The Dissertation Committee for Xuewei Jiang
certifies that this is the approved version of the following dissertation:

Financing Competitors: Essays on Shadow Banks' Funding

Committee:

Laura Starks, Co-Supervisor

Gregor Matvos, Co-Supervisor

Amit Seru

Cesare Fracassi

Daniel Neuhann

Financing Competitors:
Essays on Shadow Banks' Funding

by

Xuewei Jiang

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Dedicated to my better half, Yanxin, for his affection and inspiration, and my parents, Mr Jiang and Ms Xue, for their unconditional love.

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Financing Competitors:
Essays on Shadow Banks' Funding

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Xuewei Jiang , Ph.D.
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Co-Supervisors: Laura Starks
Gregor Matvos

This dissertation provides an overview of the interaction between banks and shadow banks in the two markets: the warehouse lending market, in which banks supply funding to shadow banks, and in the mortgage origination market, in which banks and shadow banks compete with each other. It studies how their interaction in one market affects their interaction in the other market, the equilibrium feedback between the two markets, and the implications for policy pass-though.

I collect shadow bank call reports through FOIA requests and document that most of shadow banks' warehouse funding is obtained from the banks that compete with them in the mortgage market. I provide evidence that banks trade off information advantage in warehouse lending against the loss in profits from increased mortgage market competition: (i) warehouse lending is clustered between competitors in local mortgage markets, especially in regions where public information of local housing value is less reliable; (ii) shadow banks cannot easily substitute to alternative funding sources if their relationship banks exogenously reduce warehouse lending; and (iii) a bank lends less to shadow banks in regions where it has greater market share in mortgage origination. To study the net effect on mortgage market competition in equilibrium, I calibrate a quantitative model that links warehouse lending and mortgage market competition. Warehouse lending market power is substantial. Banks charge 30% extra markups to the competing shadow banks relative to non-competitors. In the counterfactual, a faster GSE loan purchase program, which changes the warehouse lending market structure, would increase mortgage market competition, improving consumer welfare by $3.5 billion.

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Chapter 1

Shadow Banks in the Consumer Credit Market: An Overview

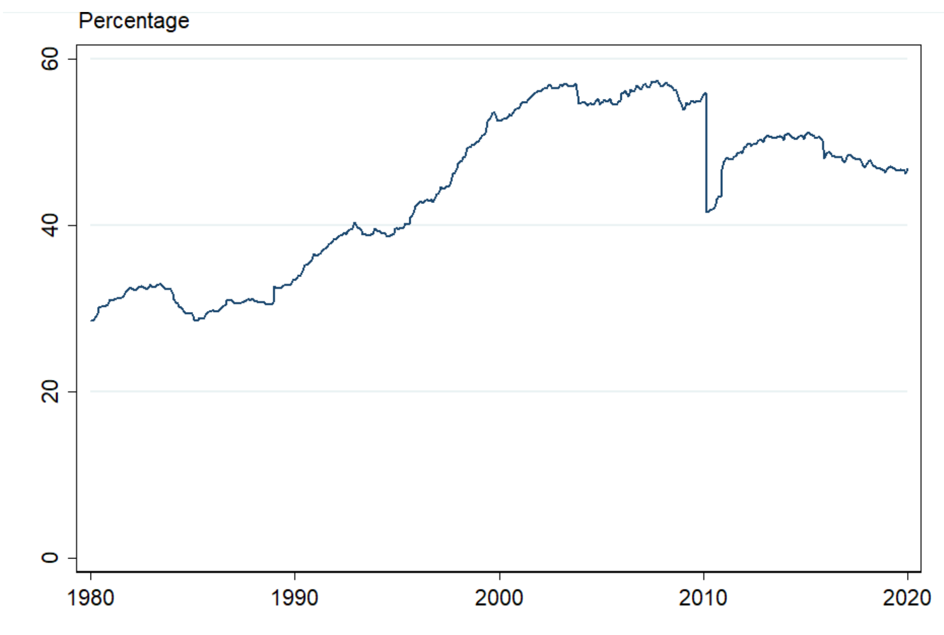
Shadow banks play an important role in supplying credit to households. Their holding of total outstanding consumer credit grew from 30% in 1980 to more than 50% right before the financial crisis, as depicted in Fig. 1.1. Despite of a market share decline in 2009, they experienced a rapid growth post crisis, which was partially driven by stricter regulation imposed on the traditional banking sector.[1]

In this chapter, I first define shadow banks and describe their importance in various consumer credit markets. I then focus on the U.S. residential mortgage market. I discuss the interaction between shadow banks and traditional banks in this largest consumer credit market that makes up about two-thirds of total consumer credit.[2] I also provide a review of existing academic literature and ongoing regulatory and policy conversations closely related to shadow banks.

[1]See, e.g. Buchak, Matvos, Piskorski, and Seru (2018a) and Irani, Iyer, Meisenzahl, and Peydro (2018).

[2]"Quarterly Report on Household Debt and Credit", Federal Reserve Bank of New York. https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/hhdc_2019q2.pdf.

Figure 1.1. Share of Consumer Credit Held by Nonbanks



Source: G.19 Consumer Credit by Board of Governors of the Federal Reserve System.

1.1 What is a Shadow Bank?

Shadow bank is a broad term frequently used by regulators, academics, and media to refer to different institutions. The term has been applied to the collection of non-depository financial institutions that provide services similar to traditional commercial banks. Examples of shadow banks include securitization vehicles, asset-backed commercial paper conduits, money market mutual funds, broker-dealers, and mortgage companies.[3] In this dissertation, shadow banks refer to non-depository lenders. This definition is also used in Demyanyk and Loutskina (2016), Buchak et al. (2018a), and Buchak, Matvos, Piskorski, and Seru (2018b) and is consistent with the definition by the Financial Stability Board (FSB).

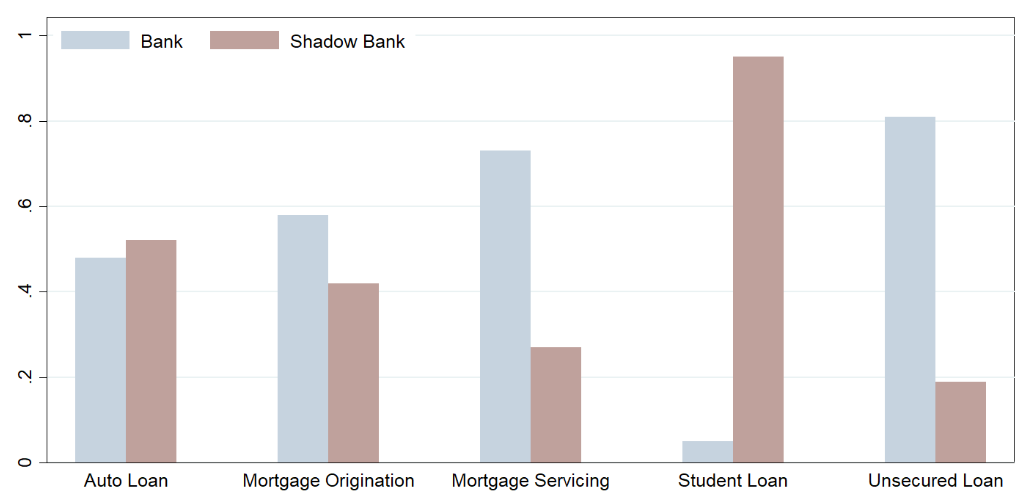
There are four major consumer credit market: auto loan, residential mortgage, student loan, and unsecured personal loan. Shadow banks in the auto loan market are auto finance companies, including the financing arms of auto manufacturers (captive finance companies) and non-captive finance companies, e.g., Exeter Finance. Shadow banks in the mortgage market are non-depository mortgage companies, including mortgage bankers, mortgage brokers that use their own money for origination, and real estate investment

[3]According to Ben Bernanke's speech at the Russell Sage Foundation and The Century Foundation Conference on "Rethinking Finance," shadow banking are defined as comprising "a diverse set of institutions and markets that, collectively, carry out traditional banking functions but do so outside, or in ways only loosely linked to, the traditional system of regulated depository institutions." https://www.federalreserve.gov/newsevents/speech/bernanke20120413a.htm. See also Adrian and Ashcraft (2016).

trusts, e.g., Quicken Loans. Shadow banks in the student loan market are personal finance companies, e.g., SoFi and Earnest. Shadow banks in the unsecured personal loan market are payday lenders, e.g., Advance America.

As shown in Fig. 1.2, banks face competition from shadow banks in all types of consumer credit markets. In auto loan and student loan markets, the shares of lending falling out of the banking system were more than 50% as of 2015. In 2017, the shares of lending in the residential mortgage market also exceeded 50%, which I will discuss in details in the next section. While unsecured personal loan market observes the smallest share of shadow bank lending, shadow banks still lend almost 20% of total loans.

Figure 1.2. Consumer Credit Market Share Estimates by Lender Type in 2015



Source: Goldman Sachs Global Investment Research and Experian Automotive.

1.2 Shadow Banks in the Largest Consumer Credit Market

The residential mortgage market is the largest consumer loan market in the United States. The average annual mortgage origination was about $2 trillion over the past decade. Lenders in this market can be classified into depository-taking financial institutions, e.g. banks and credit unions, and shadow banks. The largest five shadow banks ranked based on their mortgage origination volumes in 2017 are Quicken Loans, LoanDepot, Caliber Home Loans, United Shore Financial Service, and Fairway Independent Mortgage.

