have default rates 4.5 percentage points lower than the otherwise similar mortgages originated before the cutoff dates. As long as the exclusion condition satisfies, this default performance difference can only be ascribed to the 61.4-percentage-point difference in their CDS coverage levels. Column (2) consolidates these two quantities, and illustrates that a one-percentage-point increase of CDS coverage would lead to a 0.074-percentage-point decrease of the default rate. This is larger than the controlled regression estimates in section 2.3 with the full sample.

2.5 Mechanism of Ex Post Distortion

The two sections above have illustrated clearly that the mortgages with CDS coverage have higher probability to refinance, and lower probability to default. This is not due to ex ante selection but due to CDS sellers' ex post manipulation. This section aims to better understand the mechanics of the CDS sellers' ex post influence.

CDS Sellers Fix Mortgage Performance Through Mortgage Servicers

In securitization, the mortgages are pooled together in common ownership held by a trust. The trust passively collects mortgage payments after the mortgages are sold to the trust, and passage the cash flows to its investors according to predetermined rules. And CDS buyers and sellers swap cash flows based on the default performance in the underlying mortgage pools. Practically, both trust and CDS investors do not directly interact with mortgage borrowers, and can hardly influence their decisions. Instead, the trust delegates mortgage servicers to collect mortgage payments on a monthly basis.

The servicer stands in for the trust, the beneficial owners of the loans, and the investors in virtually all dealings with homeowners. It is the servicer who collects homeowners' monthly payments, provides billing and tax statements for them, and addresses a petition for a loan modification if a homeowner is in distress. If CDS sellers want to influence the mortgage borrowers' refinance decisions, it would be very costly for them to do it directly due to lack of the infrastructure. It is instead much easier if they can do it through mortgage servicers. However, the mortgage servicers stand apart and separate from both CDS buyers and sellers, and have fiduciary duty on behalf of the trust investors. The CDS sellers and mortgage servicers cannot easily come to collusion to influence the mortgage borrowers' decisions, unless their incentives are extremely aligned.

Here I hypothesize if the CDS sellers and mortgage servicers are affiliated, it is possible and not costly for them to collude to influence the mortgage borrowers' refinance decisions in a way that benefits the CDS sellers. To test this hypothesis, I investigate into the CDS-covered mortgage pools, and compare mortgages with affiliated servicers and CDS sellers with those without such affiliations. If the protection sellers are associated with the mortgage servicers, they can use the connection to reach the borrowers and provide tailored refinance promotions to them. So the mortgages are more likely to be refinanced. Formally, I test if refinance rate will be even higher if the CDS protection sellers and mortgage servicers are within the same financial holding company.

To test this hypothesis, I resort to the following regression

$$Y_i = \alpha' + \beta_0 D_i^{CDS} + \beta_1 D_i^{\text{Seller-Servicer}} + \beta_2 D_i^{\text{Buyer-Servicer}} + \gamma' X_i + \varepsilon_i, \tag{2.5}$$

where D_i^{CDS} and X_i are defined as in Equation (2.1). $D_i^{\text{Seller-Servicer}}$ is a dummy variable equal to one if the CDS sellers and the mortgage servicers are within the same financial holding company, and $D_i^{\text{Buyer-Servicer}}$ is a dummy variable equal to one if the CDS buyers and the mortgage servicers are affiliated. The affiliation relationship is manually identified using the names of involved corporations and Bureau Van Dijk Orbis company ownership database.

Table 2.11 reports the regression estimates of Equation (2.5) for different mortgage outcomes. Column (1) illustrates the effect for mortgage prepayment and shows that a mortgage with CDS coverage has prepayment probability 4.2 percentage points higher than that without CDS coverage. In the cases where the CDS sellers and mortgage servicers are affiliated, the difference is 11.4 percentage points higher, but if the CDS buyers and mortgage servicers are affiliated, the CDS coverage effect is statistically indistinguishable with the cases where there is no affiliation. Column (2), (3) and (4) further explore different types of prepayment, and show that refinance is what drives the prepayment difference in column (1). Specifically, if mortgage servicers have no affiliation with either CDS sellers and buyers, the mortgages covered by CDS have 3.5 percentage points higher level of refinance rate. But if the CDS sellers and the mortgage servicers are affiliated, the CDS effect is 9.6 percentage points greater, while the CDS effect is not different if the CDS buyers and the mortgage servicers are affiliated. This proves the hypothesis that the refinance likelihood is higher if the CDS sellers and mortgage servicers are within the same financial holding company.

The mortgage servicers are supposed to act independently regardless of any parties' interest other than the mortgage investors, the corporate linkage between them and CDS sellers, however, turns out to distort their incentive to fulfill their fiduciary duty, and make them influence the mortgage borrowers to benefit CDS sellers. Given that the CDS sellers and mortgage servicers are under the same corporate umbrella, it is for the best interest to the ultimate owner of both functioning arms take this action. This might potentially hurt the mortgage servicers' own interest since their service fee is a *pro rata* share of the interest paid by the borrowers, but refinancing shortens the mortgage life and thus reduces the total interest amount. But if they are able to continue servicing the borrowers in their new mortgages, or the forgone service fee could be sufficiently compensated by the profit made by the CDS sellers, the mortgage servicers will be incentivized to influence their mortgage borrowers' refinancing decisions. The common ownership provides a channel to transfer the benefit under a common owner, which facilitates the cooperation or collusion of the CDS sellers and mortgage servicers. This is related to some recent works that document how common ownership distorts firms' operating behaviors (Azar, Schmalz, and Tecu, 2018).

But for the CDS buyers, why are they not able to collude with the mortgage servicers to influence the mortgage borrowers' refinancing decisions if they are affiliated with them? This is due to the asymmetric nature of the influence on mortgage refinancing decisions. For the CDS buyers, they would like to reduce the refinance rate to keep more potential defaulters in the mortgage pool. Even if they can collude with the mortgage servicers, it is hard for the mortgage servicers to prevent the borrowers from refinancing given the fact that the borrowers tend to under-refinance than they should. Therefore, we only see a significant interactive effect for the affiliation between CDS sellers and the mortgage servicers, but not for the CDS buyers.

Column (3) shows that the servicer-CDS-seller affiliation adds 2.6 percentage points to the probability of prepayment due to moving on top of the benchmark case with CDS coverage. This is very likely due to the fact that the CDS sellers have incentives to facilitate the short-sale process if the mortgage borrowers are not able to repay their mortgages. The mortgage servicers are able to influence this process since they are in charge of liquidation process of the mortgages. Again, this effect is asymmetric between the CDS buyers and sellers.

Finally, since the mortgaged pools with CDS coverage and servicer-CDS seller affiliation has a higher refinance rate, this will remove some potential defaulters out of the mortgage pools, and reduce the ex post default rate, as illustrated in column (5).

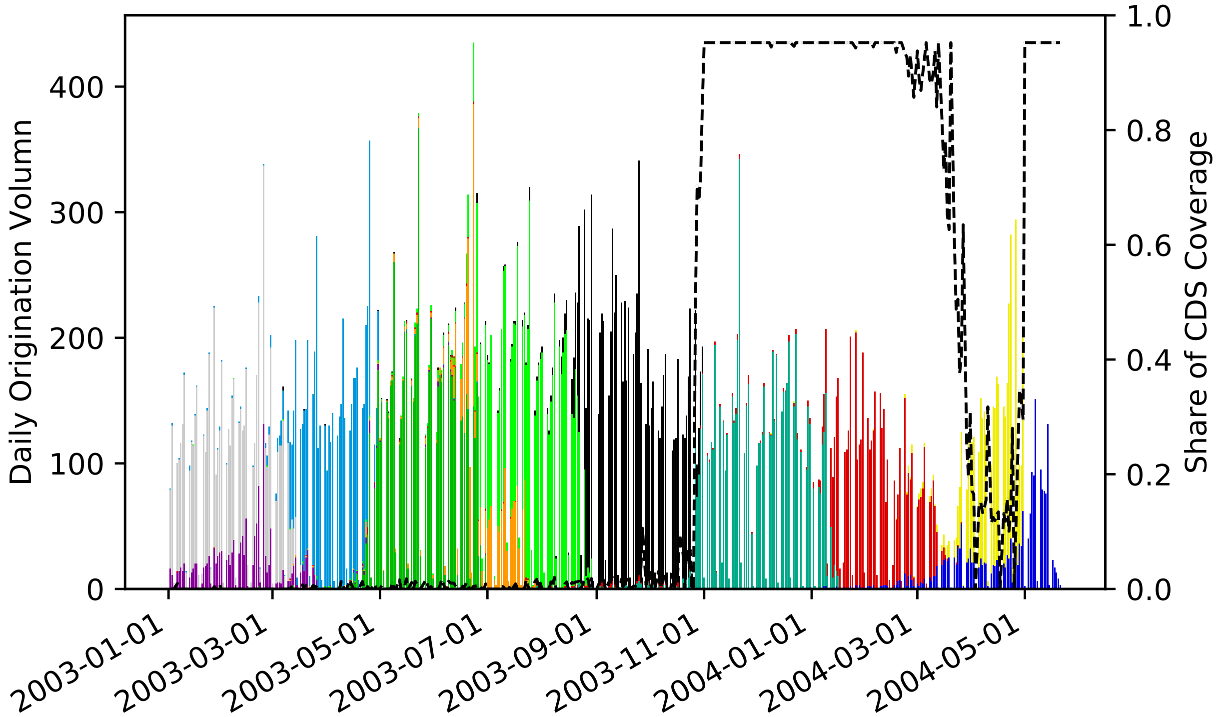
2.6 Conclusion

The US mortgage market greatly depends on its well-developed secondary market to channel cheap funding from global investors to the mortgage borrowers. All kinds of structured finance products facilitate this process by catering to the demand of different investors. So it is very important to understand how these structured finance products affect the underlying mortgages. While the literature mainly focuses on their effect on ex ante mortgage screening process, this paper studies their distortion on ex post mortgage performance.

In the empirical analysis, I focus on a specific type of credit derivatives—CDS written on mortgage backed securities. CDS is basically an insurance contract, that requires the CDS sellers to compensate the buyers any short cash flows due to the default of underlying mortgages. So the CDS sellers have incentives to improve the mortgage performance. Then the question is whether they do, and how? I find that if a CDS is written on the mortgage backed securities, the underlying mortgages will be more likely to be refinanced and less likely to default. An interaction analysis shows that the effect is largely driven by the cases where the CDS sellers and the mortgage servicers are affiliated, which suggests that CDS sellers are using their affiliated servicers to refinance the mortgages they cover, because this will unload their insurance obligations.

Figures

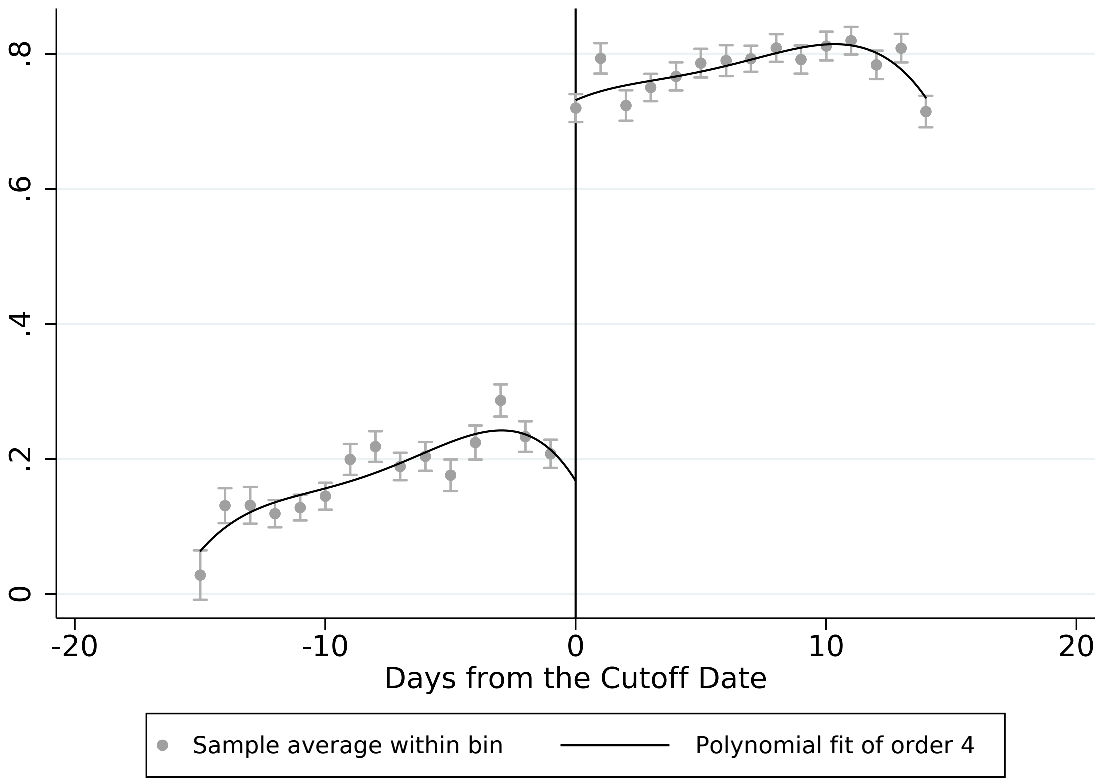
Figure 2.1 Daily Origination Count for an Originator



Note: This figure counts daily mortgage origination for a specific originator from the beginning of 2003 to the mid of 2004. It aims to serve as an example to show how mortgage origination and sale works. The length of the bars marks the number of mortgage origination for different dates. The bars with the same color represent the mortgages in the same securitization pool. And we can clearly see this originator focuses on one specific mortgage pool during one period. But it does not sell the loans all the time. Instead, it stack the originated mortgages into its inventory, and sell a whole bulk very 2 months. The dash line (right-axis) depicts the proportion of mortgages that are ex post covered by CDS.