Fig. 1.3 presents the mortgage origination activities by shadow banks from 2000 to 2017. The nature of lenders in the mortgage market changed substantially after the financial crisis. Shadow banks experienced a rapid growth post crisis. Buchak et al. (2018a) show that about two-thirds of such expansion was caused by increased regulatory compliance costs on traditional banks while one-third of shadow banks' expansion was driven by technological development. Moreover, despite of the relatively small magnitude, there was another expansion of shadow bank origination before the crisis from 2003 to 2005. Drechsler, Savov, and Schnabl (2019) argue that this expansion coincided with a big change in monetary policy that raised rates by 4.25%, which led to an expansion of private securitization.[4] Since shadow banks heavily

[4]In their seminal work, Buchak et al. (2018a) uses HMDA data to show that shadow banks sell more than xx of mortgages in the same year as they originate them; and Buchak et al. (2018b) finds that shadow banks' post-crisis expansion was limited in the conforming mortgage market, where mortgages can be easily sold to the Governement Sponsored Entities

rely on originate-to-distribute, the development of private-label securitization boosted their growth. Therefore, while the post-crisis expansion was explained by the increase in relative efficiency of shadow banks, either due to their own technological development or increase in competitors' regulatory compliance cost, in the primary mortgage market, the pre-crisis expansion was driven by development in the secondary mortgage market that lowered the cost of the originate-to-distribute business model.

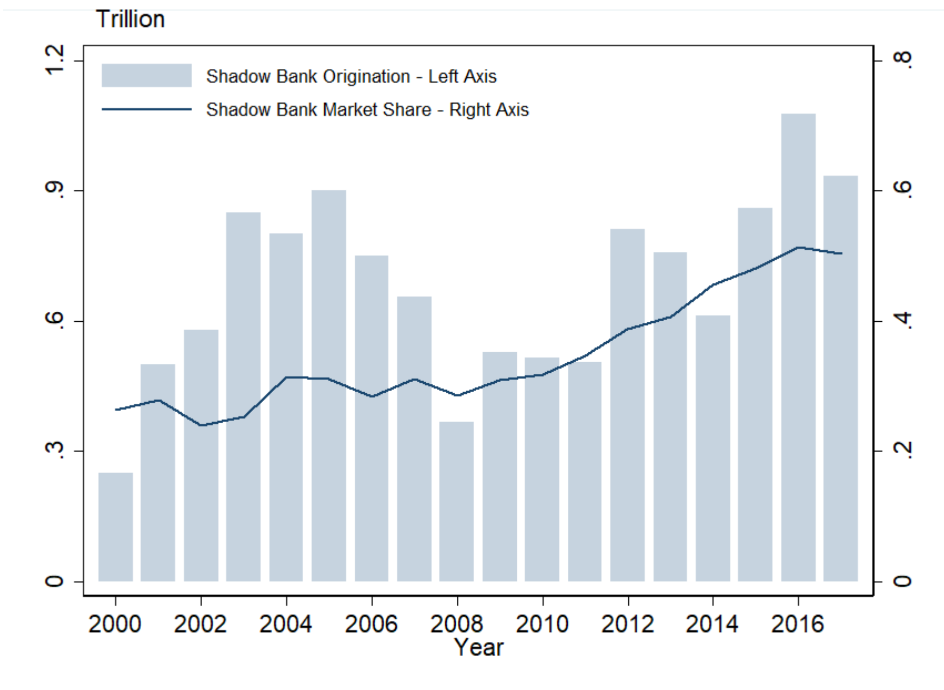
Shadow banks are subject to lighter supervision than traditional banks. They are licensed with the state departments and are regulated by either the Office of the Comptroller of the Currency (OCC) or the Department of Housing and Urban Development (HUD) (Engel and McCoy (2016)). Since 2011, they are required to submit mortgage call reports to their state regulators according to the SAFE Act of 2008.

1.2.1 Shadow Banks' Source of Funding

As mentioned above, shadow banks rely on the originate-to-distribute business model. Using shadow bank call report data, Jiang, Matvos, Piskorski, and Seru (2020) observe shadow banks' balance sheets and document that the majority of mortgages originated by shadow banks are held for sale and thus only stay on their balance sheet for a short period of time. During this period,

(GSEs). Findings in Egan, Lewellen, and Sunderam (2017b) support the argument that the lack of synergies between deposit-taking and lending activities justifies shadow banks' optimal choice of origination-to-distribute business model. They find that banks with high deposit productivity have high asset productivity, which is driven by the tendency of deposit-productive banks to hold loans on balance sheets.

Figure 1.3. Mortgage Origination by Shadow Banks



Source: HMDA.

shadow banks finance the mortgages using their own equity capital and short-term debt through warehouse lines of credit.

Jiang et al. (2020) document that about 25% of shadow banks' balance sheet assets are financed by equity, and the rest of their assets are almost exclusively financed by short-term debt through warehouse lines of credit. In addition, the equity-to-asset ratios observe huge dispersion among individual shadow banks. Shadow banks at the left tail of the size distribution are about four times more capitalized than shadow banks at the right tail of the size distribution.

The warehouse borrowing, which plays a crucial role in the originate-to-distribute process, is essentially a repurchase agreement with heterogeneous collateral, in which the mortgage note serves as collateral until the warehouse debt is paid off. Jiang et al. (2020) show that shadow banks obtain their warehouse credit lines from, on average, 3 to 4 informed lenders. As shown in the table below, which reports the lender composition of shadow banks' warehouse lines of credit, based on Table 2 in Jiang et al. (2020), banks provide the majority of the short-term funding to shadow banks.

	Mean	p25	Median	p75
Banks	93.1%	100%	100%	100%
GSE	0.7%	0%	0%	0%
Non-Bank Financial Institution	5.8%	0%	0%	0%
Other	0.4%	0%	0%	0%

Source: Jiang et al. (2020) and shadow bank call report filings to state regulators. Number of institutions: 413.

After mortgage origination, shadow banks fund the mortgage using a draw from their warehouse credit lines while preparing for the loan sale to the purchasers. Before the crisis, shadow banks sold many of their mortgages through the private-label securitization market, which dried up during the crisis. Post crisis, the Government Sponsored Entities (GSEs) are the main purchasers of their mortgage loans, followed by commercial banks and life insurance companies. Once the mortgage being delivered to the purchasers, shadow banks pay off the warehouse debt and can make another draw for the next origination.

Under this business structure, the speed of loan sale affects the warehousing duration: the quicker this process is, the shorter the warehouse credit is utilized to finance the mortgage, which in turn increases shadow banks' capacity to originate new mortgage. There are two factors that determine the speed of sale. The first factor is technology. Williams and Lewellen (2020) examine the effects of the Mortgage Electronic Registration System (MERS), a major innovation in the secondary mortgage market that significantly reduces the time and costs associated with loan sales. They find that the increased speed of securitization increased mortgage origination volumes, especially for non-bank lenders. Buchak et al. (2018a) finds that FinTech lenders' time-to-sale is shorter than both traditional banks and non-FinTech lenders. Fuster, Plosser, Schnabl, and Vickery (2019) document that FinTech lenders process mortgage applications about 20% faster than traditional lenders, which alleviate capacity constraints associated with traditional mortgage lending. The second factor is information friction. Adelino, Gerardi, and Hartman-Glaser (2019) finds a strong relationship between mortgage performance and time to sale for privately securitized mortgages. Their findings suggest that larger information asymmetry between originators and secondary market investors may cause longer delay of sales. The two factors speak to the benefits and costs of reducing shadow banks' time-to-sale.

While a large literature has studied the effect of the funding supply through the secondary mortgage market, e.g. development of securitization and role of the GSEs (e.g. Loutskina and Strahan (2009),Keys, Piskorski, Seru, and Vig (2012), Nadauld and Sherlund (2013), Bhutta (2012), Hurst, Keys, Seru, and Vavra (2016), and Elenev, Landvoigt, and Van Nieuwerburgh (2016)), monetary policy that affects the demand for mortgage-backed securities (e.g. Di Maggio, Kermani, and Palmer (2016), Wong (2019), Drechsler et al. (2019), Buchak et al. (2018b), Chakraborty, Goldstein, and MacKinlay (2019)), and regulatory treatment of mortgage-backed securities (Gete and Reher (2017)), relatively little is known about the supply of warehouse funding that finances shadow banks' origination activities. As a substantive share of mortgage origination and servicing migrated from banks to shadow banks, a systematic examination of shadow banks' funding sources is necessary for evaluating banking regulation, monetary policy pass-through, financial stability, and consumers' access to credit.[5]

[5]"Trends in Mortgage Origination and Servicing: Nonbanks in the Post-Crisis Period," FDIC, 2019: https://www.fdic.gov/bank/analytical/quarterly/2019-vol13-4/fdic-v13n4-3q2019-article3.pdf.

Kim, Laufer, Stanton, Wallace, and Pence (2018) describes the potential liquidity pressures shadow banks are vulnerable to in their mortgage origination and servicing activities. Moreover, as the COVID-19 outbreak lies fallow the economy, shadow banks' liquidity issues have drawn increased attention from regulators and policy makers.[6]

One concern regulators have is whether shadow banks that service FHA/VA mortgages will have the liquidity to make future payments to the MBS investors in case of pervasive defaults on mortgage payments.[7] Servicers of mortgages insured by Ginnie Mae are obligated to continue making payments to MBS investors regardless of whether they will be able to recover the payments. Thus, as unemployment rate soars and a massive number of mortgage borrowers default on their payment, shadow banks may encounter liquidity problems. To evaluate shadow banks' liquidity problems, the first step is to have a full picture of shadow banks' source of financing.

[6]For example, an article published on Inside Mortgage Finance writes that "as government mulls mortgage forbearance, fear over nonbank liquidity escalates." (https://www.insidemortgagefinance.com/articles/217460-as-government-mulls-mortgage-forbearance-fear-over-nonbank-liquidity-escalates-mba-sets-the-table-for-government-assistance?v=preview).

[7]"Ginnie Tries to Quell Anxiety Regarding Nonbank Liquidity. Is it Working?" Inside Mortgage Finance, https://www.insidemortgagefinance.com/articles/217653-ginnie-tries-to-quell-anxiety-regarding-nonbank-liquidity-is-it-working?id=217653-ginnie-tries-to-quell-anxiety-regarding-nonbank-liquidity-is-it-working&utm_source=IMFnews&utm_campaign=2b57c30432-EMAIL_CAMPAIGN_2020_04_03_05_53&utm_medium=email&utm_term=0_642994d65b-2b57c30432-94198031.

1.2.2 Shadow Bank Funding Providers and Their Competition with Shadow Banks

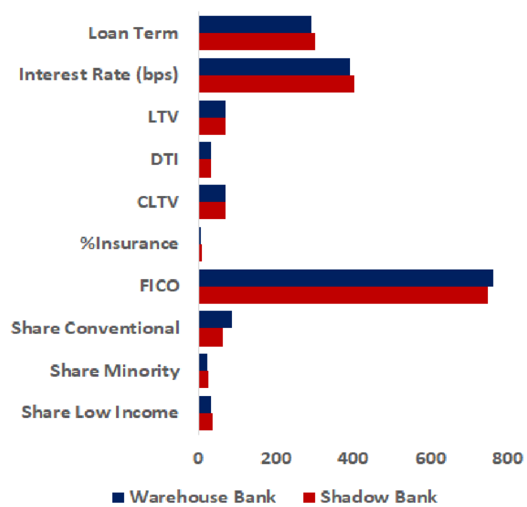
Both big national banks and regional banks participate in the market for shadow banks' short-term funding. The average asset size of warehouse banks is about $80 billion, and the standard deviation of the size distribution is about $300 billion. In this dissertation, I use *warehouse banks* or *warehouse lenders* to refer to banks that provide warehouse lines of credit to shadow banks and use *warehouse lending market* to refer to the market where banks lend to shadow banks.

All systematically important banks are warehouse lenders,[8] while regional banks also actively participate in this warehouse lending market. Among the ten warehouse banks that provided the most warehouse credit to shadow banks in 2017 Q4 in Table 3, there were both big national banks, such as Bank of America, JPMorgan Chase, Well Fargo and Citibank, and regional banks, such as Texas Capital Bank and Comerica Bank. National banks did not lend to as many shadow banks as regional banks. Instead, they extended more warehouse credit to bigger shadow banks. In contrast, regional banks lent to more relatively small shadow banks. For example, Texas Capital Bank, a regional bank headquartered in Dallas, lent to more than 100 shadow banks and was the largest warehouse bank in terms of the number of shadow bank borrowers.

[8]According to the Economic Growth, Regulatory Relief, and Consumer Protection Act (EGRRCPA), the minimum threshold for national banks to be considered as systematically important rises from $10 billion to $250 billion.

Warehouse banks are big originators in the US residential mortgage market. Mortgage assets comprise 70% of their loan assets on average. They originated about 40% of total mortgages in 2011. Since they both originate mortgages, warehouse banks are likely to compete with shadow banks in the primary mortgage market, especially in the conforming mortgage market, where borrowing amount is less than the conforming loan limit of the GSEs.

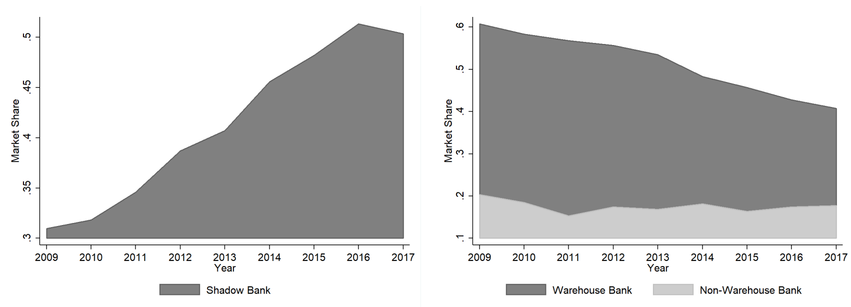
Figure 1.4. Mortgage Characteristics by Lender Type



Source: HMDA and GSE Single-Family Loan Purchase and Performance Data.

Fig. 1.4 compares the characteristics of mortgages originated by warehouse banks and shadow banks. As shown in Fig. 1.4, shadow banks and warehouse banks originate mortgages with similar loan terms, loan-to-value (LTV), and insurance, and also lend to borrowers with similar FICO score, race, income and debt-to-income (DTI). While shadow banks are more likely to originate FHA/VA loans than warehouse banks, they still seem to compete in originating conventional mortgages.[9]

Figure 1.5. Aggregate Mortgage Market Share by Lender Type



Source: HMDA and shadow bank call report filings to state regulators.

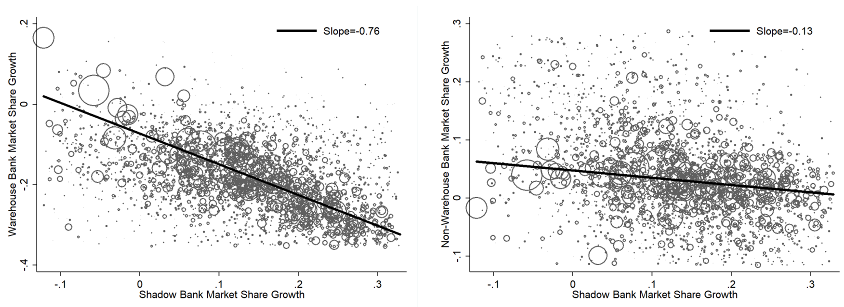
Moreover, as shadow banks grew, they directly competed with warehouse banks. Fig. 1.5 plots the market shares of different lender types in the U.S. mortgage market. Consistent with the literature, the figure shows that shadow banks gained about 20% market share after the financial crisis due to their enhanced comparative advantage that resulted from increased regulation on traditional banks and technological development.[10] The new fact as indicated by this figure is that most of this market share growth was gained from warehouse banks. From 2011 to 2017, about 15% market share migrated from warehouse banks to shadow banks that were funded by them. The fact that the market share of non-warehouse banks stayed almost constant over

[9] See Buchak et al. (2018a) and Buchak et al. (2018b) for a detailed discussion about the competition between banks and shadow banks.

[10] See, e.g. Buchak et al. (2018a), Buchak et al. (2018b), Kim et al. (2018), Gete and Reher (2017).

this period indicates that this pattern is not a mechanical result of the way market share is calculated.

Figure 1.6. County-Level Market Share Growth from 2011 to 2017



Source: HMDA and shadow bank call report filings to state regulators.

Similar market share migration patterns can be observed at the county level. Fig. 1.6 plots the changes in warehouse bank market shares, and the changes in non-warehouse bank market shares, against the changes in shadow bank market shares in each counties from 2011 to 2017. Benchmarked to the market share changes of non-warehouse banks, the market shares of warehouse banks moved more closely in the opposite direction with the market shares of shadow banks across counties. The slope of warehouse banks' plot is -0.76, while the slope of non-warehouse banks' plot is -0.12. This result again suggests that shadow banks directly compete with their warehouse funding providers for mortgage borrowers in local markets. This plot suggests that at least at the aggregate level, shadow banks compete with their warehouse banks in the primary mortgage market.

1.3 Related Literature

This dissertation is most closely related to other studies examining the changing nature of mortgage origination in the United States. The rapid growth of shadow banks in the residential mortgage market has drawn attention to the comparative advantage of shadow banks and their interactions with traditional banks (Buchak et al. (2018a), Fuster et al. (2019), and Gete and Reher (2017)). The existing literature has mainly focused on the competition between these two types of mortgage lenders and has largely ignored the financial connection between them. Buchak et al. (2018b) find that banks have a comparative advantage in balance-sheet intensive lending activities and analyzes the impact of the competition between banks and shadow banks on the effect of bank regulations. Drechsler et al. (2019) study how monetary policy impacted the growth in mortgage lending before the financial crisis through the lens of the deposit channel and find that shadow bank origination offsets the contraction of bank origination during the period of Fed tightening. Most papers in this literature treat shadow banks as pass-through and neglect the possible frictions in their financing that may potentially affect their origination activities. Kim et al. (2018) collect data about systematically important banks' lending to shadow banks and discussed potential liquidity risks faced by shadow banks. However, they do not observe shadow banks' balance sheets nor the total amount of credit shadow banks obtain. I collected shadow bank call reports by submitting FOIA requests to all states in the United States. Using this data set, Jiang et al. (2020) provide the first set of analysis about shadow banks' capital structure and find that 25% of their assets are financed by equity, whereas about 60% of total assets are financed by short-term debt through warehouse lines of credit, where 90% of these warehouse lines of credit are provided by banks.

This dissertation provides the first systematic examination of the lending relationship between the two dominant types of lenders in the US mortgage market. Stanton, Walden, and Wallace (2014) argue the importance of such a funding channel but they do not empirically examine it due to lack of data. My new regulatory data collected through FOIA requests allow me to systematically examine this issue. The findings of this paper serve as direct evidence for shadow banks' dependence on warehouse lending and provide evidence regarding the effects on mortgage market competition. The previous works that study the competition between shadow banks and banks have largely ignored such lending relationships. My work fills in an important gap in this literature.