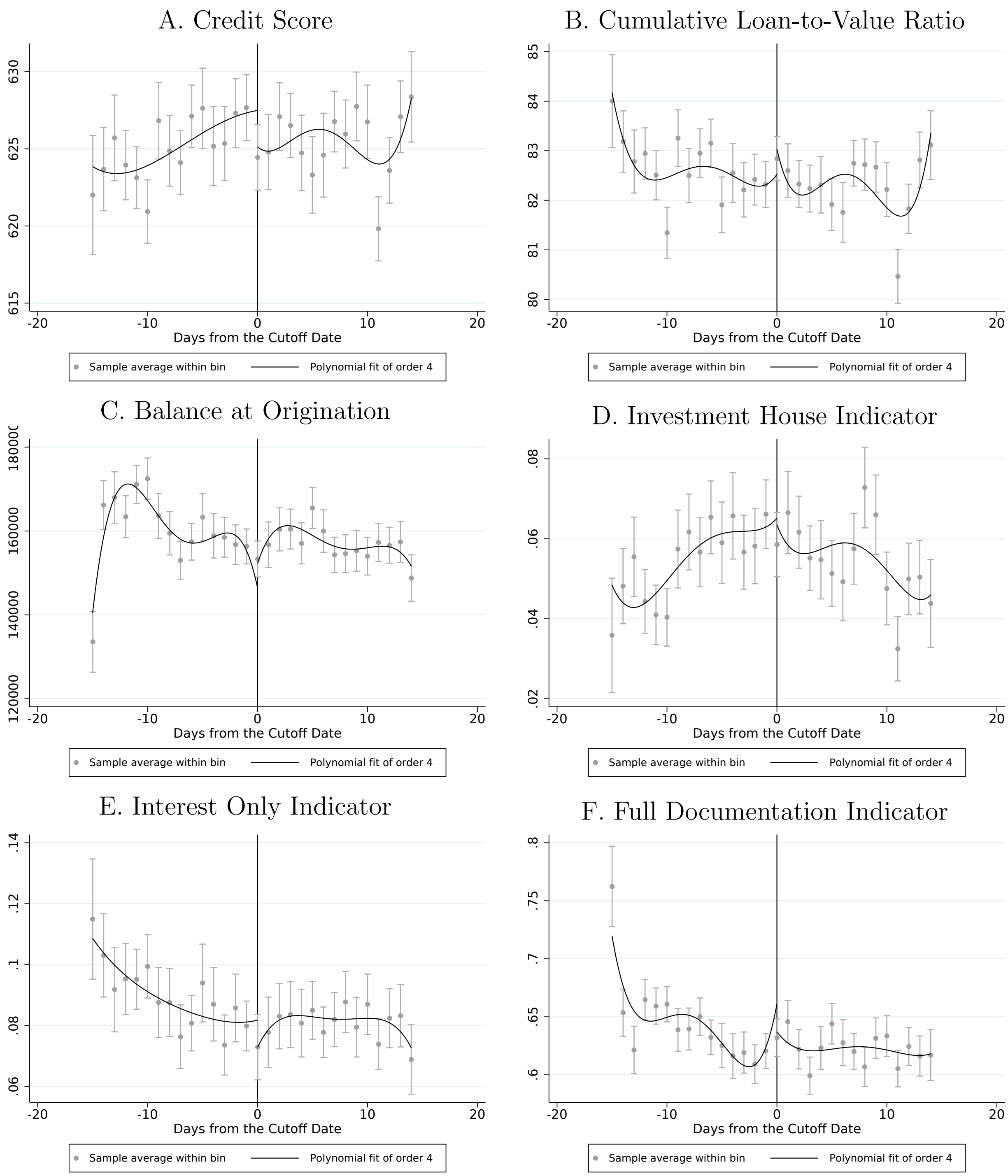
Source: Lewtan ABSnet.

Figure 2.2 CDS Coverage Around the Identified Cutoff Date



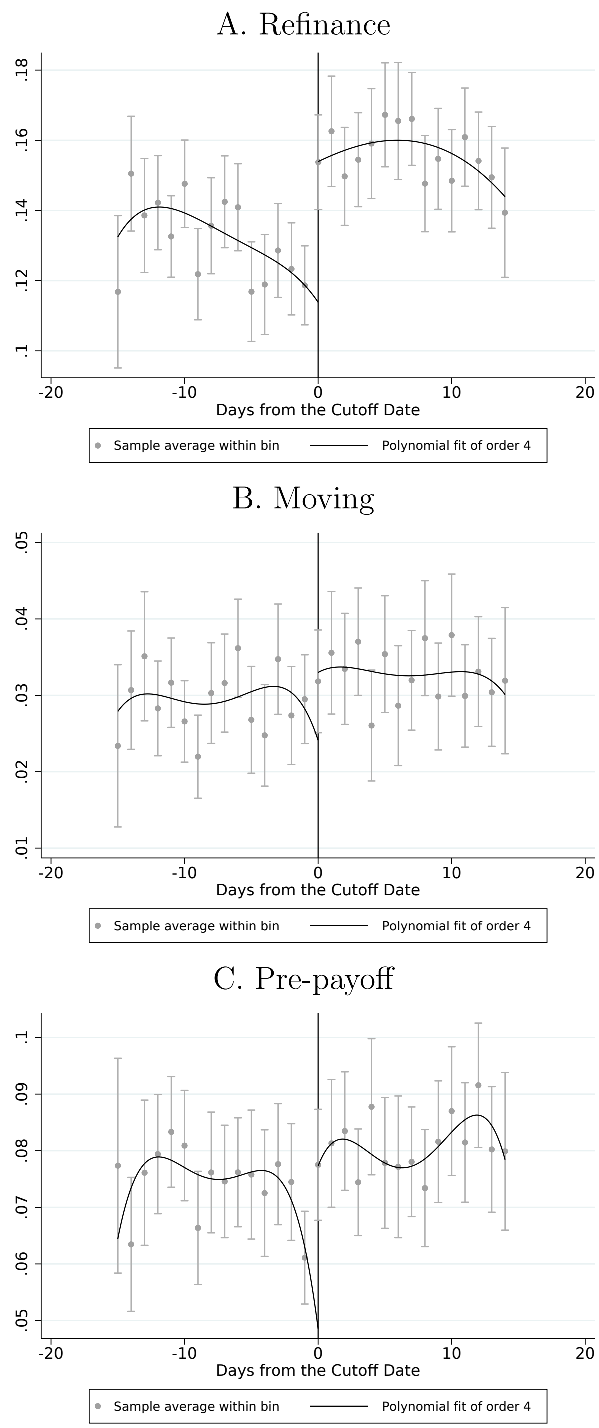
Note: This figure plots the average CDS coverage share for mortgages in the short window around the identified cutoff dates. These cutoff dates are those with the daily absolute change of CDS coverage share above 0.5. I reverse the calendar dates for part of the events with a negative share change, so the treated group always falls on the right side of the cutoff date. 95% confidence intervals are reported around the sample average within each bin. Plotted RD functions are estimated using the Calonico et al. (2014) robust RD estimator with fourth-degree polynomials.
Source: Lewtan ABSnet, and author's own calculations.

Figure 2.3 Balance of Loan Characteristics Around the Identified Cutoff Date



Note: This figure plots characteristics for mortgages originated in the short window around the identified cutoff dates. See the note under Figure 2.2 for how cutoff dates are constructed. 95% confidence intervals are reported around the sample average within each bin. Plotted RD functions are estimated using the Calonico et al. (2014) robust RD estimator with fourth-degree polynomials.
Source: Lewtan ABSnet, and author's own calculations.

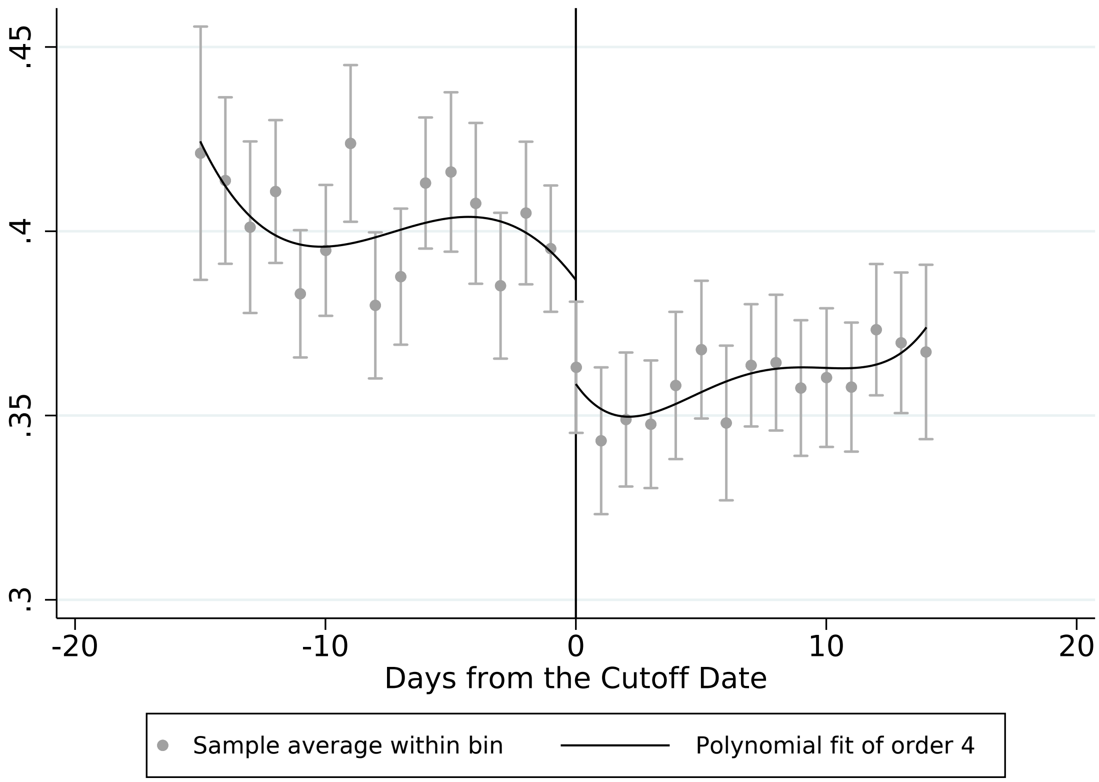
Figure 2.4 Effect of Cutoff Discontinuity on Prepayment Performance



Note: This figure plots refinance, moving and pre-payoff performance for mortgages originated in the short window around the identified cutoff dates. See the note under Figure 2.2 for how cutoff dates are constructed. 95% confidence intervals are reported around the sample average within each bin. Plotted RD functions are estimated using the Calonico et al. (2014) robust RD estimator with fourth-degree polynomials.

Source: Lewtan ABSnet, and author's own calculations.

Figure 2.5 Effect of Cutoff Discontinuity on Default Performance



Note: This figure plots default performance for mortgages originated in the short window around the identified cutoff dates. See the note under Figure 2.2 for how cutoff dates are constructed. 95% confidence intervals are reported around the sample average within each bin. Plotted RD functions are estimated using the Calonico et al. (2014) robust RD estimator with fourth-degree polynomials.
Source: Lewtan ABSnet, and author's own calculations.

Tables

Table 2.1 Sample Descriptive Statistics

	No CDS Covered	CDS Covered	Total	Obs
Panel A: Number of subprime Mortgages and Pools in the sample				
Mortgages	5,189,001	2,934,787	8,123,788	
Pools	3,290	1,466	4,756	
Panel B: Borrower and loan characteristics				
Loan amt.	179,963	176,069	178,556	8,123,771
Securitized amt.	178,373	174,836	177,122	7,023,087
Credit Score	628.20	617.96	624.56	7,710,408
CLTV(%)	83.52	81.61	82.84	7,155,742
Prepayment Penalty	0.45	0.40	0.44	6,044,016
Balloon Payment	0.15	0.05	0.11	8,123,788
ARM	0.64	0.71	0.66	8,123,788
Interest Only	0.13	0.12	0.12	7,869,502
First Lien	0.83	0.85	0.84	8,123,788
Investment House	0.06	0.04	0.06	7,554,674
Full Documtation	0.54	0.54	0.54	7,614,619

Note: This table summarizes the characteristics of the subprime mortgages in the data sample. All the subprime mortgages are originated during 2003–2007. A mortgage is defined to be covered by CDS if at least one of the bonds or tranches that the mortgage pool is backing is referenced by CDS. Column (1) and (2) report the characteristics for non-CDS-covered and CDS-covered subsamples respectively. Column (3) reports the average characteristics for the full sample, and column (4) reports the total number of observation.
Source: Lewtan ABSnet and ATTOM.

Table 2.2 CDS Coverage Effect on Mortgage Prepayment

	OLS				Logit
	(1)	(2)	(3)	(4)	(5)
CDS	0.054***	0.054***	0.055***	0.042***	0.038***
	(0.008)	(0.008)	(0.007)	(0.006)	(0.007)
Controls	✓	✓	✓	✓	✓
Ori Year FE	✓	✓			
CBSA FE		✓			
Ori Year × CBSA FE			✓	✓	✓
Servicer FE				✓	✓
Cluster	Mort. Pool	Mort. Pool	Mort. Pool	Mort. Pool	Mort. Pool
Observations	4,323,566	4,250,635	4,250,635	4,192,057	4,192,057

Note: This table reports the effect of CDS coverage effect on mortgage prepayment, obtained from estimating equation (2.1). The controlled borrower and loan characteristics varibles include CLTV, credit score, Loan purpose, as well as prepayment penalty, interest only, balloon payment, ARM, first lien, investment house and full documentation indicators. Column (1) controls observed borrower and loan characteristics and origination year fixed effect. To match geographical distribution of the mortgages, column (2) further includes core-based statistical area (CBSA) fixed effect. Column (3), instead, includes Ori Year × CBSA fixed effect to compare mortgages only originated in the same year and located in the same CBSA. I control servicer fixed effect in specification (4) and resort to a logit model in specification (5). All observations are weighted by securitized amount of the loan. Standard errors in parentheses are clustered at the mortgage pool level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In column (5), marginal effect of CDS coverage is reported.
Source: Lewtan ABSnet, and author's own calculations.

Table 2.3 CDS Coverage Prepayment Effect Breakdown

	Refinance		Moving		Pre-Payoff	
	OLS	Logit	OLS	Logit	OLS	Logit
	(1)	(2)	(3)	(4)	(5)	(6)
CDS	0.036***	0.036***	0.002*	0.002	0.003	0.003
	(0.005)	(0.007)	(0.001)	(0.002)	(0.002)	(0.002)
Controls	✓	✓	✓	✓	✓	✓
Ori Year × CBSA FE	✓	✓	✓	✓	✓	✓
Servicer FE	✓	✓	✓	✓	✓	✓
Cluster	Mort. Pool	Mort. Pool	Mort. Pool	Mort. Pool	Mort. Pool	Mort. Pool
Obs.	3,369,571	3,369,571	3,369,571	3,369,571	3,369,571	3,369,571

Note: This table reports the effect of CDS coverage effect on various types of mortgage prepayment: refinance, moving and payoff, obtained from estimating equation (2.1). All regressions control borrower and loan characteristics include CLTV, credit score, Loan purpose, as well as prepayment penalty, interest only, balloon payment, ARM, first lien, investment house and full documentation indicators. Also all regressions control origination year by core-based statistical area (CBSA) fixed effect and servicer fixed effect. For each outcomes, I apply both the linear probability model and logit model. All observations are weighted by securitized amount of the loan. Standard errors in parentheses are clustered at the mortgage pool level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In column (5), marginal effect of CDS coverage is reported.
Source: Lewtan ABSnet, ATTOM, and author's own calculations.

Table 2.4 CDS Coverage Effect on Mortgage Refinance

	OLS				Logit
	(1)	(2)	(3)	(4)	(5)
CDS	0.061***	0.059***	0.058***	0.036***	0.036***
	(0.007)	(0.007)	(0.006)	(0.005)	(0.007)
Controls	✓	✓	✓	✓	✓
Ori Year FE	✓	✓			
CBSA FE		✓			
Ori Year × CBSA FE			✓	✓	✓
Servicer FE				✓	✓
Cluster	Mort. Pool	Mort. Pool	Mort. Pool	Mort. Pool	Mort. Pool
Observations	3,437,007	3,406,643	3,406,643	3,369,571	3,369,571

Note: This table reports the effect of CDS coverage effect on mortgage refinance, obtained from estimating equation (2.1). The controlled borrower and loan characteristics varibles include CLTV, credit score, Loan purpose, as well as prepayment penalty, interest only, balloon payment, ARM, first lien, investment house and full documentation indicators. Column (1) controls observed borrower and loan characteristics and origination year fixed effect. To match geographical distribution of the mortgages, column (2) further includes core-based statistical area (CBSA) fixed effect. Column (3), instead, includes Ori Year × CBSA fixed effect to compare mortgages only originated in the same year and located in the same CBSA. I control servicer fixed effect in specification (4) and resort to a logit model in specification (5). All observations are weighted by securitized amount of the loan. Standard errors in parentheses are clustered at the mortgage pool level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In column (5), marginal effect of CDS coverage is reported.
Source: Lewtan ABSnet, and author's own calculations.