Furthermore, this dissertation expands our knowledge on banks' decisions to allocate credit between direct lending to consumers versus warehouse lending to shadow banks (i.e., lending to consumers through shadow banks) for a given level of regulation. Buchak et al. (2018a) document that the regulatory burden imposed on banks post-crisis was a key driver of banks' retreat from direct lending. This paper points out a novel economic trade-off that banks are faced with for any given level of regulation. My findings suggest that shadow banks' expansion, as documented in Buchak et al. (2018a), was likely limited in less competitive, more profitable mortgage markets; and banks retreated more direct mortgage lending from more competitive mortgage markets. Moreover, the counterfactual analysis of this paper uncovers a new channel through which technological development improves consumers' access to credit. It suggests that the shorter warehouse duration of FinTech lenders documented in Buchak et al. (2018a) and Fuster et al. (2019) provide them with a competitive advantage in mortgage lending, and directly affect competition in the mortgage market.

This dissertation also contributes to the traditional banking literature. The main contribution is twofold. First, it provides a nice setting to help understand banks' lending incentives when they also compete with their potential borrowers. This setting is unique to the traditional banking literature, in which prior research typically focuses on banks' lending to non-financial firms (e.g., Petersen and Rajan (1995), Petersen and Rajan (2002), Stein (2002), Hubbard, Kuttner, and Palia (2002), Berger and Udell (1995), Engelberg, Gao, and Parsons (2012), Karolyi (2018), Paravisini, Rappoport, and Schnabl (2015), Schwert (2018), Bolton, Freixas, Gambacorta, and Mistrulli (2016), Gan (2007), Khwaja and Mian (2008), Paravisini (2008), Iyer and Peydro (2011), Chava and Purnanandam (2011), and Schnabl (2012)). An important missing piece of knowledge is how banks make decisions in lending to other financial firms, which is a common phenomenon but has been understudied. The findings in this paper have broader implications for lending behaviors among financial firms.

Second, the finding that the consequences of banks' market power in warehouse lending spill over to the mortgage market has broader implications for similar issues in industries that rely on bank loans (Saidi and Streitz (2018), Cetorelli and Strahan (2006), Cestone and White (2003), Cetorelli (2004)). Literature has shown that bank concentration lowers output in non-financial sectors due to a higher incidence of competing firms sharing common lenders. Saidi and Streitz (2018) study this in a more general setting and only focus on non-financial sectors. I am using a more specific setting, which allows me to provide additional insights.

This dissertation is also connected to recent quantitative equilibrium models of mortgage and other consumer financial product markets (e.g. Favilukis, Ludvigson, and Van Nieuwerburgh (2017), Kaplan, Mitman, and Violante (2016), Berger, Milbradt, Tourre, and Vavra (2018), and Eichenbaum, Rebelo, and Wong (2018)). My model follows the form of consumer demand models, such as Berry, Levinsohn, and Pakes (1995), and applies these modeling techniques for the purpose of answering policy questions in finance (e.g. Egan, Hortaçsu, and Matvos (2017a), Buchak et al. (2018b), Buchak et al. (2018a), Benetton (2018), Robles-Garcia (2019), and Xiao (2018)). My paper further extends these models by incorporating the funding choices of shadow banks and the competition in the warehouse lending market, allowing me to study the joint decisions in mortgage pricing as well as warehouse lending pricing.

In Chapter 2 I introduce new facts about the market structure of the warehouse lending market and provides a systematic examination of the lending relationships between banks and shadow banks in the US residential mortgage market. I show that warehouse lending relationships are more likely to be formed between banks and shadow banks that originate mortgages in the same local markets. Moreover, the warehouse lending relationships seem to be persistent over time. Lastly, shadow banks seem to not be able to easily switch to other lenders if their relationship banks terminate their lending relationships. As a result, shadow banks reduce their origination volume and raise their mortgage interest rates in response to an exogenous termination of warehouse lending relationship.

In Chapter 3 I discuss the possible explanation for the funding market structure and provide a trade-off in banks' decisions to finance shadow banks. On one hand, originating mortgages in the same local markets as the shadow banks gives banks an information advantage (over other banks) in lending to them. On the other hand, financing shadow banks increases competition, lowering banks' mortgage origination profit. Banks trade off these sources of rents and exploit marker power in warehouse lending to limit shadow banks' expansion in the most profitable, least competitive mortgage origination markets. These limits to competition are passed on to consumers in the form of more expensive mortgages.

In Chapter 4 I develop a quantitative model linking warehouse lending and product market competition to study how changes in the warehouse lending market affect mortgage market competition. In the model, banks trade off the margins in the two markets. The model clarifies the equilibrium feedback between competition and market power in both markets, allowing me to study the extent to which warehouse lending softens the mortgage market competition. I use the model to quantify the welfare implications of policies and technologies that effectively reduce banks' warehouse lending market power.

Chapter 2

Lending Relationships Between Banks and Shadow Banks

2.1 Introduction

This chapter introduces new facts about shadow banks' source of warehouse funding and provides a systematic examination of the lending relationships between banks and shadow banks in the US residential mortgage market. I construct a novel data set containing quarterly warehouse lending relationships between banks and shadow banks using shadow bank call reports from 2011 to 2017. Pursuant to the S.A.F.E. Mortgage Licensing Act of 2008, shadow banks that hold a state license or state registration to conduct mortgage origination have been required to complete a call report on a quarterly basis since 2011. The call report contains two components, Residential Mortgage Loan Activity (RMLA) and Financial Condition (FC). The RMLA collects detailed information about mortgage loan related activities in each state and warehouse lines of credit information at the company level. The RMLA reports information at the end of the quarter about each warehouse line of credit, including the provider name, the credit limit, and the remaining credit limit, i.e., how much line has not been used. The FC collects balance sheet and income statement at the company level.

Through the Freedom of Information Act (FOIA) requests I collected shadow banks' call report filings to state regulators. I submitted FOIA requests to all 50 states and obtained the data from the state of Washington and Massachusetts state. As long as a shadow bank is registered or licensed in either of these states, I obtain information on its operations across all states. Therefore, even sampling two states allows for extensive coverage of about 80% of total shadow bank mortgage origination in the US. Appendix D provides greater details about sample coverage.

2.2 Sample Construction and Summary Statistics

I describe how I construct the sample through bringing together a number of data sets.

First, I merge shadow bank call reports with the Home Mortgage Disclosure Act (HMDA) database to obtain loan-level mortgage origination data for each shadow bank. HMDA captures the vast majority of residential mortgage applications in the United States. Each shadow bank has a unique ID in the National Mortgage License System (NMLS ID), which is used as an identifier in the call reports. However, the NMLS ID is not publicly disclosed in HMDA. To link the two data sets, I construct a crosswalk table between HMDA institution ID and NMLS ID by using the NMLS Consumer Access platform, where consumers can search for shadow bank registration information using company name and address.

To identify each warehouse line of credit provider, I manually assign the bank regulatory call report ID and the holding company ID by searching for line of provider names on the FDIC BankFind website. For line of credit providers that are not banks, I searched their information online to categorize them. Using this data set, I identify quarterly funding relationships between 544 shadow banks and 399 funding providers from 2011 to 2017, where 222 (202) providers are banks (identified-banks). I then link each warehouse line of credit to its provider's mortgage origination activity recorded in HMDA.

I obtain data on bank balance sheet, income statement, and branch addresses from bank regulatory call report filings, Form 031 and Form 041, and Summary of Deposits. Form 031 and Form 041 are publicly available on the Federal Financial Institutions Examination Council (FFIEC) website. Summary of Deposits are publicly available on the FDIC website.

This paper also uses data on banks' commercial and industrial loans from the DealScan Commercial Loan Database, which covers between half and 3-quarters of the volume for outstanding commercial and industrial loans in the US, residential property tax assessment records in CoreLogic Property Transaction Tax Records, and local demographics from US Census data. Appendix D provides supplementary details about sample construction.

HMDA: The Home Mortgage Disclosure Act (HMDA) collects the vast majority of mortgage applications in the United States, along with their approval status. In addition to the application outcome, the data set records year of origination, amount, and location information down to the borrower's census tract. It further contains demographic information on the borrower, including race and income. Important for this paper, it includes the identification information of the originator.

The sample contains quarterly funding relationships between 184 banks and 528 shadow banks that originate mortgages in the US from 2011 to 2017.[1] Table 1 displays the average characteristics of shadow banks and their warehouse lines of credit provider banks in my sample. Panel A shows shadow banks' summary statistics. Panel B shows banks' summary statistics.

Shadow Bank: Shadow banks have a wide range of asset sizes. The average asset size is \$0.48 billion assets, while the size distribution has a standard deviation of \$1.51 billion. A number of shadow banks have much larger balance sheets than other shadow banks: the median shadow bank is \$0.4 billion smaller than the sample average. Mortgage loans comprise the majority of shadow banks' assets. About 68% of shadow banks' assets on average are mortgage loans, and the median shadow bank has almost 80% of total assets being mortgage loans. The amount of assets being financed by warehouse credit is about 7pp smaller than the amount of mortgage loans on their balance sheets. Therefore, about 90% of mortgage assets on shadow banks' balance sheets are financed by short-term funding provided by their warehouse lines of credit provider. This is consistent with the practice that warehouse lenders typically do not fund the entire amount of the mortgage balance to leave shadow banks some "skin-in-the-game" for each mortgage loan. For a

[1] Shadow banks may enter my sample after 2011 or exit from my sample before 2017. Shadow banks that do not receive any warehouse lines from a bank are not excluded.

detailed discussion about shadow banks' balance sheet, see Jiang et al. (2020).

In terms of geographic reach of their mortgage business, the average shadow bank originates \$2 billion mortgages a year in 22 states in the US, while some are more geographically concentrated than others with a standard deviation of 16 states.

On average each shadow bank has about 4 warehouse lines of credit to finance their mortgage origination. Some shadow banks may have as many as 10 warehouse lines, while others may have only one line. The standard deviation is about 2 lines. The average total credit limits that each shadow bank receives is more than \$110 million, about half of which is typically used by each shadow bank. The amount of credit limits provided by different warehouse lenders are not equal. Within each shadow bank, the standard deviation of the share of total credit limits provided by different lenders is about 14% on average. The average estimated interest rate spread on these credit lines is about 3%,[2] which varies over time with an average time-series standard deviation of 1% within a shadow bank.

To provide an example, Table 2 shows the warehouse funding sources of Quicken Loans in 2017 Q4. Quicken Loans is a shadow bank that became the largest mortgage originator by the end of 2017. Quicken Loans received a total of \$13.59 billion warehouse credit line limit in 2017 Q4, of which it used \$8.5 billion by the quarter end. It obtained 55% of its warehouse funding from

[2]Detailed estimation procedure can be found in Appendix D.

7 banks, including both big national banks, such as Credit Suisse First Boston, JPMorgan Chase, and Bank of America that provide, respectively, about 16%, 13%, and 7% of Quicken's total credit limit, and relatively small banks, such as Fifth Third Bank that provides less than 2%. Besides, Quicken Loans also received warehouse funding from the Government Sponsored Entities (GSE), Fannie Mae and Freddie Mac, that together provided 25% of its total warehouse funding. In terms of credit used, Fannie Mae was the largest provider accounting for about 25% of warehouse credit used followed by JPMorgan Chase that accounts for 18% of the warehouse credit used.

2.3 Clustering in Lending Relationships

I begin by examining whether individual funding relationships are clustered between competitors in local mortgage markets. Since mortgage borrowing is typically taken locally, one might imagine that warehouse lending would occur between banks and shadow banks that originate mortgages in different markets. This would allow banks to reach more mortgage markets through shadow banks, increasing their business scope without harming their own origination business, in the spirit of Dixit (1983) and Mathewson and Winter (1984). To this end, I use loan-level mortgage application data from HMDA to measure the geographic market overlap in mortgage origination between banks and shadow banks.

2.3.1 Measure Construction

I construct a sample of all possible pairs between banks and shadow banks to examine if there is an endogenous sorting of warehouse lending. A bank is included in the data set if it conducts warehouse lending business and lends to at least one shadow bank in a particular year. For each pair, I calculate their geographic market overlap in mortgage origination in terms of the number of counties in which they both originate mortgages:

$$\%OverlapMkt_{i,j,t} = \frac{\Sigma_k I(\sigma_{i,k,t} > 0, \sigma_{j,k,t>0})}{\Sigma_k I(\sigma_{i,k,t} > 0) + \Sigma_k I(\sigma_{j,k,t} > 0)}. \tag{2.1}$$

where $\sigma_{i,k,t} = \frac{LoanVolume_{i,k,t}}{\Sigma_k LoanVolume_{i,k,t}}$ is the share of institution i's total loan origination in county k in year t. As an alternative measure, I calculate the geographic market *distribution* overlap to account for different weights of counties in their origination business:

$$MktOverlap_{i,j,t} = 1 - \frac{1}{2}\Sigma_k \left|\sigma_{i,k,t} - \sigma_{j,k,t}\right|, \tag{2.2}$$

$MktOverlap_{i,j,t}$ ranges from 0 to 1, where 1 means that bank i's origination activities shares exactly the same distribution with shadow bank j's origination activities across counties.

Moreover, to control for distance-related search costs or transaction costs, I calculate the minimum distance between each shadow bank's headquarter and all branches of a particular warehouse bank.

2.3.2 Extensive Margin: Warehouse Lending Relationship

I begin by comparing the group of bank-shadow bank pairs that have a warehouse lending relationship (i.e. matched pairs) and the group of bank-shadow banks that do not have a warehouse lending relationship (i.e. unmatched pairs). Table 4 shows the distance from the shadow bank's headquarter to the bank's branch network and the two metrics of geographic market overlap in mortgage origination. Panel A shows the statistics for the matched pairs. Panel B shows the statistics for the unmatched pairs.

The mortgage origination market overlap of the matched pairs is more than twice as large as that of the unmatched pairs on average. The average (median) geographic market overlap in mortgage origination among the matched pairs is 18% (11%), compared to 8% (4%) geographic market overlap among the unmatched pairs on average. In terms of geographic market distribution overlap, the matched pairs have an average of 20%, while the unmatched pairs have an average of 7%. The average minimum distance from shadow banks' headquarters to their matched warehouse banks' branch networks is much shorter than the average minimum distance to their unmatched warehouse banks. The average (median) minimum distance is 952 (520) miles among the matched pairs, compared to 1,559 (1,341) miles among the unmatched pairs.

Fig. 2.1 illustrates this finding by sorting bank-shadow bank pairs into 20 bins based on their geographic market overlap in mortgage origination, where each bin contains an equal number of bank-shadow bank pairs. The figure shows that warehouse lending relationships are rarely formed between non-competitors. About 50-percent of the lending relationships are formed between banks and shadow banks whose geographic market overlap in mortgage origination is in the top quartile. Similarly, I also sort bank-shadow bank pairs by the minimum distance between shadow banks' headquarters to warehouse banks' branch network in Fig. 2.1. The first five bins show that about 50-percent of the lending relationships are formed between bank-shadow bank pairs whose geographic distance is less than 500 miles. These findings suggest that warehouse lending is clustered between competitors in local mortgage markets.

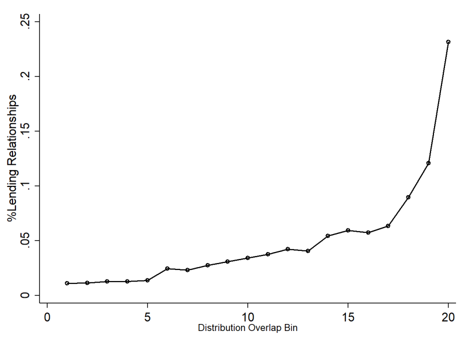
To analyze this further, I estimate the following specification to examine whether warehouse lending is more likely to happen between banks and shadow banks that have higher geographic market overlap:

$$Pr(Lend_{i,j,t}) = \alpha + \beta \% MktOverlap_{i,j,t} + \gamma Ln(HQDistance_{i,j,t}) + \mu_{i,t} + \mu_{j,t} + \epsilon_{i,j,t} \tag{2.3}$$

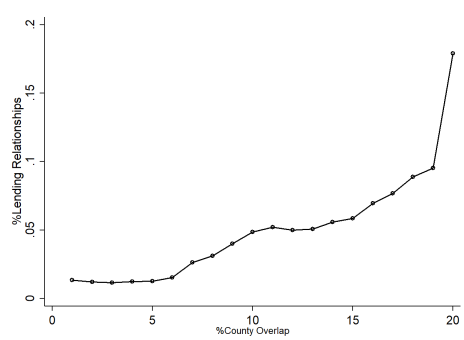
The dependent variable is an indicator of whether there is a lending relationship between shadow bank i and bank j. $\% MktOverlap_{i,j,t}$ is the geographic market overlap measure. $Ln(HQDistance_{i,j,t})$ is log minimum distance between shadow bank i's headquarter and all branches of warehouse bank j, which controls for distance-related search costs and transaction costs. In the specification I condition on bank-by-year fixed effects and shadow bank-by-year fixed effects. The inclusion of fixed effects ensures that my results are not driven by certain characteristics of warehouse banks or shadow banks; and the

Figure 2.1. Lending to Competitors

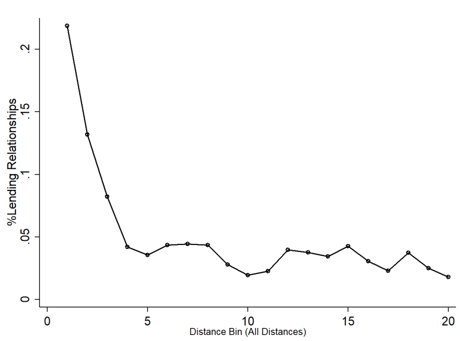
Fig. 2.1 shows the determinants of lending relationships between banks and shadow banks. Panel (a) and (b) plot the share of total credit lines (out of total credit lines) by overlap percentile bin. Each bin is defined by assigning 5-percent of all bank-shadow bank pairs based on the mortgage market overlap. In Panel (a), *overlap* is measured by geographic distribution overlap (*Market Overlap*). In Panel (b), *overlap* is measured by the share of overlapped counties (*%Overlapped Markets*). Panel (c) plots the share of total credit lines in each distance bin. Each bin is defined by assigning 5-percent of all bank-shadow bank pairs based on the minimum distance between banks' branch network and the headquarter of each shadow bank. Panel (d) plots the share of credit lines by distance bin in the subset of bank-shadow bank pairs within a 500-mile minimum distance. Each bin is constructed by assigning 5-percent of all bank-shadow bank pairs within 500 miles according to the minimum distance between banks' branch network and the shadow bank's headquarter.