Table 2.5 CDS Coverage Effect on Mortgage Default

	OLS				Logit
	(1)	(2)	(3)	(4)	(5)
CDS	-0.022***	-0.020***	-0.022***	-0.021***	-0.018***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Controls	✓	✓	✓	✓	✓
Ori Year FE	✓	✓			
CBSA FE		✓			
Ori Year × CBSA FE			✓	✓	✓
Servicer FE				✓	✓
Cluster	Mort. Pool	Mort. Pool	Mort. Pool	Mort. Pool	Mort. Pool
Observations	4,323,566	4,250,635	4,250,635	4,192,057	4,191,070

Note: This table reports the effect of CDS coverage effect on mortgage default, obtained from estimating equation (2.1). The controlled borrower and loan characteristics varibles include CLTV, credit score, Loan purpose, as well as prepayment penalty, interest only, balloon payment, ARM, first lien, investment house and full documentation indicators. Column (1) controls observed borrower and loan characteristics and origination year fixed effect. To match geographical distribution of the mortgages, column (2) further includes core-based statistical area (CBSA) fixed effect. Column (3), instead, includes Ori Year × CBSA fixed effect to compare mortgages only originated in the same year and located in the same CBSA. I control servicer fixed effect in specification (4) and resort to a logit model in specification (5). All observations are weighted by securitized amount of the loan. Standard errors in parentheses are clustered at the mortgage pool level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In column (5), marginal effect of CDS coverage is reported.
Source: Lewtan ABSnet, and author's own calculations.

Table 2.6 Summary Statistics for Local Randomization Sample

	Mean	Std. Dev.	Percentile 25th	Percentile 50th	Percentile 75th	Obs.
	A. Loan and Borrower Characterisitics					
Loan amt.	164,899	126,985	80,800	130,500	212,000	26,372
Securitized amt.	167,639	124,758	83,378	131,781	211,887	25,137
Credit Score	626.48	59.14	585	624	664	26,271
CLTV(%)	82.19	12.95	79	80	90	25,987
Prepayment Penalty	0.50	0.50	0	1	1	15,968
Balloon Payment	0.10	0.30	0	0	0	26,372
ARM	0.56	0.50	0	1	1	26,372
Interest Only	0.09	0.28	0	0	0	26,329
First Lien	0.94	0.24	1	1	1	26,372
Investment House	0.05	0.23	0	0	0	25,422
Full Documtation	0.61	0.49	0	1	1	26,372
	B. Ex Post Loan Performance Measures					
Prepayment	0.36	0.48	0	0	1	26,372
Refinance	0.14	0.35	0	0	0	26,372
Moving	0.03	0.18	0	0	0	26,372
Pre-Payoff	0.08	0.26	0	0	0	26,372
Default	0.38	0.49	0	0	1	26,372

Note: This table reports summary statistics for the mortgages in the identified local randomization sample (the set of loans originated within 5 days of one of the detected cutoff dates) used in estimation. Panel A reports loan and borrower characteristics. Panel B summarizes the outcome variables, including prepayment (refinance, moving, pre-payoff) and default.
Source: Lewtan ABSnet, ATTOM, and author's own calculations.

Table 2.7 First Stage Difference of CDS Coverage Around the Identified Cutoff Dates

	CDS Coverage
	(1)
Discontinuity Coefficient (δ)	0.614^{***}
	(0.157)
Controls	✓
Ori Year × CBSA FE	✓
Servicer FE	✓
Cluster	Mort. Pool
Observations	70,249

Note: This table reports regression discontinuity estimate of equation 2.4. The estimation applies the method in Calonico et al. (2014) using a triangular kernel and a bandwidth of 5 days. The regression controls borrower and loan characteristics include CLTV, credit score, Loan purpose, as well as prepayment penalty, interest only, balloon payment, ARM, first lien, investment house and full documentation indicators. Also the regression controls origination year by core-based statistical area (CBSA) fixed effect and servicer fixed effect. All observations are weighted by securitized amount of the loan. Robust standard errors in parentheses are clustered at the mortgage pool level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Lewtan ABSnet, ATTOM, and author's own calculations.

Table 2.8 Loan Characteristic Balance Regressions

	Credit Score	CLTV(%)	Loan Amount	Invest-ment House	Interest Only	Full Docum-tation
	(1)	(2)	(3)	(4)	(5)	(6)
Discontinuity Coeff.	-5.976	0.446	153	-0.006	-0.004	0.021
	(3.579)	(0.867)	(8946)	(0.019)	(0.020)	(0.025)
Controls	✓	✓	✓	✓	✓	✓
Ori Year × CBSA FE	✓	✓	✓	✓	✓	✓
Servicer FE	✓	✓	✓	✓	✓	✓
Cluster	Mort. Pool	Mort. Pool	Mort. Pool	Mort. Pool	Mort. Pool	Mort. Pool
Observations	70,249	70,044	68,646	70,249	68,402	70,131

Note: This table reports regression discontinuity estimate using equation 2.4. The estimation applies the method in Calonico et al. (2014) using a triangular kernel and a bandwidth of 5 days. The regressions control borrower and loan characteristics as in Table 2.7 excluding the dependent variables. Also the regressions control origination year by core-based statistical area (CBSA) fixed effect and servicer fixed effect. All observations are weighted by securitized amount of the loan. Robust standard errors in parentheses are clustered at the mortgage pool level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Lewtan ABSnet, ATTOM, and author's own calculations.

Table 2.9 Loan Characteristic Balance Regressions

	Refinance		Moving		Pre-Payoff	
	R.F.	2SLS	R.F.	2SLS	R.F.	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Discontinuity Coeff.	0.049**		0.005		0.024***	
	(0.022)		(0.006)		(0.007)	
CDS		0.080**		0.008		0.039***
		(0.038)		(0.009)		(0.014)
Controls	✓	✓	✓	✓	✓	✓
Ori Year × CBSA FE	✓	✓	✓	✓	✓	✓
Servicer FE	✓	✓	✓	✓	✓	✓
Cluster	Mort. Pool	Mort. Pool	Mort. Pool	Mort. Pool	Mort. Pool	Mort. Pool
Observations	70,249	70,249	70,249	70,249	70,249	70,249

Note: This table reports regression discontinuity estimate of mortgage prepayment performance. The outcome variables are indicators for refinance, moving or pre-payoff. Column (1), (3) and (5) report the reduced form estimates directly obtaining from Equation 2.4. Column (2), (4) and (6) report the 2-stage least square estimates of the effect of CDS coverage. The estimation applies the method in Calonico et al. (2014) using a triangular kernel and a bandwidth of 5 days. The regressions control borrower and loan characteristics as in Table 2.7 excluding the dependent variables. Also the regressions control origination year by core-based statistical area (CBSA) fixed effect and servicer fixed effect. All observations are weighted by securitized amount of the loan. Robust standard errors in parentheses are clustered at the mortgage pool level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Lewtan ABSnet, ATTOM, and author's own calculations.

Table 2.10 Loan Characteristic Balance Regressions

	Default	
	Reduced Form	2SLS
	(1)	(2)
Discontinuity Coeff.	-0.045**	
	(0.019)	
CDS		-0.074**
		(0.033)
Controls	✓	✓
Ori Year × CBSA FE	✓	✓
Servicer FE	✓	✓
Cluster	Mort. Pool	Mort. Pool
Observations	70,249	70,249

Note: This table reports regression discontinuity estimate of mortgage default performance. The outcome variable is an indicator for default. Column (1) reports the reduced form estimates directly obtaining from Equation 2.4. Column (2) reports the 2-stage least square estimates of the effect of CDS coverage. The estimation applies the method in Calonico et al. (2014) using a triangular kernel and a bandwidth of 5 days. The regressions control borrower and loan characteristics as in Table 2.7 excluding the dependent variables. Also the regressions control origination year by core-based statistical area (CBSA) fixed effect and servicer fixed effect. All observations are weighted by securitized amount of the loan. Robust standard errors in parentheses are clustered at the mortgage pool level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Lewtan ABSnet, ATTOM, and author's own calculations.

Table 2.11 CDS Party-Servicer Affiliation Effect

	Prepay	Refinance	Moving	Pre-Payoff	Default
	(1)	(2)	(3)	(4)	(5)
CDS	0.042***	0.035***	0.001*	0.004***	-0.018***
	(0.006)	(0.005)	(0.001)	(0.001)	(0.004)
Servicer-CDS Seller	0.114**	0.096***	0.026***	0.007	-0.044***
	(0.045)	(0.035)	(0.008)	(0.011)	(0.015)
Servicer-CDS Buyer	-0.021	-0.007	-0.002	-0.005	-0.032
	(0.033)	(0.026)	(0.003)	(0.004)	(0.021)
Controls	✓	✓	✓	✓	✓
Ori Year × CBSA FE	✓	✓	✓	✓	✓
Servicer FE	✓	✓	✓	✓	✓
Cluster	Mort. Pool	Mort. Pool	Mort. Pool	Mort. Pool	Mort. Pool
Observations	4,192,057	3,369,571	3,369,571	3,369,571	4,191,880

Note: This table reports the interactive effect of CDS coverage with CDS sellers' and buyers' affiliation with mortgage servicers, obtained from estimating equation (2.5). The outcome variables include dummy variables for mortgage prepay, various types of mortgage prepayment (refinance, moving and pre-payoff), and default. The CDS sellers (buyers) and mortage servicers affiliation is equal to one if they are within the same financial holding company. All regressions control borrower and loan characteristics include CLTV, credit score, Loan purpose, as well as prepayment penalty, interest only, balloon payment, ARM, first lien, investment house and full documentation indicators. Also all regressions control origination year by core-based statistical area (CBSA) fixed effect and servicer fixed effect. For each outcomes, I apply both the linear probability model and logit model. All observations are weighted by securitized amount of the loan. Standard errors in parentheses are clustered at the mortgage pool level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In column (5), marginal effect of CDS coverage is reported.

Source: Lewtan ABSnet, ATTOM, and author's own calculations.

Chapter 3

Residential Investment and the Business Cycle

3.1 Introduction

Huge effort has been devoted to predict the business cycle both in the industry and academic communities, but the performance of such prediction is notoriously poor. Leamer (2007) first documents a very stable leading relationship between residential investment and the business cycle, which provides a hope of market-timing. But to make the best use of this leading relationship, we need to understand the underlying mechanism, which has not been fully explored in the literature.

The leading relationship can be seen in the panel (a) of Figure 3.1. The ratio of residential investment to GDP (the residential investment component, black solid line) well leads the business cycle (defined by NBER, shaded area covering recessions) in the postwar period. To make this point more clear, I extract the one-year-period residential investment component before the start of each recession into panel (b). For illustration convenience, I shift the end of each path to 0 so that each point on the path denotes the percentage difference from the level of the residential investment component at the start of the coming recession. Strikingly, in ten of the eleven postwar recessions, the residential investment component had been signaling a decreasing momentum since almost one year before the economy began to turn down. The only exception is the early 2000s recession which is triggered by the dot-com bubble. Similarly, I extract the paths in the one-year period before the end of each recession, which are illustrated in panel (c). For at least six out of the eleven times, recovery signals were found in the residential investment component paths before the trough of the business cycle.

Such a striking leading relationship with the business cycle is not found in other investment classes, but unique to the construction sector. The red dash lines in Figure 3.1 depict the historical dynamics of the ratio of non-residential investment to GDP (the business investment component), and exhibit exactly the opposite pattern. The business investment component synchronizes better with the business cycle. It rises before the advent of economic downturn, and drops over the full course of the recession. Such "Residential Leading, Business Lagging" pattern is further demonstrated in the correlation structure shown in Table 3.1. Residential investment indicators have stronger positive correlation with the real GDP in the next year, while business investment indicators are more correlated with the one year lag of the real GDP.

Macroeconomists have tried to reproduce the stylized facts of the residential investment, including procycalicality, volatility and leading relationship, by adding one more construction sector and housing consumption into the standard real business cycle (RBC) model (e.g. Davis and Heathcote (2005), Piazzesi and Schneider (2016) for a comprehensive survey). While successfully reconciling the other patterns, such multi-sector models are not able to account for the "Residential Leading, Business Lagging" pattern, mostly because construction sector and other sectors are functionally symmetric. As a result, both residential and business investment should react to exogenous demand or TFP shocks in the same direction. Therefore, it is impossible to generate a diverging pattern of residential and business investment before the advent of an economic peak or trough.

This paper aims to explain the "Residential Leading, Business Lagging" pattern by stressing the heterogeneity in the value storage technology between construction and manufacturing sectors. Residential investment is a technology that transforms perishable consumption goods into durable houses that deliver housing service in the future, while business investment is to transform the same perishable consumption goods into production capital that could generate more perishable consumption goods later. Production assets are highly specialized, and are exposed to large value reduction when the holding firm goes bankrupt (for example, due to capital displacement). Houses, however, do not suffer from such displacement losses, because the houses provide generic housing service, and hence are equally valuable to any owner.

Therefore, the value stored in the form of production capital through business investment technology is exposed to corporate bankruptcy risk, while that in the form of houses through residential investment technology does not. With such difference in mind, the representative agent optimally allocates the resources between residential and business investment, in response to the time-varying corporate bankruptcy rate, as can be seen in Figure 3.2. At the period of economic booms, bankruptcy risk is low, so business investment is less risky. More of the value should be stored in the form of business investment, rather than residential investment. As a result, we see a decreasing residential investment component and a rising business investment share when the economy is running up.

Specifically, I introduce an exogenous corporate bankruptcy shock into a two-sector (manufacturing and construction) real business cycle (RBC) model, and assume that bankruptcy brings value destruction (economic inefficiency) on top of the physical depreciation to the living capital, while house structures only suffer from constant physical deprecation. When the bankruptcy rate is low (booms), the firm has little probability to suffer from huge bankruptcy losses. Hence it is optimal to invest more on the manufacturing sector, taking advantage of the low bankruptcy rate. Therefore, we observe the business investment component rising, and the residential investment component decreasing before the advent of economic downturn.

While the model in this paper takes the different value destruction features in the two storage technologies as granted, it can be microfounded by the idea of capital specificity. Manufacturing capital is built for specific purposes. If the holding firm goes bankrupt, liquidating such specialized capital would incur economic inefficiency, since the capital has lower value in its second best use (Brunnermeier, Eisenbach, and Sannikov, 2012). For example, aerospace companies invest huge amount of money to build wind tunnels that are able to produce winds as fast as 270 miles per hour. But when the companies are liquidated and sell these tunnels to other businesses such as bicycle helmet designers, at most one third of the tunnel value can be recovered (Ramey and Shapiro, 2001). Such economic inefficiency due to displacement is further amplified through two channels. Ramey and Shapiro (2001) propose that assets with higher specificity have higher searching cost and hence, have higher probability of displacement. Shleifer and Vishny (1992) argue that the firms in the same industry are likely to be financially distressed at the same time due to industry-wide adverse shocks. Therefore, when a firm goes bankrupt and tries to liquidate its specialized assets, the natural second-best users might not be able to afford the assets, which aggravates capital displacement and economic inefficiency. Empirically, Pulvino (1998) studies the airline industry, and shows such displacement cost can be as high as 30% of the market price when liquidating aircraft during market recessions.

Residential structures, on the other hand, deteriorate constantly, and is not exposed to displacement risk, because the function of the house is much more generic. Although we do see mortgage defaults and very low recovery rate during the following foreclosure process, the economy does not necessarily incur inefficiency as long as there are buyers that fully value the housing services filling in the houses soon. From social planner's point of view, such "fire sale" is only a transfer of value from the left hand to the right.

In the spirit of the house filtering literature (Baer and Williamson, 1988), homeowner vacancy rate is indicative of the social inefficiency of the housing utilization. From Figure 3.2, we can see that historical homeowner vacancy rate is much less volatile than corporate default rate. It varies within the range from 1% to 2% before the recent crisis. In this paper, I assume the cost due to vacancy to be constant over time, and attribute such cost to the physical deterioration of housing structures without loss of generality.