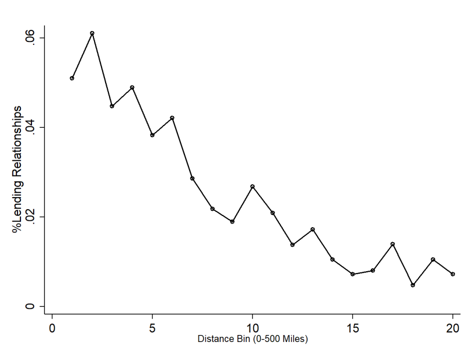
(a) % Credit Lines by Market Overlap



(b) % Credit Lines by %Overlapped Markets



(c) % Credit Lines by Distance (Full)



(d) % Credit Lines by Distance (0-500 miles) fixed effects subsume any time variation, such as aggregate trends in shadow bank growth post crisis. Therefore, the variation in my estimates plausibly comes from the differences in mortgage market overlap between shadow banks and banks.

Table 5 Panel A reports the regression results. Column (1) and (3) only include the main *Market Overlap* measure and the alternative measure, respectively, while controlling for the distance between shadow banks' headquarters and the banks' branch networks. Consistent with Fig. 2.1, the estimates show that it is 1.86% (1.82%) more likely to observe a warehouse lending relationship between banks and shadow banks that commonly originate mortgages in 10% more counties, conditional on the distance between shadow banks' headquarters to the banks' branch networks. Column (2) and (4) further include bank-by-year fixed effect and shadow bank-by-year fixed effects to subsume all bank/shadow bank characteristics. The estimated coefficients on both *Market Overlap* measures are statistically significant and greater than the OLS results. A one standard deviation (8pp) increase in geographic market overlap increases the likelihood of having a lending relationship by 1.8pp, which is about 70% of the unconditional probability (2.6pp). The inclusion of bank-by-year and shadow bank-by-year fixed effects ensures that the effect is not driven by a specific banks' propensity to engage in warehouse lending at a specific point in time, such as its business model, availability of funding, or the profitability of mortgage origination. Nor is it driven by shadow bank specific differences, such as differences in shadow banks' capital structure, or demand for bank funding. In fact, the results are robust to controlling for the distance between shadow banks' headquarter and banks' branch networks. These results indicate that warehouse lending relationships are more likely to be formed between banks and shadow banks that compete for local mortgage demand.

Robustness: In addition to the full sample analysis, I perform three robustness checks to ensure that the results are not driven by size effect. Specifically, I sort banks and shadow banks by their geographic dispersion and construct sub-samples of geographically concentrated and geographically dispersed banks and shadow banks. A bank, or a shadow bank, is defined as geographically concentrated (geographically dispersed) if its geographic dispersion is below (above) the median. Similarly, I construct sub-samples based on mortgage origination volume and asset size. I then estimate Eqn. 2.3 using the sub-samples. Table 6 shows the robustness checks. The estimated coefficients on the two *Market Overlap* measures are statistically significant and positive in all regressions, suggesting that the effect is not driven by sorting on size.

2.3.3 Intensive Margin: Warehouse Credit Line Size

Next, I examine whether similar clustering pattern can be observed at the intensive margin. Conditional on having a warehouse lending relationship, do shadow banks receive larger credit lines from their competing banks in local mortgage markets?

A typical identification concern of such analysis is that unobserved shadow bank or bank characteristics may jointly affect geographic market overlap and credit limits. For example, a geographically diversified shadow bank may have larger origination market overlap with banks, and the diversification allows the shadow bank to obtain a larger credit limit. Alternatively, a national bank may have larger market overlap with shadow banks, while it has more funding capacity to extend larger credit lines. To address such concerns, I exploit the within-shadow bank variation and compare credit limits a particular shadow bank receives from different lenders while controlling for bank fixed effects. I estimate the following specification:

$$Limit_{i,j,t} = \alpha + \beta \% MktOverlap_{i,j,t} + \gamma Ln(HQDistance_{i,j,t}) + \mu_{i,t} + \mu_{j,t} + \epsilon_{i,j,t} \tag{2.4}$$

The fixed effects subsume all cross-sectional variation and ensure that the results are not driven by shadow bank demand or unobserved characteristics of banks or shadow banks. Consequently, the parameter β is identified by the variation in origination market overlap between any bank-shadow bank pairs.

Table 5 Panel B shows the regression results. Column (1) and (3) only include the main *Market Overlap* measure and the alternative measure, respectively, while controlling for the distance between shadow banks' headquarters and the banks' branch networks. The estimated coefficients on both *Market Overlap* measures are positive and statistically significant. This relationship is robust to the inclusion of bank-by-year and shadow bank-by-year fixed effects, shown in Column (2) and (4). With fixed effects, the estimated coefficient on *%MktOverlap* is 111.7. Given the 12% standard deviation of *%MktOverlap* between matched pairs, the result indicates that the average shadow bank obtains $13.4 million larger credit limit from warehouse banks with one standard deviation higher market overlap. The estimation with the alternative market overlap measure yields similar results. A one standard deviation increase in *MktOverlap* is associated with $11.78 million larger credit limit. The estimated γ is not statistically significant. Conditional on having a lending relationship, the distance between the shadow bank's headquarter and the bank's branch networks does not affect the size of the credit limit. This suggests that while distance affects the likelihood of forming a lending relationship, once the lending relationship is formed, distance does not affect banks' lending decisions. These results again suggest that warehouse lending is clustered between banks and shadow banks that compete in local mortgage markets.

2.4 Persistent Lending Relationships

Warehouse lending relationships between individual banks and shadow banks are persistent. Fig. 2.2 plots the likelihood of receiving warehouse funding from the same bank again in the future years. Conditional on receiving warehouse funding from a particular bank in the current year, the likelihood of receiving warehouse funding from the same bank is 88.6% in the following year, 64.5% in three years, and 52.8% in five years. To put these numbers in perspective, the unconditional likelihood of receiving funding from a bank is 0.8%.

Figure 2.2. Persistent Lending Relationships

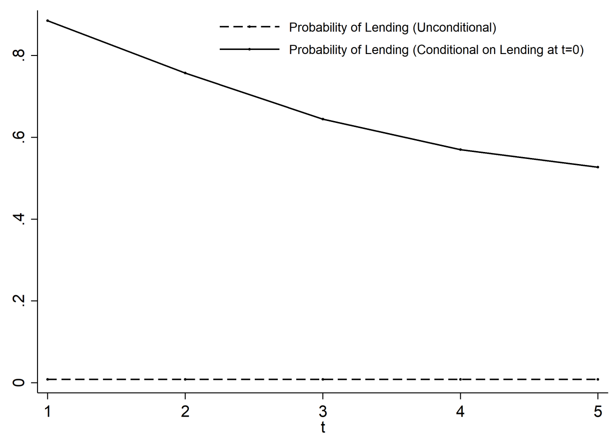


Fig. 2.2 displays the likelihood of having a Lending relationship in year 1 to 5, conditional on a lending relationship in year 0. The dashed line displays the unconditional probability of having a lending relationship in each year. The underlying sample is a panel data set that contains all possible pairs between warehouse banks and shadow banks. A bank is included in the data set if it conducts warehouse lending business and lends to at least one shadow bank in a particular year. I construct the solid line by calculating the percentage of lending relationships in year t (for $t = 1, 2, ..., 5$) given that the lending relationship is observed in year 0.

To analyze this further, I estimate a linear probability model to examine whether past lending relationships predict future lending relationships after controlling for a rich set of covariates:

$$Pr(Lend_{i,j,t}) = \alpha + \beta_0 PastLend_{i,j,t} + \beta_1 PastLend_{i,j,t} \times Bank_{j,t} + \mu_{i,t} + \mu_{j,t} + \epsilon_{i,j,t}. \tag{2.5}$$

The dependent variable is a dummy variable indicating whether shadow bank i obtains funding from lender j in year t. $PastLend_{i,j,t}$ and its interaction with $Bank_{j,t}$ are the main independent variables of interest. $PastLend_{i,j,t}$ indicates if shadow bank i obtained funding from lender j in year $t-1$. $Bank_{j,t}$ indicates whether lender j is a bank. To ensure robustness, I control for borrower-by-year fixed effects and lender-by-year fixed effects. In such specification, I only exploit variation within the same borrower, implying that I account for differences in borrowers' demand for funding and different business risk profiles, while lender-year fixed effects subsume any cross-sectional variation in lenders' funding supply and lending preferences. Moreover, since only within year variation is being exploited, any aggregate shocks to funding demand or supply are also absorbed by the fixed effects.

Table 7 presents the estimates. The main coefficient of interest measures how likely a shadow bank will obtain funding from the same lender again in the following year relative to from other lenders. Column (1) includes only $PastLend$, borrower-by-year fixed effects, and lender-by-year fixed effects. The coefficient of 85.55% suggests that the high propensity for obtaining funding from the same lender is both economically and statistically significant. Column (2) adds the interaction of *PastLend* and *Bank*. The results suggest that banks are 10% more likely to form persistent lending relationships with shadow banks than non-bank warehouse lenders, such as the GSE and other non-bank financial institutions.

Column (3) and (4) show shadow banks' characteristics that affect the lending relationships. As suggested by Column (3), shadow banks that are larger in terms of asset size and have less equity are more likely to obtain funding from banks than to obtain funding from non-bank warehouse lenders. Column (4) exploits time-series variation within any particular lending relationships. The negative and statistically significant coefficients on the interaction of *Bank* and lagged ETA and the interaction of *Bank* and the negative net income growth dummy indicate that banks are less likely to terminate a lending relationship if the shadow bank becomes less profitable or experiences a reduction in net worth.

The results in Column (3) and (4) suggest that, compare to other types of warehouse lender, banks have two advantage in lending to shadow banks. First, banks have funding capacity to lend to big shadow banks. Second, banks have better monitoring technology and develop relationship lending to reduce information frictions in lending to shadow banks. These findings suggest that banks should have market power in warehouse lending to shadow banks. As argued in the traditional banking literature, bank relationship lending reduces information frictions, while the information acquired is not transferable to other banks. Therefore, individual bank lending relationships are not substitutable, giving them market power in warehouse lending.