Literature review. This paper contributes to the real business cycle (RBC) literature by explicitly including an exogenous bankruptcy shock. Different from classic RBC models that assume the firms are long-lived, and recycle the capital after constant physical depreciation, this paper interprets the capital depreciation as the aggregate of constant physical depreciation and dynamic capital displacement losses due to corporate bankruptcy. Inclusion of such dynamic depreciation rate would enrich the bare-bone RBC model, as Ambler and Paquet (1994) do to reconcile the weak correlation between production and working hours. Specifically, the bankruptcy shock triggers out the diverging behavior of the residential investment and the business investment due to their different exposure to bankruptcy risk.

The opposite reactions to the bankruptcy shock between the residential and business investment are empirically verified in my vector autocorrelation analysis. With a mild identification assumption that both residential and business investment do not react to the contemporaneous bankruptcy shock, which is consistent with the empirical observation that the average time between investment decision and completion ranges from 6 months to 14 months (Edge, 2000), I am able to identify the structural bankruptcy shock, and capture the impulse responses to such a structure shock. When bankruptcy risk is lower than equilibrium level, the residential investment component will dip down gradually with the business investment component spiking up, which matches my model predictions. Most importantly, it provides empirical evidence that bankruptcy risk is a valid state variable to differentiate the dynamics of residential investment from that of other investment classes.

Overview. In what follows, I set up a real business cycle model with two production sectors in section 3.2. The simulated results from the theoretical model are shown in section 3.3. Section 3.4 describes my empirical strategy, the data I used for testing, and the empirical results which coincide with my theoretical predictions. Section 3.5 compares the results from both theoretical part and empirical part, and section 3.6 concludes.

3.2 The Model

To formalize the idea, I introduce a stylized real business cycle model with multiple production sectors. Different from other multi-sector RBC models (Davis and Heathcote, 2005), I introduce a new bankruptcy shock, which is represented by a stochastic depreciation rate process in the model. Given constant physical depreciation rate, the aggregate depreciation rate can be seen as a sufficient statistic of bankruptcy losses. A key assumption of the model is that such stochastic bankruptcy losses are incurred only on the production capital, but not on the housing stock.[1]Corporate bankruptcy triggers the displacement of the assets due to their specificity, while houses do not incur such dead-weight losses for their generic function.

At this stage, I have made two more restrictions to the model for simplicity. First, the model considered here abstracts labor supply away to highlight the interactions of the capital investment and the bankruptcy risk. Alternatively, we can think that labor supply is fixed at its natural level. Second, the ex ante and ex post bankruptcy rates are equal. This assumption allows me to apply log-linearization technique to the problem.

A representative household with constant population growth rate $\log(\eta)$ rents homogeneous capital K_t to perfectly competitive firms. These firms allocate the capital frictionlessly across two different sectors: manufacturing K_{mt} and construction K_{ht}. The manufacturing

[1] In fact, this is an extreme case without any loss of generality. We can, alternatively, assume housing structures suffer from displacement losses, but the risk exposure is lower than manufacturing capital. The result would be the same qualitatively.

sector has the following production technology:

$$Y_{mt} = A_{mt} K_{mt}^{\alpha_m} \tag{3.1}$$
$$A_{mt+1} = A_{mt}^{\rho_m} e^{(1-\rho_m)(g_{Am}+\epsilon_{mt+1})} \tag{3.2}$$

where the production shifter A_{mt} represents a combination of labor supply and manufacturing productivity. Since the labor supply per person is fixed in the model, the trend of A_{mt} is controlled by population growth as well as the manufacturing productivity long-run trend, while the short-run dynamics of A_{mt} reflects the short-run variation of manufacturing productivity.

Similarly, the construction technology follows

$$Y_{ht} = A_{ht} K_{ht}^{\alpha_h} \tag{3.3}$$
$$A_{ht+1} = A_{ht}^{\rho_h} e^{(1-\rho_h)(g_{Ah}+\epsilon_{ht+1})} \tag{3.4}$$

where the production shifter A_{ht} represent a combination of construction labor supply, construction productivity and land supply. To simplify the interpretation, let us assume land supply is also fixed, then the short-run dynamics of A_{ht} just represent the short-run variation of construction productivity.

The perishable goods produced by the manufacturing sector have three uses. C_t amount will be sold to households for consumption, I_{mt} amount will be reinvested to build specialized capital (e.g. wind tunnels) by manufacturing firms themselves, and I_{ht} amount will be sold to construction firms for their investment. For example, construction firms need to buy cranes, excavators and trucks from manufactures. These construction investment would eventually be transformed into durable housing structures.

$$Y_{mt} = C_t + I_{mt} + I_{ht} \tag{3.5}$$

The capital in either of the sectors follows the following evolution process:

$$K_{it+1} = (1 - d_t\delta_k)K_{it} + I_{it}, \quad i \in \{m, h\} \tag{3.6}$$

where $d_t\delta_k$ is the aggregate depreciation rate, which includes both physical depreciation and bankruptcy losses. As I have argued in the introduction, the bankruptcy of the holding firm would bring a huge depreciation to the capital due to displacement of the specialized assets. Therefore, δ_k captures the historical mean of the physical depreciation plus bankruptcy losses, and d_t captures its short run dynamics, which is modeled as a mean reversion process:

$$d_{t+1} = d_t^{\rho_d} e^{\epsilon_{dt+1}} \tag{3.7}$$

where ϵ_t is a white noise, ρ_d captures the persistence of the exogenous shocks. Here I hold the physical depreciation rate to be constant, so d_t is a sufficient statistic of the bankruptcy rate. For this reason, I interchangeably use the depreciation shock and the bankruptcy shock to refer to d_t thereafter. Noticeably, this exogenous bankruptcy shock is the key feature that distinguishes my framework from other RBC models in this line of literature.

For the construction sector, the newly constructed houses Y_{ht} will be added into the current housing stock H_t, providing housing service to the households.

$$H_{t+1} = (1 - \delta_h)H_t + Y_{ht} \tag{3.8}$$

The housing stock also suffers from physical depreciation, but at a constant rate δ_h. The housing depreciation comes from the depreciation of housing structures, such as roof repair and drainage maintenance. I assume that the housing depreciation does not involve stochastic terms because the service of houses is much more generic than production machines and other manufacturing assets. Even if the house owner goes bankrupt, and has to foreclose his or her house at a discounted price, displacement cost is not incurred as long as the house is as valuable to the buyer as to the seller.

The model is closed by the optimization problem of a representative household, whose family member derives utility from both consumption and housing stock.

$$U_t = \frac{\left(c_t^{\mu} h_t^{1-\mu}\right)^{1-\sigma}}{1-\sigma} \tag{3.9}$$

From here forward, the letters in lower cases denote the amount per capita of the corresponding variables. The preference assumption is standard in macro and real estate literature. The utility exhibits constant relative risk aversion toward the composite consumption bundle, which combines non-durable consumption and housing stock in a Cobb-Douglas way. The intertemporal elasticity of substitution is $1/\sigma$, and the non-durable consumption share in the composite consumption bundle is μ.

The number of family members grows at the rate of $\log(\eta)$, and the discounting factor is denoted by β. The household maximizes its expected utility of all family members.

$$\max_{c_t, h_t} U = \mathbb{E} \sum_{t=0}^{\infty} (\beta\eta)^t \frac{\left(c_t^{\mu} h_t^{1-\mu}\right)^{1-\sigma}}{1-\sigma}$$

Social Planner's Problem

Since the firms are perfectly competitive, and there are no other market frictions, the First Welfare Theorem applies to this model. So we can equivalently solve the following social planner's problem to achieve the model solution.

$$\max_{c_t,h_t} U = \mathbb{E}\left[\sum_{t=0}^{\infty}(\beta\eta)^t \frac{\left(c_t^{\mu}h_t^{1-\mu}\right)^{1-\sigma}}{1-\sigma}\right] \tag{3.10}$$

$$s.t.\ c_t + \eta k_{t+1} = (1-d_t\delta_k)k_t + A_{mt}k_{mt}^{\alpha_m} \tag{3.11}$$

$$\eta h_{t+1} = (1-\delta_h)h_t + A_{ht}(k_t-k_{mt})^{\alpha_h} \tag{3.12}$$

$$d_{t+1} = d_t^{\rho_d}e^{\epsilon_{dt+1}} \tag{3.13}$$

$$A_{mt+1} = A_{mt}^{\rho_m}e^{(1-\rho_m)(g_{Am}+\epsilon_{mt+1})} \tag{3.14}$$

$$A_{ht+1} = A_{ht}^{\rho_h}e^{(1-\rho_h)(g_{Ah}+\epsilon_{ht+1})} \tag{3.15}$$

As can be seen, the model has three exogenous shocks in total: two productivity shocks (ϵ_{mt+1} and ϵ_{ht+1}) and one bankruptcy shock (ϵ_{dt+1}). They can give us rich dynamics of the modeled economy. But for now, let us shut down the productivity shocks ($\epsilon_{mt+1} = \epsilon_{ht+1} = 0$), and focus on the dynamics driven only by the bankruptcy shock. Then the productivity in both sectors are deterministic trends, with growth rate g_{Am} and g_{Ah} respectively.

The social planner does not have to concern either the trading between firms and households, or the price of the production inputs and outputs. She just optimally allocates the capital to the two sectors, and decides the policy of consuming and investing, based on the realized productivity and bankruptcy rate dynamics.

Detrending and Reparametrization

Since the two technologies have deterministic trends, all the other variables in this system also contain long-run trends, and thus are not stationary. Technically, it is much easier to deal with a stationary system. So the solution strategy is to first detrend each variable in the original system, and then solve the detrended system.

Table 3.2 displays the balanced growth rate of each running variable per capita in the model. Overall, the growth rates are determined by the productivity growth rate and the capital share in the two sectors.

Then I detrend all the running variables by taking off their corresponding long term treads:

$$\hat{s}_t = e^{-g_s t}s_t. \tag{3.16}$$

Then the hatted variables are all stationary, and the social planner's problem can be transformed into a stationary system:

$$\max_{\hat{c}_t,\hat{h}_t} U = \mathbb{E}\sum_{t=0}^{\infty}\hat{\beta}^t\frac{\left(\hat{c}_t^{\mu}\hat{h}_t^{1-\mu}\right)^{1-\sigma}}{1-\sigma} \tag{3.17}$$

$$s.t.\ \hat{c}_t + \hat{\eta}_1\hat{k}_{t+1} = (1-d_t\delta_k)\hat{k}_t + \hat{A}_m\hat{k}_{mt}^{\alpha_m} \tag{3.18}$$

$$\hat{\eta}_2\hat{h}_{t+1} = (1-\delta_h)\hat{h}_t + \hat{A}_h(\hat{k}_t - \hat{k}_{mt})^{\alpha_h} \tag{3.19}$$

$$d_{t+1} = d_t^{\rho_d}e^{\epsilon_{dt}} \tag{3.20}$$

with reparametrization

$$\hat{\beta} = \beta\eta\exp\left\{\frac{\mu+(1-\mu)\alpha_h}{1-\alpha_m}g_{Am} + (1-\mu)g_{Ah}\right\} \tag{3.21}$$

$$\hat{\eta}_1 = \eta\exp\left\{\frac{1}{1-\alpha_m}g_{Am}\right\} \tag{3.22}$$

$$\hat{\eta}_2 = \eta\exp\left\{\frac{\alpha_h}{1-\alpha_m}g_{Am} + g_{Ah}\right\} \tag{3.23}$$

$$\hat{A}_m = A_{m,0} \tag{3.24}$$

$$\hat{A}_h = A_{h,0} \tag{3.25}$$

Since I shut down the short-run variation of the two productivity shocks, the detrended productivity of both sectors are degenerated into two constants, $\hat{A}_m$ and $\hat{A}_h$.

3.3 Model Results

The model solution is included in the technical note A.4. Before we jump into the solution and the simulated results of the model, we can anticipate some key properties in this simple setting. The social planner has two types of storage technologies to save perishable goods. One is to transform these perishable goods into manufacturing capital, and the other is to transform them into houses. Both storage technologies could yield utility to the representative agents every period. The key difference between these two technologies is that the value of manufacturing capital is controlled by the volatile bankruptcy dynamics, while the value of housing structures is free from the bankruptcy risk. As a result, the social planner would optimally allocate the investment between the manufacturing and construction sectors in response to the time-varying bankruptcy risk. When the economy is running well, corporate bankruptcy rate is low. It is optimal to increase the share of business investment and decrease the share of residential investment. This pattern will be seen in the model simulation below.

Parameters

To simulate the model, we first need to feed the system with appropriate parameters. Table 3.3 summarizes the parameter values I use for the simulation. The time unit of the model is 1 year, so the parameter values are on the annual basis.

The nondurable good share is set to 61% in the composite consumption bundle, so that the steady state level of residential investment component matches its historical mean. Relative risk aversion coefficient is 2, and discounting factor is 0.95, which are widely used in the RBC literature (Davis and Heathcote, 2005). The historical mean of aggregate depreciation rate is 6.5% every year, which is the sum of the annual manufacturing depreciation rate estimated by Bureau of Economic Analysis, and the historical average of the corporate default rate published by Moody's. The depreciation rate of residential structures is 1.4%, estimated by Bureau of Economic Analysis. Capital production share in the manufacturing sector is 31%, much higher than that in the construction sector (13.2%). Technology is developing at an annual rate of 1.86% in the production sector, and 0.81% in the construction sector. All the capital share and technology trend parameters are estimated by NIPA data. Population is growing at a rate of 1.67% per year, and the average rate of growth of hours worked in the private sector in the postwar period. The bankruptcy shock is highly persistent with the first order autocorrelation of 0.9. For the moment, I just set $A_{c,0}$ and $A_{h,0}$ to be 1, because their values do not affect the impulse response functions of the detrending system.

Impulse Response Functions

With the parameter values listed above, I can fully solve the log-linearized model. To illustrate how the system, especially residential investment and business investment, reacts to the bankruptcy shock, I plot the impulse response functions as shown in Figure 3.3.

First, we can notice from the impulse response of aggregate depreciation rate that, the effect of bankruptcy shock is rather persistent. The half life is about 5 years.

If the economy is hit by one unit of negative bankruptcy shock, after a period of economic booms, the aggregate depreciation rate is low due to lower bankruptcy rate. The firm would first increase its investment in the manufacturing sector, taking advantage of very low depreciation rate right after the shock, as shown in the middle panel of Figure 3.3.

If we look closely on the impulse response of the business investment, it starts from 0 since it takes one period for capital to adjust for the exogenous depreciation shock. It is consistent with the fact that the average time between investment decision and completion ranges from 6 months to 14 months (Edge, 2000). Then the business investment will rise first, and then decrease down below 0. Since the economy expects aggregate depreciation is coming back to its equilibrium level slowly, it is optimal for the firms to frontload investment, taking advantage of very low depreciation rate right after the shock. After a few years, the firms have accumulated enough capital, and begin to reduce their capital investment.

The residential investment share is defined as the value of residential investment (new housing structures) over the value of overall capital investment. It corresponds to the residential share of aggregate investment used in the following VAR analysis. Since I directly solve the social planner's problem to achieve the solutions. Price level of new houses does not show up in the solution part. But we can easily set up firms' profit maximization problem for the two sectors, and get the price level from the first order conditions.

The impulse response of the residential investment share exhibits the opposite pattern from that of the business investment. When the economy is running well, the bankruptcy rate goes down. Residential investment decreases initially since the economy optimally shifts more resource to the business side, taking advantage of the high level of sustainability of manufacturing capital. After a few years when the aggregate depreciation rate recovers closer to its equilibrium level, more and more resource is moved away from the manufacturing sector, back to the construction sector. Thus, we see a "check" curve of the residential investment share.

3.4 Empirical Testing

To examine the fitness of my model with the data, I employ the Vector AutoRegression (VAR) model to estimate the response of the residential investment and the business investment to bankruptcy shocks. The VAR representation can be written as:

$$\begin{bmatrix} r_t \\ i_t \\ d_t \end{bmatrix} = \Phi(L) \begin{bmatrix} r_t \\ i_t \\ d_t \end{bmatrix} + \begin{bmatrix} e_{rt} \\ e_{it} \\ e_{dt} \end{bmatrix}$$

where r_t denotes the ratio of residential investment to aggregate investment, i_t represents real business investment, and d_t is a bankruptcy rate variable, which captures the full dynamics of aggregate depreciation rate. The time trend of all the 3 variables are removed. e_t are the reduced-form residuals, which are linear combinations of the exogenous shocks:

$$\begin{bmatrix} e_{rt} \\ e_{it} \\ e_{dt} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} \epsilon_t^r \\ \epsilon_t^i \\ \epsilon_t^d \end{bmatrix}$$

In such a VAR specification, I have maintained most characteristics from the model. The dimension of state variables are kept to be 3, as required by the model. The bankruptcy shock does not have instant effect on the contemporary investment both on the residential and business side. It is consistent with the fact that the average time between investment decision and completion ranges from 6 months to 14 months (Edge, 2000). This is the key condition to my identification strategy.

There are also differences between the model and the empirical framework. The model regards bankruptcy shock as the only exogenous shock ($\epsilon_t^r = \epsilon_t^i = 0$), and the bankruptcy rate, therefore, does not react to any other shocks ($a_{31} = a_{32} = 0$), while the VAR specification allows more flexibility. The stylized model focuses on illustrating the most striking facts that are only motivated by bankruptcy concerns. The data, however, contain much more complex economic components and noises. Therefore, we need a more flexible specification to accommodate the data. But the inclusion of two more shocks brings up a new question: how we can disentangle the bankruptcy shock from the other shocks. Now let me discuss my identification strategy.

Identification Strategy

Cholesky Decomposition is widely used to identify structure shocks in VAR systems. To apply Cholesky Decomposition, we need to make sure that the structure shocks are indeed lower-triangularly arranged. If $a_{12} = 0$, the transformation matrix is then lower-triangular, Cholesky decomposition applies naturally.

In our case, however, it is not realistic to argue that overall investment decisions do not affect the residential investment share contemporaneously. In fact, such two investment-level indicators are often simultaneously driven by some other shocks, such as monetary policy, and hence are very likely to be interdependent.

Fortunately, strictly lower-triangularity is not a necessary condition to identify the bankruptcy shock through Cholesky Decomposition. As an application of Keating (1996), Cholesky Decomposition is able to correctly identify the bankruptcy shock as long as the transformation matrix is block lower-triangular, which is the case in my VAR specification.

Specifically, the existence of a_{12} does affect the identification of the residential investment shock ϵ_t^r and the business investment shock ϵ_t^i, but the bankruptcy shock ϵ_t^d can still be identified due to the block recursiveness of the structural matrix. And the bankruptcy shock is what we really care about.

Data Description

All the time series used in this paper are annual data, and the range is from 1948 to 2010. All the macro variables except for default rate are from national income and product accounts (NIPA). Specifically, the nominal residential investment is directly taken from NIPA table 1.1.5, while the nominal business investment aggregates different pieces including total private business investment, gross federal non-defense investment and state and local gross investment. Real terms of corresponding variables use chained-dollar value whenever they are available from NIPA, as the advantage of such statistic method is widely accepted and stressed by Landefeld, Moulton, and Vojtech (2003).

The ex post bankruptcy rate is hard to estimate, especially at the aggregate level. I use annual default rate punished by Moody's (Emery, Ou, Tennant, Kim, and Cantor, 1920) as a proxy for bankruptcy rate, by assuming ex ante and ex post bankruptcy rates are the same. Although Moody's focuses on the firms with long-term debt issuance, the default rate is still highly correlated with economy-wide operation status of firms, and acts as my best guess.

In the VAR system, the variable r_t is constructed by detrending the ratio of the residential investment to the aggregate investment, and i_t is detrended log real business investment. Such choice corresponds to the simulated impulse response function in Figure 3.3. Alternative choice of variables will be tested in the robustness part.

Empirical Results

I first estimate the VAR representation with the Matlab routines. Bayesian Information Criterion (BIC) chooses 1 as the maximal lag number. Then I apply Cholesky Decomposition to disentangle the default rate shock (D shock) from the VAR residuals. As argued in the Identification Strategy part, Cholesky Decomposition is sufficient to identify the D shock under my structural assumption and ordering of r_t, i_t and d_t.

Figure 3.4 depicts the empirical counterpart of the simulated impulse response functions in Figure 3.3 under my VAR specification. The confidence intervals are constructed by bootstrapping the implied VAR residuals 2000 times, and are delimited at 90% confidence level.

Overall, the empirical impulse response functions follow the same pattern as the simulated ones. The default rate decays geometrically as the aggregate depreciation rate in the model. When default rate is below its balanced path, business investment will bounce up from the next period onward, though the instant response is forced to be zero. As analyzed in the model part, in the first few periods, the firms would "over-invest" to take advantage of the low default rate. When they feel that enough capital has been accumulated, the pace of investment would slow down, and come back to its equilibrium level. As indicated by the 90% confidence interval, such effect is statistically significant.

On the residential side, the effect is the opposite. When the default rate is low, more of the resources would be devoted to the manufacturing sector. So the residential share of the investment would drop from 0 to below. The point estimate of the response in the first few years ranges from 1% to 1.5%, which means that if the default rate drops by 1%, the residential share of the investment for the next year would decrease by 1% to 1.5%, stay at that level for a few more years, and then slowly come back. Again, the effect is statistically significant.

Robustness

As implied by the model, any three running variables would be sufficient to span the state variable space, and fully capture the dynamics of the economy. When we try to explore the pattern of the data, the model seems too skinny. The choice of state variables are actually important to the key results of this paper. To avoid the concern of data mining, I illustrate here the results from an alternative choice of state variables.

In the VAR specification above, the second variable is detrended log real business investment, which has a totally different denomination from the other two percentage series. So we should also try to include percentage data to represent the dynamics of business investment.

The business share of aggregate investment first comes to our mind, but does not work, since it is perfectly negatively correlated with residential share. My choice here is the business investment component of GDP.

I rerun the above estimation and decomposition, and depict the impulse response functions to the identified D shock in figure (3.5). The pattern of the responses squares almost perfectly with the pattern I have shown above. Notably, the point estimation of the first period impulse response of business investment share is 0.2, which means that if the default rate drops by 1%, the business investment share of the aggregate output for the next year would increase by about 0.2%.

3.5 Discussion

It is exciting to see that the impulse response pattern implied by my model echoes in its empirical counterpart. But there is still some mismatch between them.

First, although the initial empirical response of the business investment matches the model, it slowly comes back to its initial level. The model, on the other hand, has different implication, that investment would dip down below its equilibrium level, and then recovers. Such model pattern results from a dynamic optimization choice when firms face a long-lived rising aggregate depreciation rate. The firms frontload large amount of investment to take advantage of the low depreciation rate. The followed underinvestment is unavoidable because the shock itself reduces the depreciation of the production capital, and that is the first-order effect. The same problem applies to the response of the residential investment.

To solve such problems, we should shock the economy in a different way. To be specific, the shock itself should not have first order effect. For example, the shock might be a decrease of ex ante bankruptcy volatility, or the decrease of the bankruptcy tail risk, while the expectation of bankruptcy rate remains the same. For risk aversion incentives, the firm should also increase their business investment, and reduce new construction of houses. A technical difficulty of such model is that we cannot use log-linearization any more, since log-linearization first shuts down all the randomness, and only solves the first-order problem. A full characterization of the solution dynamics is needed to conduct such experiments in the higher order. I will further invest more in such models.

Second, we really need highly persistent bankruptcy rate to have the right impulse response functions. However, the persistence of the default rate is smaller than that I use in the simulated data. But this can be jointly solved with the first problem.

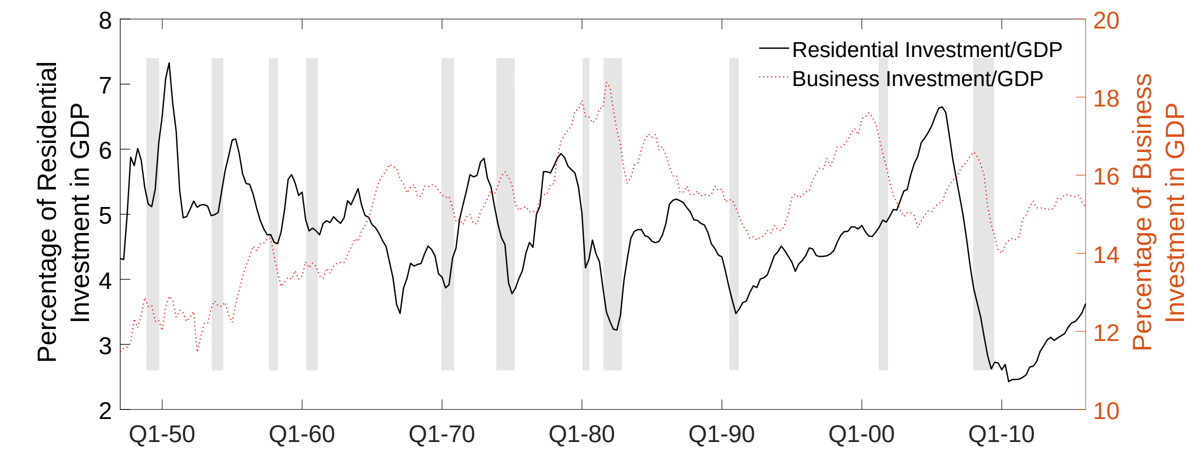
3.6 Conclusion

I introduce a new state variable, bankruptcy rate, to explain the stylized fact, that residential investment drops before the advent of economic downturn and recovers earlier than the recession ends. After the period of economic booms, the bankruptcy rate is low, and the business investment is expected to suffer from low level of bankruptcy losses. As a result, more of the resource would be shifted away from the residential side, where there is little bankruptcy concern. Thus, we see a decreasing residential investment share of aggregate output, and an increasing business investment share. Whether such over-investment in the business side contributes to the crisis, is out of my model, but definitely worth investigating further.

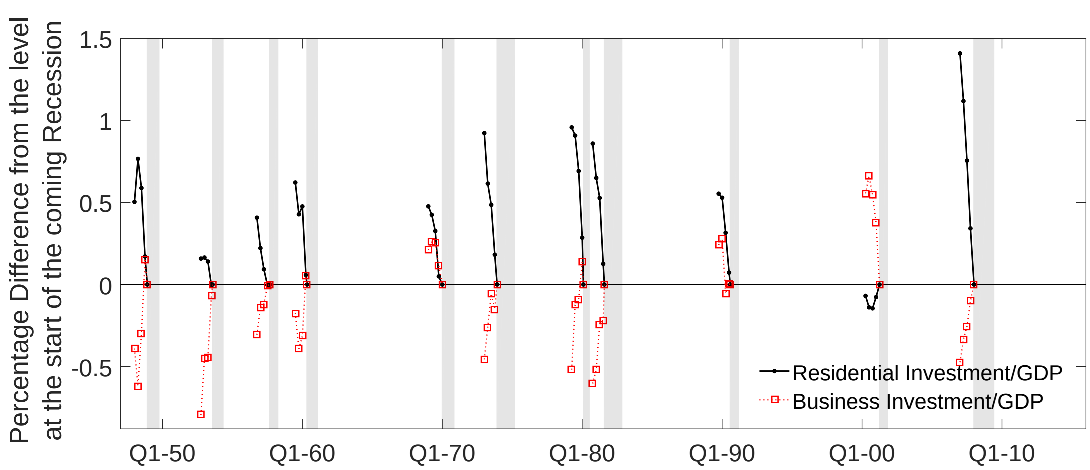
This paper picks up a key difference between the residential and business investment, that the residential investment is subject to smooth depreciation, while the business investment is exposed to volatile depreciation due to bankruptcy and asset displacement.

Figures

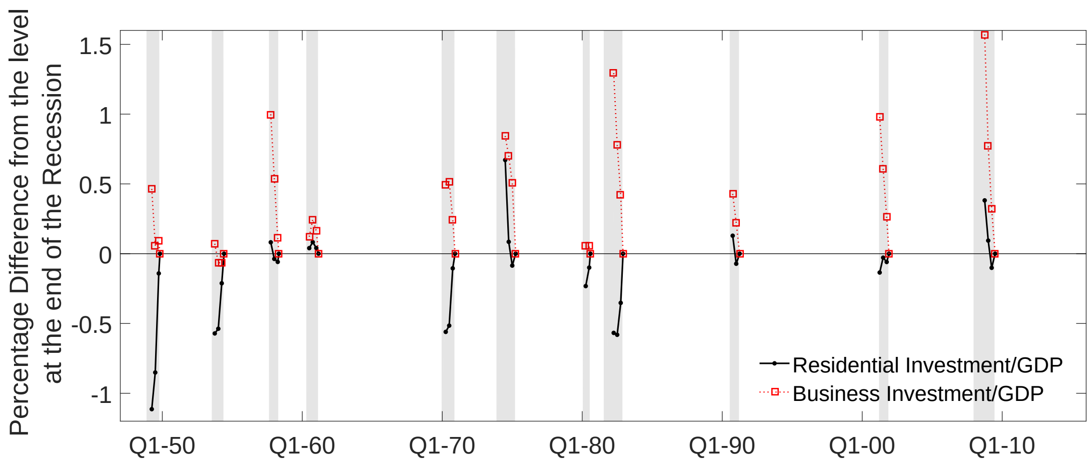
Figure 3.1 Residential Investment Leads the Business Cycle



Panel (a) Historical Paths Of Residential And Business Investment



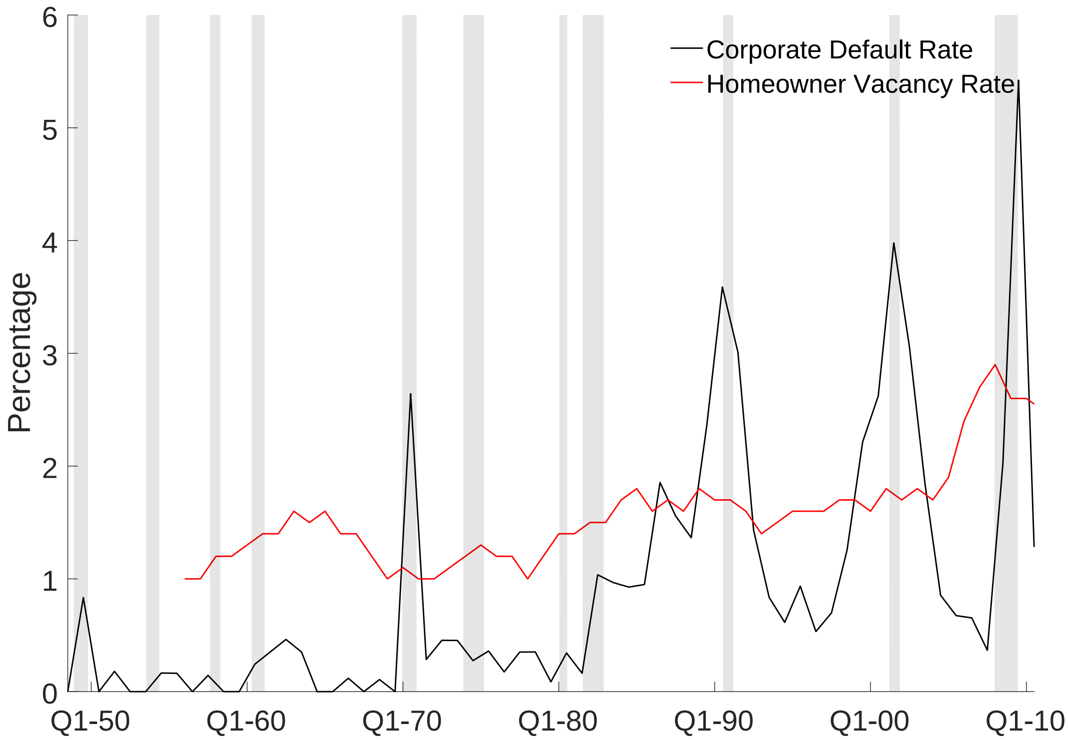
Panel (b) The Paths During The One Year Before The Start Of Each Recession