2.5 Banks' Market Power in Warehouse Lending

I further examine the idea that shadow banks are not able to easily substitute their current warehouse lending relationships with alternative funding sources, giving individual banks market power in warehouse lending. I exploit a semi-natural experiment where treated banks reduce their funding supply to shadow banks for reasons exogenous to shadow banks' business fundamentals, similar to Khwaja and Mian (2008) and Fisman, Paravisini, and Vig (2017).

The oil price halved from the second quarter of 2014 to the first quarter of 2015, which was one of the most remarkable macroeconomic shocks post crisis (Hou, Keane, Kennan, and te Velde (2015)). This sharp decline in oil prices dampened the loan performance in the oil and gas (O&G) industry. Using detailed bank loan data from the FR Y-14 filings, Bidder, Krainer, and Shapiro (2018) shows that the rate of O&G loans past due, charged off, or in non-accrual status spiked following the oil price decline, while no trend is observed in the performance of loans in all other sectors.[3] According to their analysis, banks with large balance sheet exposure to O&G industry by the time of the oil price decline experienced significant net worth shock. Consequently, exposed banks tightened credit on corporate lending and on loans to be retained on their balance sheets. I exploit the variation in warehouse

[3]Bidder et al. (2018) shows that the fraction of O&G loans that were in problem status rose from 0.6 percent in 2014Q2 to 10.4 percent in 2016Q3.

banks' balance sheet exposure to the O&G sector before the oil price decline to conduct a difference-in-differences analysis.

The data used in this section come from DealScan.[4] I restrict to loans in DealScan that were originated within 5-year window before the shock and had not matured by 2014. For each warehouse bank, I find the ratio of the O&G loans to total loans outstanding as a proxy for its exposure to the O&G industry. I classify warehouse banks into two groups, *exposed banks* and *non-exposed banks*, based on their O&G exposure relative to the median O&G exposure. In Appendix C.2, consistent with Bidder et al. (2018), I find that, within the same shadow bank, the funding received from exposed banks dropped relative to the funding received from unexposed banks after the oil shock, and the lending relationship with any exposed bank was more likely to be terminated than the lending relationship with an unexposed bank after the shock.

2.5.1 Exogenous Credit Reduction and Shadow Bank Funding

I begin by analyzing whether shadow banks' cost of funding rose relative to others if their warehouse banks were more exposed to the oil price shock. I divide shadow banks into the treatment group and the control group. A shadow bank is in the treatment group if its primary warehouse banks were heavily engaged in lending to the O&G sector prior to the oil price shock. I first plot the average cost of warehouse funding of the treatment group and the

[4]DealScan covers between half and 3-quarters of the volume for outstanding commercial and industrial loans in the US.

control group over time in Fig. 2.3(a). The figure shows that the change in the average funding cost of the treated shadow banks was about 1 percentage point larger than the change in the average funding cost of the untreated shadow banks after the oil price shock, while there was no apparent pre-trend before the oil price decline.

Figure 2.3. Exogenous Credit Reduction and Shadow Bank Borrowing

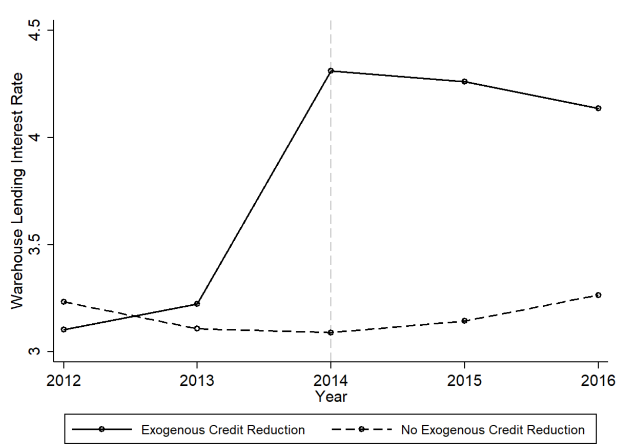


Figure **??** plots the average warehouse interest rates of shadow banks whose primary lenders were heavily exposed to the oil price shock and of shadow banks whose primary lenders were not exposed to the oil price shock, respectively.

I run the following difference-in-differences regression:

$$\hat{r}_{i,t} = \alpha + \beta HighOilShock_i \times Post_t + \gamma Post_t + \Gamma X_{i,t} + \mu_i + \epsilon_{i,t}, \qquad (2.6)$$

where $HighOilShock_i$ indicates whether the average O&G exposure of banks that the shadow bank have lending relationships with is above the median, and $X_{i,t}$ are lagged shadow bank controls, including net income to asset ratio, equity ratio, and operating cash flow to asset ratio. I use data from 2012 to

2016, i.e. the four years surrounding the oil price shock.

Table 8 Column (1) and (2) show the regression results. While the average cost of warehouse funding were declining over time, the change in the funding cost of the treated shadow banks was significantly smaller than that of the untreated shadow banks. The cost of funding paid by shadow banks that had funding relationships with less exposed banks dropped by 1.295 percentage-points on average in 2015 and 2016, whereas the cost of funding paid by shadow banks that had funding relationships with more exposed banks dropped by only 0.41 percentage-points on average in 2015 and 2016. The positive and statistically significant coefficient on the interaction term indicates that the treated shadow banks' cost of funding increased due to exogenous reduction in credit supply from their relationship banks.

I then focus on the extensive margin and examine whether shadow banks are able to substitute to other warehouse banks if their relationship banks exogenously terminated the lending relationships. I divide shadow banks into the treatment group and the control group based on whether they experienced a major funding relationship termination that is plausibly exogenous to their credit demand or credit risk. Specifically, the funding relationship terminations are restricted to those happened within two years since the oil price shock, where the lender provided at least 25% of total funding and has high O&G exposure. For each termination, I keep eight quarters surrounding the termination date. For each termination cohort, e.g. 2014Q4, I then form a control group containing untreated shadow banks that borrowed from low-O&G exposure warehouse banks before the oil price shock and did not experience a major funding relationship termination.

Figure 2.4. Exogenous Credit Reduction and Shadow Bank Origination Volume

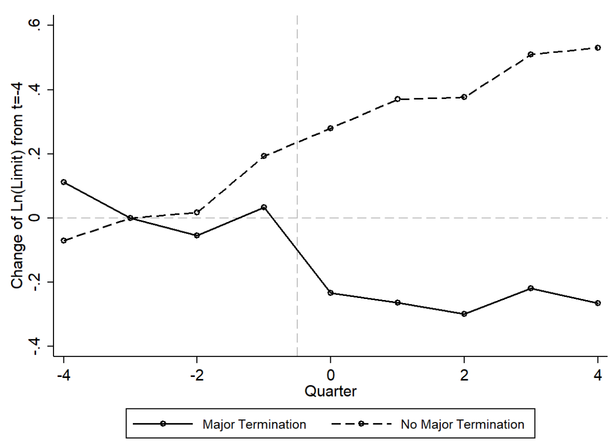


Figure 2.4 plots the average total warehouse line of credit limit of shadow banks that experienced major credit line termination and of shadow banks that did not experience such termination, respectively. In either plot, the averages are calculated from the residualized values after controlling for shadow bank fixed effects and time fixed effects.

A simple plot in Fig. 2.4 shows that the average credit line size of the treated group dropped relative to that of the control group after the termination, while there was no apparent difference in the credit line size between the two groups before the termination. Moreover, the difference in credit line size persists for about four quarters after the termination. Taking this to a regression setting, I estimate the following difference-in-differences specification:

$$Ln(Limit)_{i,t} = \alpha + \beta Termination_i \times Post_t + \gamma Post_t + \Gamma X_{i,t} + \mu_i + \epsilon_{i,t}, \quad (2.7)$$

where $Termination$ indicates whether the shadow bank experiences a primary funding relationship termination, and $X_{i,t}$ are shadow bank controls, including lagged net income to asset ratio and mortgages held for sale to asset ratio.

Table 8 Column (3) and (4) show the regression results. While the average credit line size was growing over time, the shadow banks whose primary funding relationships were exogenously terminated experienced a significantly slower growth in credit limits. The average credit line size of shadow banks without a lending relationship termination grew by 28.7%, whereas the average credit line size of shadow banks with a lending relationship termination grew by only 2.8%. The results suggest that shadow banks are not able to quickly substitute to an alternative funding source after an exogenous reduction in credit supply from relationship banks, which implies that lending relationships differentiate individual banks.

2.5.2 Exogenous Credit Reduction and Shadow Bank Mortgage Origination

Does an exogenous reduction in warehouse funding supply from relationship banks affect shadow bank mortgage origination? If shadow banks are not financially constrained, either because they can sell the mortgages to GSEs relatively quickly or because they have enough internal funding, a credit reduction may not affect shadow banks' mortgage supply. This section examines whether shadow banks originate fewer mortgages and/or raise mortgage interest rates if their relationship banks reduce lending to them.