Panel (c) The Paths During The One Year Before The End Of Each Recession

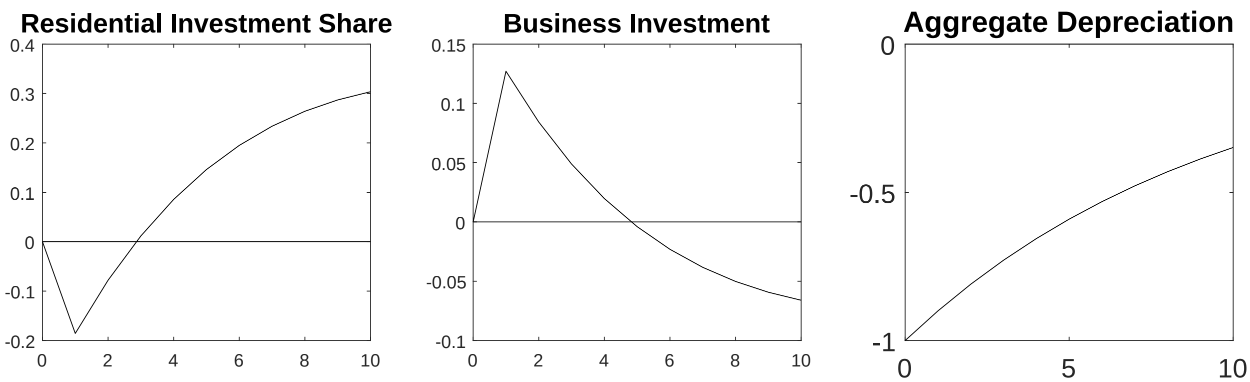
Note: The data are quarterly. The shaded areas are NBER-designated recessions. Panel (b) depicts the paths of residential investment/GDP (black solid) and business investment/GDP (red dash) during the one-year period before the start of each recession. The end of each path is shifted to 0 so that each point on the path denotes the percentage difference from the corresponding level at the start of the coming recession. Panel (c) depicts the paths during the one year before the end of each recession.
Source: NIPA and author's own calculations.

Figure 3.2 Historical Dynamics of Corporate Default Rate



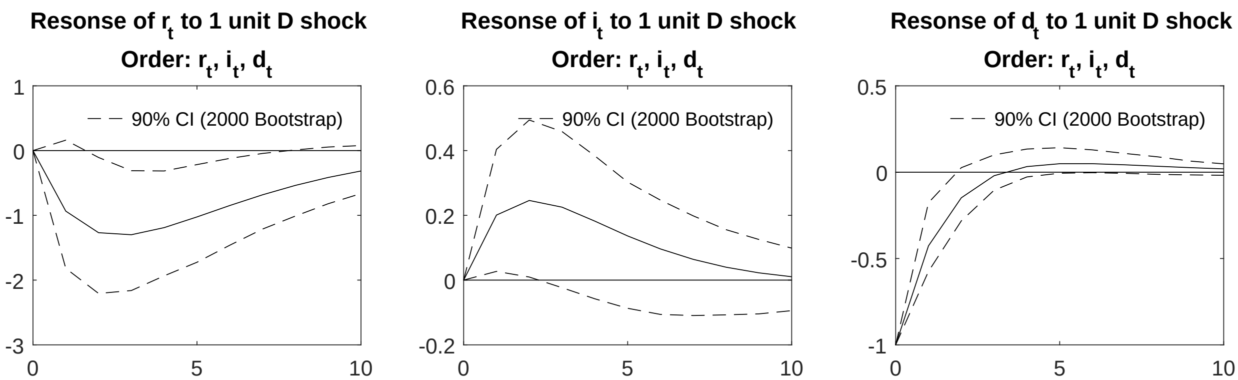
Note: The time series are annual. The corporate default rate is from Moody's, and the homeowner vacancy rate is from US. Bureau of the Census. The shaded areas are NBER-designated recessions.
Source: Moody's and US. Bureau of the Census.

Figure 3.3 Impulse Response to One Unit Negative Bankruptcy Shock (Simulated)



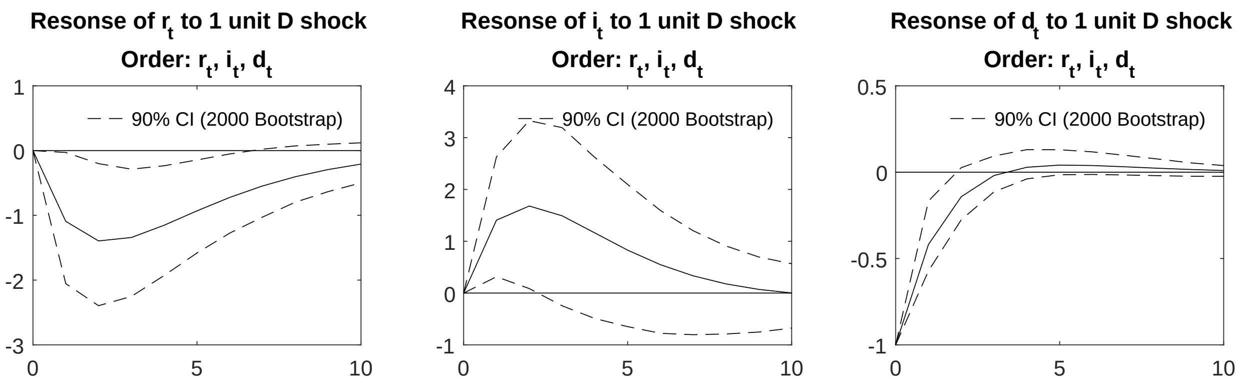
Note: The three impulse responses are simulated using the model in section 3.2 with parameters in Table 3.3. The shock is one unit of negative bankruptcy shock. The horizon is 10 years after the economy is hit by the negative bankruptcy shock. The residential investment share is defined as the value of residential investment (new housing structures) over the value of overall capital investment.
Source: Author's own calculations.

Figure 3.4 Impulse Response to One Unit Negative Default Shock (VAR)



Note: The three impulse responses are estimated through the VAR framework in section 3.4. r_t denotes the ratio of residential investment to aggregate investment, i_t represents real business investment, and d_t is a bankruptcy rate variable, which captures the full dynamics of aggregate depreciation rate. The horizon is 10 years after the economy is hit by the negative bankruptcy shock. The confidence intervals are constructed by bootstrapping the implied VAR residuals 2000 times, and are delimited at 90% confidence level. Bayesian Information Criterion (BIC) chooses 1 as the maximal lag number.
Source: NIPA, Moody's and author's own calculations.

Figure 3.5 Impulse Response to One Unit Negative Default Shock (Alternative VAR)



Note: The three impulse responses are estimated through the alternative VAR specification by refining i_t. r_t denotes the ratio of residential investment to aggregate investment, i_t represents the ratio of business investment to aggregate investment, and d_t is a bankruptcy rate variable, which captures the full dynamics of aggregate depreciation rate. The horizon is 10 years after the economy is hit by the negative bankruptcy shock. The confidence intervals are constructed by bootstrapping the implied VAR residuals 2000 times, and are delimited at 90% confidence level. Bayesian Information Criterion (BIC) chooses 1 as the maximal lag number.
Source: NIPA, Moody's and author's own calculations.

Tables

Table 3.1 Correlation Structure With Real GDP, Its Lead And Lag

	GDP_{t+1}	GDP_t	GDP_{t-1}
Real Residential Investment	0.657	0.528	0.292
Real Business Investment	0.530	0.709	0.732
Residential Investment Component	0.555	0.389	0.169
Business Investment Component	0.157	0.359	0.535

Note: This table lists the correlation between the four investment variables in the first column with the real GDP and its value in the previous year and the next year. All the variables are detrended by Hodrick–Prescott filter with $\lambda = 1600$. The residential investment component is the share of residential investment in the sum of residential and business investment. And the business investment component is the share of business investment in the sum of residential and business investment.
Source: NIPA and author's own calculations.

Table 3.2 Long Term Trend for the Running Variables

Running Variables	Growth Rate
k, k_m, c	$\frac{1}{1-\alpha_m} g_{Am}$
h	$\frac{\alpha_h}{1-\alpha_m} g_{Am} + g_{Ah}$

Note: This table displays the balanced growth rate of each variable per capita in the model of section 3.2. The manufacturing technology productivity grows at the rate of g_{Am}, and the housing technology productivity grows at the rate of g_{Ah}.

Table 3.3 Parameter Value for Model Simulation

Parameter	Value
μ	0.61
σ	2
β	0.95
δ_k	0.065
δ_h	0.014
α_m	0.309
α_h	0.132
g_{Am}	0.0186
g_{Ah}	0.0081
η	1.0167
ρ_d	0.9
$A_{m,0}, A_{h,0}$	1

Note: This table lists the parameters used to calibrate the model in section 3.3. The nondurable good share μ is set to 61% in the composite consumption bundle, so that the steady state level of residential investment component matches its historical mean. Relative risk aversion coefficient σ is 2, and discounting factor β is 0.95, which are widely used in the RBC literature (Davis and Heathcote, 2005). The historical mean of aggregate depreciation rate δ_k is 6.5% every year, which is the sum of the annual manufacturing depreciation rate estimated by Bureau of Economic Analysis, and the historical average of the corporate default rate published by Moody's. The depreciation rate of residential structures δ_h is 1.4%, estimated by Bureau of Economic Analysis. Capital production share in manufacturing sector α_m is 31%, and that in the construction sector α_h is 13.2%. Technology is developing at an annual rate of 1.86% in the production sector (g_{Am}), and 0.81% in the construction sector (g_{Ah}). All the capital share and technology trend parameters are estimated by NIPA data. Population is growing at a rate of 1.67% per year (η), the average rate of growth of hours worked in the private sector in the postwar period. The bankruptcy shock is highly persistent with first order autocorrelation ρ_d of 0.9. I just set $A_{c,0}$ and $A_{h,0}$ to be 1, because their values do not affect the impulse response functions of the detrending system.

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Appendix A

Technical Notes

A.1 Predictability of the Measure of Default Information in Chapter 1

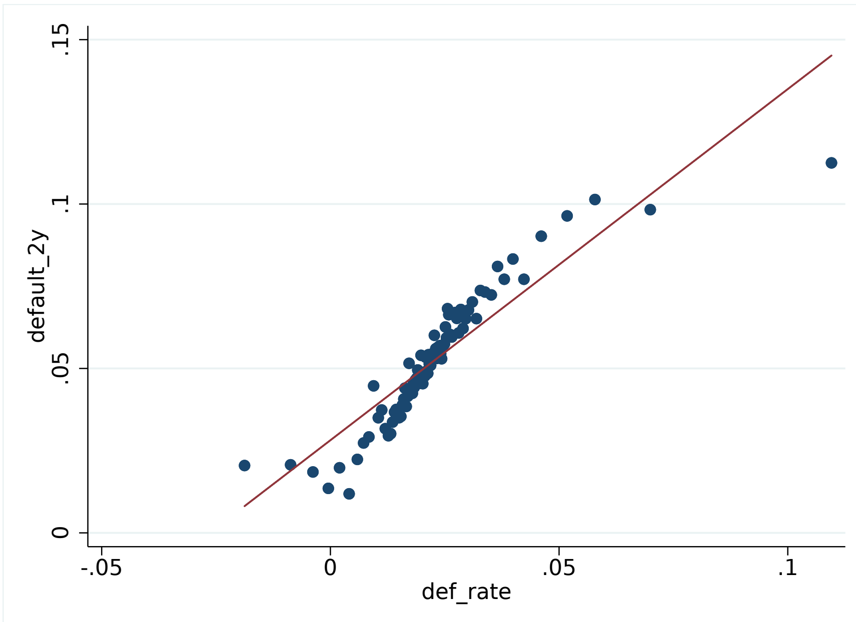
To gauge the predictability of such a measure of local default information, I plot the default rate of newly originated mortgages in the next 2 years against this lagged default measure in Figure A.1. The observations are binned into 100 percentiles, and each dot represents the average value for each percentile. We can see that the lagged default information predicts the quality of new originations pretty strongly. Table A.1 applies the linear regressions with various fixed effects. The strong predicting power of the lagged default rate is outstanding across all specifications. In terms of magnitude, the preferred specification in column (4) indicates if the default rate increased by 1% in the past two years, the likelihood of default for the current borrowers would increase by 0.53%.

Table A.1 Predicting Future Default with Lagged Default

Dependent Variable	$d_{c,t}$			
	(1)	(2)	(3)	(4)
$d_{c,t-1}$	1.455***	1.277***	1.068***	0.534***
	(0.029)	(0.026)	(0.065)	(0.052)
County FE		✓		✓
Time FE			✓	✓
R^2	0.02	0.03	0.05	0.05
Obs.	47,596,736	47,596,720	47,596,736	475,967,20

Note: This table regress the default rate of newly originated mortgages in the next 2 years against this lagged default measure. Standard errors in parentheses are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: FDIC, FHFA, HMDA, McDash, author's own calculations.

Figure A.1 Predicting Future Default with Lagged Default Rate



Note: This figure plots the mortgage default rate against the regional default rate in the past two years.
Source: McDash, author's own calculations.

A.2 Rationale for Regional Pricing

Should banks react to local past default rates? It depends on whether do local past default rates provide any useful information for banks screening process, and Table A.2 reports the results of mortgage-level regressions of the mortgage default (D_{it}) on its residualized interest rate ($\tilde{r}_{it}$). Since many observable characteristics have been taken out, the residualized interest rate $\tilde{r}_{it}$ can be thought of as the soft information known by the lenders. The significant coefficient of $\tilde{r}_{it}$ across all specifications suggest the soft information is valuable in predicting the mortgage performance. What is more, if we look at its interaction with small banks in column (1), the significant positive interaction indicates the small banks' soft information has even more predicting power. Column (2) adds the past local default ($d_{c(i),t}$) into the regression. And it is strongly predicting the mortgage default. In other words, local economic conditions are informative in predicting mortgage performance, and therefore the lenders should take the local economic conditions into consideration in their screening process. More interestingly, after controlling the past local default, the small banks' pricing advantage shrinks. And this is indicating a lot of the small banks' pricing efficiency is coming from their flexibility to react to local economic shocks. Column (3) and (4) control the lender fixed effect, and present very similar pattern.

In light of this evidence, let us now consider explanations for the uniform pricing tendency of national banks. While identifying the fundamental cause of this behavior is beyond the scope of this paper, discussions and interviews with bank managers suggest two leading explanations. The first is political risk. Fair lending laws and regulations prohibit banks from treating geographies differently based on race, religion, marital status and so on. These discriminatory factors might coincidentally be correlated with local economic conditions, and regional risk based pricing might expose the lenders to political risk and regulatory penalties. To avoid this risk, large banks might be willing to leave some money on the table and apply uniform pricing. The second is the agency problem within the bank organization. Large banks have complicated and hierarchical organization structure, which often leads to great principle-agent frictions between management and local branches (Stein, 2002). Therefore, large banks tend to give less autonomy to the local branches, and make centralized decisions. This phenomenon is more salient when decision making involves more soft information.

Table A.2 The Predictability of Mortgage Default

Dependent Variable	Mortgage Default			
	(1)	(2)	(3)	(4)
$\tilde{r}_{it}$	0.788^{***}	0.798^{***}	0.715^{***}	0.802^{***}
	(0.180)	(0.282)	(0.179)	(0.226)
$\tilde{r}_{it}\times$Small	0.750^{**}	0.485	0.663^{**}	0.382
	(0.316)	(0.430)	(0.307)	(0.352)
Past Default		2.239^{***}		2.559^{***}
		(0.468)		(0.426)
Past Default×Small		1.584^{**}		1.363^{**}
		(0.671)		(0.637)
Lender FE			✓	✓
$\bar{y}$(%)	6.40	6.40	6.40	6.40
Obs	4,748,419	4,748,419	4,747,735	4,747,735

Note: This table reports the results of mortgage-level regressions of mortgage default on its residualized default rate. Mortgage is defined as default if it is at least 2 month delinquent in the first 2 years after origination. The residualized interest rate $\tilde{r}_{it}$ is the residual from regression 1.3. A bank is small if it is either a regional or community bank The unit of both independent and dependent variables is percentage. Standard errors in parentheses are clustered at the lender level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: FDIC, FHFA, HMDA, Attom, McDash, author's own calculations.

A.3 Chapter 1 Micro Foundation: Moral Hazard of Branch Manager (Costly State Verification Framework)

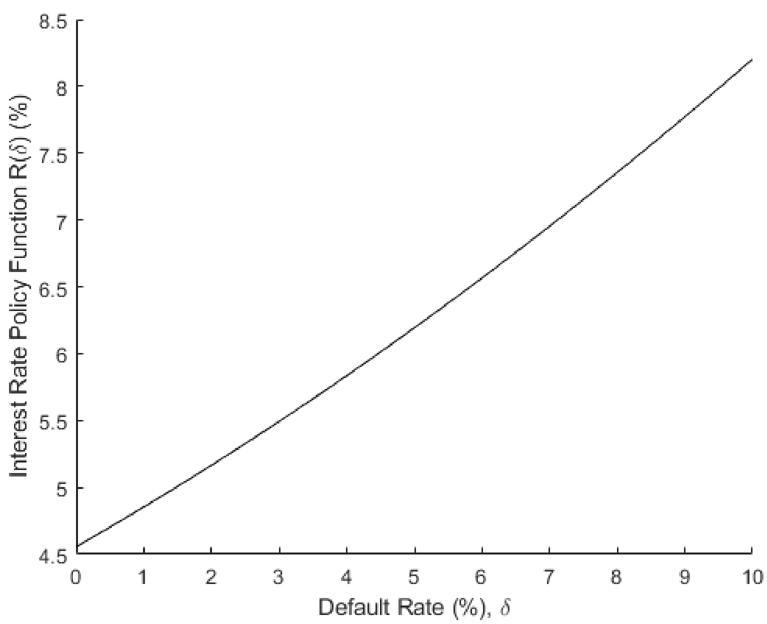
In this part, I provide a micro foundation for the assumption that a lender's perception of local economic conditions is a function of the lender's size in section 1.7. This micro foundation builds on the agency frictions between the lender management and local branch managers, a la Stein (2002), and attributes national banks' low responsiveness to local shocks to their great cost in verifying local branch managers' report on local default prediction.

For a bank b with a branch network $\{b_j\}_{j=1}^{N(b)}$, each of its branch b_j recoups interest income from mortgage lending in market $M(b_j)$, and incur cost from funding the mortgages and other operational expenses. The (expected) profit can be written as:

$$\max_{r_{b_j,M(b_j),t}} \pi_{b_j,M(b_j),t} = I_{M(b_j)} S_{b_j,M(b_j),t} \bar{Q}\bar{T} \left[(r_{b_j,M(b_j),t} - c_{b_j,M(b_j),t}) - \bar{l} E_b[d_{M(b_j),t}] \right] \tag{A.1}$$

where $S_{b_j,M(b_j),t}$ is the market share of bank branch b_j its market $M(b_j)$ at period t.

Figure A.2 Interest Rate Policy Function



For simplicity, I assume there is no heterogeneity in household disutility coefficients ($\alpha_i = \alpha$). Solving the first order condition for problem (A.1), we get the optimal interest rate at the branch level

$$r_{b_j,t} - \frac{1}{\alpha[1 - S_{b_j,M(b_j),t}(r_{b_j,t})]} = c_{b_j,t} + \bar{l} E \left[d_{M(b_j),t} \middle| \mathcal{I}_{M(b_j),t} \right], \tag{A.2}$$

which implies the interest rate policy function

$$r_{b_j,t} = R\left(E\left[d_{M(b_j),t} \left| \mathcal{I}_{M(b_j),t}\right.\right]\right) \tag{A.3}$$

Since the left hand side of equation (A.2) is increasing with $r_{b_j,t}$ and the right hand side is increasing with $E\left[d_{M(b_j),t} \left| \mathcal{I}_{M(b_j),t}\right.\right]$, we can conclude $R(\cdot)$ is an increasing function as illustrate by Figure A.2.

Branch Manager's Problem

The local branch manager can observe the local economic condition with some noise

$$\begin{gathered} \hat{\delta}_{b_j,M(b_j),t} = \delta_{M(b_j),t} + \epsilon_{\delta,t}, \\ \begin{bmatrix} \delta_{M(b_j),t} \\ \epsilon_{\delta,t} \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \bar{\delta} \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_\delta^2 & 0 \\ 0 & \sigma_{\epsilon_\delta}^2 \end{bmatrix} \right) \end{gathered} \tag{A.4}$$

and would report to the central management for rate setting. She will choose the optimal level of report $\tilde{\delta}_{b_j,M(b_j),t}$ to maximize her utility.

$$\max_{\tilde{\delta}_{b_j,M(b_j),t}} u_{b_j,t} = E\left[u(S_{b_j,M(b_j),t}) | \hat{\delta}_{b_j,M(b_j),t}, \tilde{\delta}_{b_j,M(b_j),t}\right]$$

Following Stein (2002), I assume the branch manager's utility depends on her total market share in the local market, which can be motivated by the manager's private benefits of control that are proportional to gross lending. The function $u(\cdot)$ transform the branch's market share to the manager's utility, and $u'(\cdot) > 0$. Since the market share is a decreasing function with interest rate, and thus expected default rate, the local manager has an incentive to underreport the local default prediction ($\tilde{\delta}_{b_j,M(b_j),t} \leq \hat{\delta}_{b_j,M(b_j),t}$).

Bank Central Management's Problem

To prevent the local branch manager from underreporting, the central management of the bank could audit the local branch and get to know the realization of $\delta_{M(b_j),t}$ at a cost of A. And the central management should decide under what condition they would carry out the audit, and how they set the interest rate according to their available information. With this moral hazard issue, the central management's profit maximization problem becomes

$$\max_{r_{b_j,t}, a_{b_j,t}} \pi_{b_j,M(b_j),t} = E\left[I_{M(b_j)} \bar{Q}\bar{T} S_{b_j,M(b_j),t} \left[(r_{b_j,t} - c_{b_j,t}) - \bar{l} d_{M(b_j),t}\right] - A a_{b_j,t} \left| \mathcal{I}_{M(b_j),t}\right.\right] \tag{A.1$'$}$$

$$s.t. \qquad \mathcal{I}_{M(b_j),t} = \begin{cases} \{\tilde{\delta}_{b_j,M(b_j),t}\} & \text{if } a_{b_j,t} = 0 \\ \{\tilde{\delta}_{b_j,M(b_j),t}, \delta_{M(b_j),t}\} & \text{if } a_{b_j,t} = 1 \end{cases}$$

Optimal Contract with Costly State Verification

Following Townsend (1979), this paper focuses on the contract space with deterministic audit. In another word, the decision whether the central management audits the local branch is deterministic conditional on the reported default prediction $\tilde{\delta}_{b_j,M(b_j),t}$.

Theorem 1. *Under the deterministic audit assumption, the optimal contract is specified only by two parameters δ^c and r^c. And the optimal contract is*

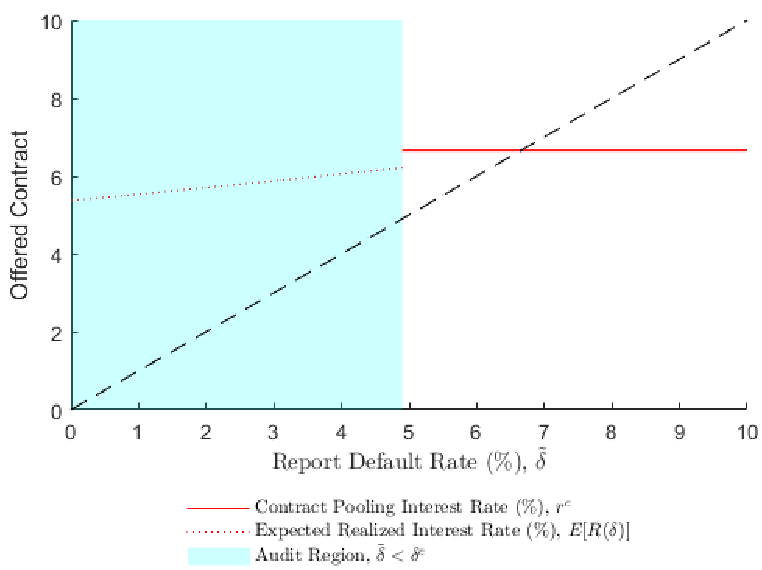
$$a_{b_j,t} = \begin{cases} 0 & \textit{if } \tilde{\delta}_{b_j,M(b_j),t} \geq \delta^c \\ 1 & \textit{if } \tilde{\delta}_{b_j,M(b_j),t} < \delta^c \end{cases}$$

$$r_{b_j,t} = \begin{cases} r^c & \textit{if } \tilde{\delta}_{b_j,M(b_j),t} \geq \delta^c \\ R(\delta_{M(b_j),t}) & \textit{if } \tilde{\delta}_{b_j,M(b_j),t} < \delta^c \end{cases}$$

And the branch manager always (weekly) prefers to report his observed default signal truthfully

$$\tilde{\delta}_{b_j,M(b_j),t} = \hat{\delta}_{b_j,M(b_j),t}.$$

Figure A.3 Optimal Contract



Proof. The general principle in the contract theory implies any optimal equilibrium can be achieved by a truth revealing contract. Without loss of generality, we focus on the truth revealing contract space.

First, we can show $r_{b_j,t}(\tilde{\delta}_{b_j,M(b_j),t})$ is a uniform function ($r_{b_j,t} = r^c$) in the non-audit region, by contradiction. Let $\mathcal{R}^{\text{audit}}$ denote the audit region. Assuming the opposite, there exist $\tilde{\delta}_1 \neq \tilde{\delta}_2$ in $\mathcal{R}/\mathcal{R}^{\text{audit}}$, so that $r_{b_j,t}(\tilde{\delta}_1) > r_{b_j,t}(\tilde{\delta}_2)$. Then

$$\begin{aligned}
&E\left[u(S_{b_j,M(b_j),t})|\hat{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_1, \tilde{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_1\right] \\
=&u(S_{b_j,M(b_j),t}(r_{b_j,t}(\tilde{\delta}_1))) \\
<&u(S_{b_j,M(b_j),t}(r_{b_j,t}(\tilde{\delta}_2))) \\
=&E\left[u(S_{b_j,M(b_j),t})|\hat{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_1, \tilde{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_2\right]
\end{aligned}$$

Such a contract is not truth revealing, since the branch manager will report $\tilde{\delta}_2$ if she observes $\hat{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_1$. This leads to a contradiction.

Second, we can prove $r_{b_j,t} = R(\delta_{M(b_j),t})$ in the audit region $\mathcal{R}^{\text{audit}}$. Conditional on auditing, the management's profit maximization problem becomes

$$\max_{r_{b_j,t}} \pi_{b_j,M(b_j),t} = I_{M(b_j)}\bar{Q}\bar{T}S_{b_j,M(b_j),t}\left[(r_{b_j,t} - c_{b_j,t}) - \bar{l}E\left[d_{M(b_j),t}\middle|\delta_{M(b_j),t}\right]\right] - A$$

so $r_{b_j,t} = R(\delta_{M(b_j),t})$, by the definition of $R(\cdot)$.

Third, let us prove $\mathcal{R}^{\text{audit}} = \{\tilde{\delta} : \tilde{\delta} < \delta^c\}$. If not, there exist $\tilde{\delta}_1 < \tilde{\delta}_2$, so that $a_{b_j,t}(\tilde{\delta}_1) = 0, a_{b_j,t}(\tilde{\delta}_2) = 1$.

$$\begin{aligned}
&E\left[u(S_{b_j,M(b_j),t})|\hat{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_1, \tilde{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_2\right] && \text{(observe } \tilde{\delta}_1\text{, report } \tilde{\delta}_2\text{)} \\
=&E\left[u(S_{b_j,M(b_j),t}(R(\delta_{M(b_j),t})))|\hat{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_1\right] \\
>&E\left[u(S_{b_j,M(b_j),t}(R(\delta_{M(b_j),t})))|\hat{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_2\right] \\
=&E\left[u(S_{b_j,M(b_j),t})|\hat{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_2, \tilde{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_2\right] && \text{(observe } \tilde{\delta}_2\text{, report truthfully)} \\
\geq&E\left[u(S_{b_j,M(b_j),t})|\hat{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_2, \tilde{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_1\right] && \text{(observe } \tilde{\delta}_2\text{, report } \tilde{\delta}_1\text{)} \\
=&E\left[u(S_{b_j,M(b_j),t})|\hat{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_1, \tilde{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_1\right] && \text{(observe } \tilde{\delta}_1\text{, report truthfully)}
\end{aligned}$$

Again, such a contract is not truth revealing, since the branch manager will report $\tilde{\delta}_2$ to trigger auditing if she observes $\hat{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_1$. This leads to a contradiction. □

Then let us investigate the quantitative restriction for the two parameters (δ^c, r^c) that specify the optimal contract.

Theorem 2. *The optimal contract (δ^c, r^c) have to satisfy*

$$u(S_{b_j,M(b_j),t}(r^c)) = E\left[u(S_{b_j,M(b_j),t}(R(\delta_{M(b_j),t})))|\hat{\delta}_{b_j,M(b_j),t} = \delta^c\right]. \tag{A.5}$$

and $r^c(\delta^c)$ is an increasing function.

Equation A.5 makes the branch manager indifferent between auditing and taking the pooling rate r^c without auditing.

Proof. Since $a_{b_j,t}(\delta^c) = 0$, it implies

$$u(S_{b_j,M(b_j),t}(r^c)) \geq E\left[u(S_{b_j,M(b_j),t}(R(\delta_{M(b_j),t})))|\hat{\delta}_{b_j,M(b_j),t} = \delta^c\right].$$

Suppose

$$u(S_{b_j,M(b_j),t}(r^c)) > E\left[u(S_{b_j,M(b_j),t}(R(\delta_{M(b_j),t})))|\hat{\delta}_{b_j,M(b_j),t} = \delta^c\right].$$

The continuity of functions $u(\cdot)$, $S(\cdot)$ and $R(\cdot)$, as well as the normality of the distributions implies there exists $\delta' < \delta^c$, so that

$$\begin{aligned} E\left[u(S_{b_j,M(b_j),t}(R(\delta_{M(b_j),t})))|\hat{\delta}_{b_j,M(b_j),t} = \delta^c\right] &< E\left[u(S_{b_j,M(b_j),t}(R(\delta_{M(b_j),t})))|\hat{\delta}_{b_j,M(b_j),t} = \delta'\right] \\ &< u(S_{b_j,M(b_j),t}(r^c)) \end{aligned}$$

which implies it is better to report $\tilde{\delta}_{b_j,M(b_j),t} = \delta^c$ if the branch manager observes $\hat{\delta}_{b_j,M(b_j),t} = \delta'$, which contracts the truth revealing principle of the contract.

Since the left hand side of the equation A.5 is decreasing with r^c, and right hand side is decreasing with δ^c, $r^c(\delta^c)$ is thus an increasing function. $\square$

Equilibrium Outcomes

Under the optimal contract, the bank management needs to determine the contract $(\delta^c, r^c(\delta^c))$ before any signal is observed by the branch managers.

$$\max_{\delta^c} \pi_{b_j,M(b_j),t} = E\left[I_{M(b_j)}\bar{Q}\bar{T}S_{b_j,M(b_j),t}\left[(r_{b_j,t} - c_{b_j,t}) - \bar{l}d_{M(b_j),t}\right] - Aa_{b_j,t}\right] \tag{A.1$''$}$$

$$s.t. \quad a_{b_j,t} = \begin{cases} 0 & \text{if } \tilde{\delta}_{b_j,M(b_j),t} \geq \delta^c \\ 1 & \text{if } \tilde{\delta}_{b_j,M(b_j),t} < \delta^c \end{cases}$$

$$r_{b_j,t} = \begin{cases} r^c(\delta^c) & \text{if } \tilde{\delta}_{b_j,M(b_j),t} \geq \delta^c \\ R(\delta_{M(b_j),t}) & \text{if } \tilde{\delta}_{b_j,M(b_j),t} < \delta^c \end{cases}$$

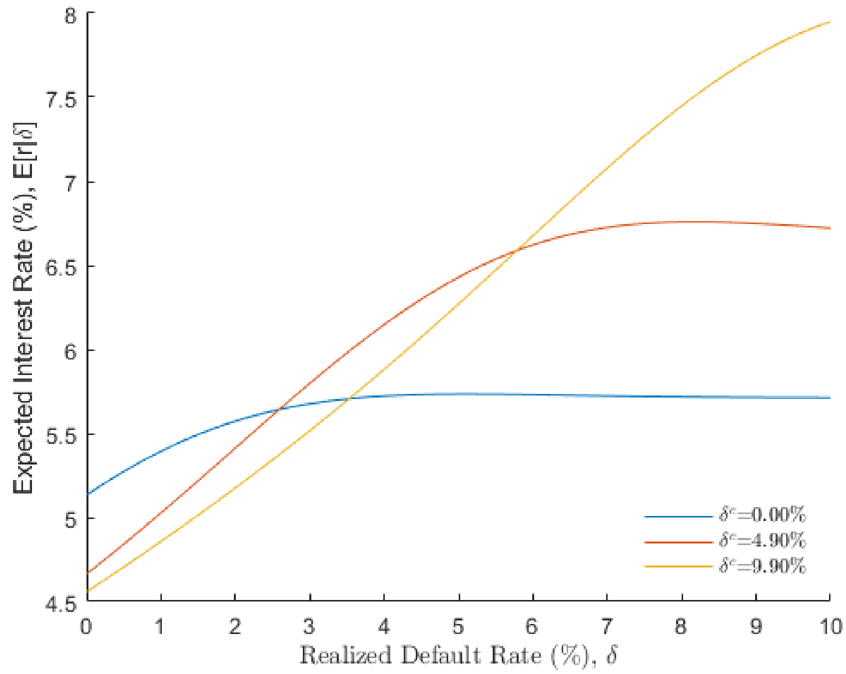
$$\tilde{\delta}_{b_j,M(b_j),t} = \hat{\delta}_{b_j,M(b_j),t} = \delta_{M(b_j),t} + \epsilon_{\delta,t}$$

Problem A.1$''$ is an ex ante optimization problem, and would pin down the cutoff default rate δ^c, and therefore the optimal contract.

Specifically, we can show δ^c is decreasing with the cost parameter A. The more costly it is to verify the state, the less likely the local branch is audited, and the more pooling the equilibrium features.

Once the optimal contract is determined, we can calculate all equilibrium outcomes. In this paper, we are specially interested in the (expected) interest rates conditional on the local realized default rate $E[r_{b_j,t}|\delta_{M(b_j),t}]$.

Figure A.4 Equilibrium Interest Rate



A.4 Solution for the Model in Chapter 3

After detrending and reparametrization, we can set up the Lagrangian as follows

$$\mathcal{L}(\mathcal{H}) = \sum_{t=0}^{\infty} \hat{\beta}^t \left[\frac{\left(c_t^{\mu} h_t^{1-\mu}\right)^{1-\sigma}}{1-\sigma} + \lambda_{mt}\left[(1-d_t\delta_k)k_t + A_m k_{mt}^{\alpha_m} - c_t - \hat{\eta}_1 k_{t+1}\right] \right.$$
$$\left. + \lambda_{ht}\left[(1-\delta_h)h_t + A_h(k_t - k_{mt})^{\alpha_h} - \hat{\eta}_2 h_{t+1}\right] \right]$$

Here I take off the expectation operator and consider the Lagrangian for any trajectory $\mathcal{H}$. Since the evolution of the system within any given trajectory does not affect that on other trajectories, we can optimize the problem for any given trajectory, and then apply the linear expectation operator.

There are 3 state variables in this system: d_t, h_t, k_t. And the solution is characterized by the following organized first order conditions:

$$\begin{aligned}
\lambda_{mt} =& \mu \hat{c}_t^{\mu(1-\sigma)-1} \hat{h}_t^{(1-\mu)(1-\sigma)} \\
\lambda_{mt} =& \frac{\hat{\eta}_1}{\hat{\beta}(1-d_t\delta_k) + \hat{\beta}\alpha_m A_m \hat{k}_{mt}^{\alpha_m - 1}} \lambda_{mt-1} \\
\lambda_{ht} =& \frac{1}{\hat{\beta}(1-\delta_h)} \left[\hat{\eta}_2 \lambda_{ht-1} - \hat{\beta}(1-\mu)\hat{c}_t^{\mu(1-\sigma)} \hat{h}_t^{(1-\mu)(1-\sigma)-1} \right] \\
\frac{\lambda_{ht}}{\lambda_{mt}} =& \frac{\alpha_m A_m \hat{k}_{mt}^{\alpha_m - 1}}{\alpha_h A_h (\hat{k}_t - \hat{k}_{mt})^{\alpha_h - 1}}
\end{aligned}$$

Since both the utility and production functions in this system satisfy Inada conditions, a bounded steady state exists. I use the letter with a bar over the head to denote the steady state value of each detrended running variable.

Disregarding the time subscripts in the first order conditions and resource constrains, we can solve the key steady state values:

$$\begin{aligned}
\bar{k}_m^{\alpha_m - 1} =& \frac{\hat{\eta}_1 - \hat{\beta}(1-\delta_k)}{\hat{\beta}\alpha_m \hat{A}_m} \\
\frac{\bar{k}_m}{\bar{k}} =& \frac{\frac{1}{\hat{\beta}} \frac{\mu}{(1-\mu)} \frac{\alpha_m}{\alpha_h} \frac{[\hat{\eta}_2 - \hat{\beta}(1-\delta_h)]}{[\hat{\eta}_2 - (1-\delta_h)]} + \frac{[\hat{\eta}_1 - (1-\delta_k)]}{[\hat{\eta}_1 - \hat{\beta}(1-\delta_k)]} \hat{\beta}\alpha_m}{1 + \frac{1}{\hat{\beta}} \frac{\mu}{(1-\mu)} \frac{\alpha_m}{\alpha_h} \frac{[\hat{\eta}_2 - \hat{\beta}(1-\delta_h)]}{[\hat{\eta}_2 - (1-\delta_h)]}}
\end{aligned}$$

With these steady-state values, we can further log-linearized the system, and get the following linear evolution equations. Here the cheched letters are used to denote the percentage deviation from its steady state value.

$$\begin{aligned}
\check{\lambda}_{mt} =& [\mu(1-\sigma) - 1]\check{c}_t + (1-\mu)(1-\sigma)\check{h}_t \\
\check{\lambda}_{mt} - \check{\lambda}_{mt-1} =& \frac{\hat{\beta}\delta_k}{\hat{\eta}_1} \check{d}_t - \left[1 - \frac{\hat{\beta}}{\hat{\eta}_1}(1-\delta_k) \right] (\alpha_m - 1)\check{k}_{mt} \\
\frac{\hat{\beta}(1-\delta_h)}{\hat{\beta}(1-\delta_h) - \hat{\eta}_2} \check{\lambda}_{ht} =& \frac{\hat{\eta}_2}{\hat{\beta}(1-\delta_h) - \hat{\eta}_2} \check{\lambda}_{ht-1} + \mu(1-\sigma)\check{c}_t + [(1-\mu)(1-\sigma) - 1]\check{h}_t \\
\check{\lambda}_{ht} - \check{\lambda}_{mt} =& (\alpha_m - 1)\check{k}_{mt} - (\alpha_h - 1) \left(\frac{\bar{k}}{\bar{k} - \bar{k}_m} \check{k}_t - \frac{\bar{k}_m}{\bar{k} - \bar{k}_m} \check{k}_{mt} \right) \\
\left(A_m \bar{k}_m^{\alpha_m - 1} \frac{\bar{k}_m}{\bar{k}} - (\hat{\eta}_1 - (1-\delta_k)) \right) \check{c}_t =& (1-\delta_k)\check{k}_t - \delta_k \check{d}_t + A_m \alpha_m \bar{k}_m^{\alpha_m - 1} \frac{\bar{k}_m}{\bar{k}} \check{k}_{mt} - \hat{\eta}_1 \check{k}_{t+1} \\
\frac{\hat{\eta}_2 \check{h}_{t+1} - (1-\delta_h)\check{h}_t}{\hat{\eta}_2 - (1-\delta_h)} =& \alpha_h \left[\frac{\bar{k}}{\bar{k} - \bar{k}_m} \check{k}_t - \frac{\bar{k}_m}{\bar{k} - \bar{k}_m} \check{k}_{mt} \right] \\
\check{d}_{t+1} =& \rho_d \check{d}_t + \epsilon_{dt+1}
\end{aligned}$$

In this model, bankruptcy shock is the only exogenous shock. Individuals and firms react to bankruptcy shocks based on historical information. Fortunately, the system exhibits Markovian properties, the current state of capital stock $\check{k}_t$, housing stock $\check{h}_t$ and bankruptcy rate $\check{d}_t$ are sufficient statistics of the information set. So the evolution of the system is pinned down by the following filter process:

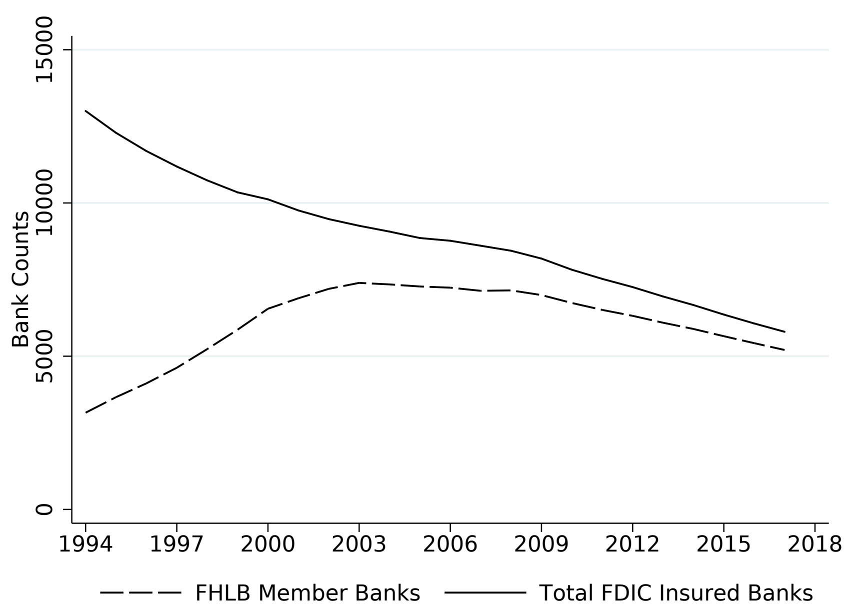
$$\begin{bmatrix} \check{k}_{t+1} \\ \check{h}_{t+1} \\ \check{d}_{t+1} \end{bmatrix} = \begin{bmatrix} v_{kk} & v_{kh} & v_{kd} \\ v_{hk} & v_{hh} & v_{kd} \\ 0 & 0 & \rho_d \end{bmatrix} \begin{bmatrix} \check{k}_t \\ \check{h}_t \\ \check{d}_t \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \epsilon_{dt+1} \end{bmatrix}$$

All the other running variables are also linear functions of the state variables.

Appendix B

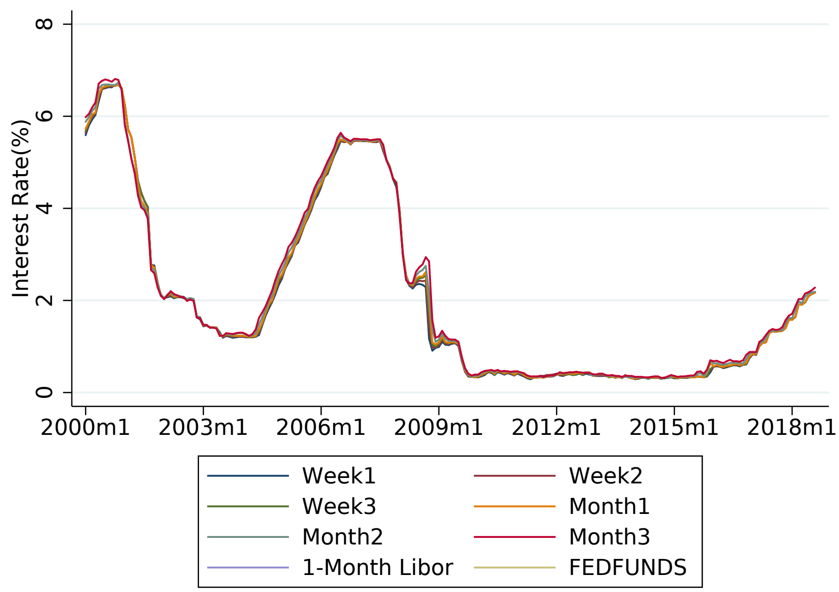
Additional Figures

Figure B.1 Historical Trend of FHLB Members



Note: This figure plots the time series of the number of all FDIC insured banks (solid line) and FHLB member banks.
Source: FDIC, FHLB.

Figure B.2 Historical Advances Rates from FHLB Des Moines



Note: This figure illustrates the historical advance rates of various maturities from an FHLB (Des Moines).
Source: FHLB of Des Moines.

Appendix C

Additional Tables

Table C.1 Residualize Interest Rates Regressions

Dependent Variable	Mortgage Interest Rates			
	(1)	(2)	(3)	(4)
Quarter FE	✓	✓	✓	✓
FICO	✓	✓	✓	✓
LTV		✓	✓	✓
Lien Status				✓
Interest Type				✓
Loan Purpose				✓
Winsorsize			✓	✓
R^2	0.55	0.60	0.68	0.71
Obs.	43,385,108	43,190,260	41,009,706	41,009,706

Note: The regressions in this table residualize the mortage rates with variable specifications. Specification (4) is the preferred one. Winsorsizing is executed at the 1% level.
Source: FDIC, FHFA, GIS.