Since banks' balance sheet exposure to the O&G sector is not exogenous, a potential endogeneity concern is that banks' choice to lend to O&G

companies is correlated with their choices of shadow banks to form lending relationships with, which leads to a correlation between shadow banks' direct exposure to the oil price shock and the credit supply from their relationship banks. For example, banks operating in counties with more O&G companies may be heavily exposed to the oil price shock; and since banks tend to lend to shadow banks originating mortgages in the same local markets, the mortgage demand faced by shadow banks that borrow from more exposed banks were likely to be affected by the oil shock as well. To this end, I compare the origination of shocked shadow banks with that of unshocked shadow banks in the same county within the same year. Specifically, I run the following regression using shadow bank-county-year level observations:

$$ln(Origin_{i,k,t}) = \alpha + \beta HighOilShock_i \times Post_t + \mu_i + \mu_{k,t} + \epsilon_{i,k,t}. \tag{2.8}$$

The dependent variable is the logarithm of shadow bank i's mortgage origination volume in market k in year t. $HighOilShock$ is an indicator of whether the share of shadow bank i's total warehouse funding obtained from *exposed* banks is above the sample median in 2013. To control for local mortgage demand, I include county-by-year fixed effects. To the extent this within county-year variation fully absorbs county-specific demand changes due to the oil shock, the estimated differences in mortgage origination can be plausibly attributed to differences in the reduction in funding supply induced by the oil price shock.

Table 9 Column (1) and (2) show the average reduction in mortgage origination in the two-year window following the oil price shock. Column (1) include county and year fixed effects, while Column (2) include county-by-year fixed effect to remove time-varying local demand changes. The estimates show a statistically significant impact of the relationship banks' liquidity shock on shadow banks' mortgage origination. The shadow banks whose relationship banks were highly exposed to the oil price shock originated 17.6% less than the unshocked shadow banks within the same county. Fig. 2.5 (a) plots the difference-in-differences coefficients over the event window. The pre-trend shows no significant effects leading up to the oil price shock, suggesting that the differences (if any) between treated shadow banks and untreated shadow banks are orthogonal to their ability to originate mortgages.

Figure 2.5. Exogenous Credit Reduction and Shadow Bank Mortgage Origination

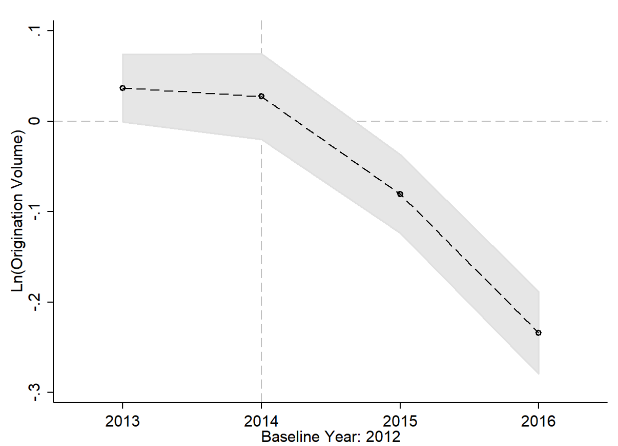


Figure 2.5 plots the difference-in-differences coefficients of Eqn. 2.8, where the dependent variable is the log of mortgage origination at the county-year level calculated using HMDA.

I then examine the effect on shadow banks' mortgage interest rates. Mortgage interest rates could be different just because of changes in borrower and loan characteristics. For example, when their relationship banks reduce warehouse lending, shadow banks may change their clientele, originate fewer sub-prime mortgages, and increase the down payment requirement, leading to lower average interest rates of their mortgage portfolio. What I am after, however, is whether shadow bank mortgage interest rates are affected by warehouse lending supply after conditioning on borrower and loan characteristics. I want to know whether a given borrower would pay a higher interest rate when taking out an otherwise identical mortgage from the same shadow bank after its relationship banks exogenously reduce warehouse lending supply.

To this end, I purge the variation in mortgage interest rates of differences in borrower and loan characteristics. I first run the following regression:

$$r_j = \alpha + \beta_1 LTV_j + \beta_2 DTI_j + \beta_3 FICO_j + \epsilon_j, \tag{2.9}$$

where r_j is the loan-level mortgage interest rate for a loan made to borrower j, and LTV_j, DTI_j, and $FICO_j$ are the loan-to-value ratio, the debt-to-income ratio, and the FICO score of borrower j. I estimate the regression year by year using the Fannie Mae and Freddie Mac loan acquisition data, where I observe mortgage interest rates as well as information on a rich array of loan and borrower characteristics. The goal of this specification is to recover ϵ_j. Once I have the residuals, I compute standardized shadow bank average mortgage interest rates, $R_{i,k,t}$. I do this separately for each three-digit zip code and for each quarter. Specifically,

$$R_{i,k,t} = \frac{1}{N_{i,k,t}} \sum_{j \in \mathbb{J}_i} \epsilon_j + \hat{\alpha}_t + \hat{\beta}_{1,t} \times \overline{LTV}_t + \hat{\beta}_{2,t} \overline{DTI}_t + \hat{\beta}_{3,t} \overline{FICO}_t, \tag{2.10}$$

where $N_{i,k,t}$ is the number of mortgages originated by shadow bank i in zip-code k in quarter t, $\mathbb{J}_i$ is the set of borrowers that obtain mortgages from shadow bank i, $\hat{\alpha}$ and $\hat{\beta}$'s are model estimated parameters, and $\overline{LTV}$, $\overline{DTI}$, and $\overline{FICO}$ are sample average values.

With the standardized zip-code level shadow bank mortgage interest rates, I run the following regression:

$$R_{i,k,t} = \alpha + \beta HighOilShock_i \times Post_t + \mu_i + \mu_{k,t} + \epsilon_{i,k,t}. \tag{2.11}$$

$HighOilShock$ is an indicator of whether the share of shadow bank i's total warehouse funding obtained from *exposed* banks is above the sample median in 2013. I include shadow bank fixed effect and zip code-by-quarter fixed effects to control for time-invariant shadow bank characteristics and changes in local demand.

Table 9 Column (3) and (4) show the average increase in the difference between the treated shadow banks' mortgage interest rates and the untreated shadow banks' mortgage interest rates after the oil price shock. The shadow banks whose relationship banks were heavily exposed to the oil price shock raise their mortgage interest rates by 10.8 basis points more than shadow banks whose relationship banks were not exposed to the oil price shock.

Fig. 2.6 (b) plots the difference-in-differences coefficients over time. The pre-trend shows no significant effects leading up to the oil price shock, suggesting that the differences between treated and untreated shadow banks are orthogonal to their mortgage pricing. The interest rates of mortgages originated by treated shadow banks remained high relative to the untreated shadow banks for more than a year.

Figure 2.6. Exogenous Credit Reduction and Shadow Bank Mortgage Interest Rate

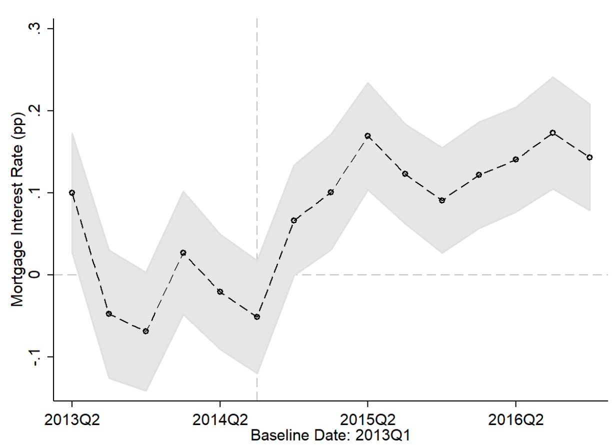


Figure 2.6 plots the difference-in-differences coefficients of Eqn. 2.11, where the dependent variable is the residualized mortgage pricing after controlling for LTV, DTI, and FICO, at the zip-quarter level from Fannie Mae and Freddie Mac loan acquisition database. The shaded area plots the 95% confidence intervals. Standard errors are double clustered at shadow bank and county/zip.

Chapter 3

Possible Explanations for Market Structure

3.1 Introduction

The two facts documented are consistent with banks lending to local competing shadow banks to enjoy the synergies between warehouse lending and mortgage origination. Mortgage origination may provide banks with information necessary for warehouse lending in the same local market, which may be costly to access for banks that do not originate mortgages in this market. For example, originating mortgages in a local market can provide better information on the reliability of house price assessments or income verification, costs of mortgage origination, or give early warning of defaults leading to put-back risk. Access to such information effectively lowers banks' cost of warehouse lending to competing shadow banks relative to non-competitors. This information advantage could be one potential source of the additional rent of warehouse lending to competing shadow banks relative to lending to non-competitors.

However, enjoying this information advantage imposes a cost on banks' mortgage origination business - financing shadow banks increases competition in the mortgage market, lowering banks' mortgage origination profit. As a result, banks may trade off the benefit, possibly arising from their information advantage over other warehouse lenders, and the cost from mortgage market competition in their decisions to lend to competing shadow banks. If local information advantage is sufficiently high, banks may choose to finance competing shadow banks, despite the loss in mortgage profit from increased competition. As the potential loss in profit from increased mortgage market competition rises, banks may reduce warehouse lending to shadow banks, limiting shadow banks' expansion in most profitable, least competitive mortgage origination markets.

In this section I first examine a source of rent in lending to competing shadow banks, which comes from banks' information advantage over other warehouse lenders. I then provide evidence that banks use their market power in warehouse lending to internalize competition in the mortgage market before discussing the implications for shadow bank cost of funding.

3.2 Benefit: Information Advantage in Warehouse Lending

To test the information advantage hypothesis, I examine cross-sectionally whether the likelihood of warehouse lending increases faster with mortgage market overlap in regions with pervasive soft information. Since valuable soft information are harder to be transmitted than hard information, local competing banks' information advantage over non-competing banks in lending to a specific shadow banks is presumably larger in markets in which hard information about local real estate markets is less reliable: if hard information is less reliable, banks need to rely more on soft information to assess shadow banks' risk (Stein (2002), Petersen and Rajan (1994), and Diamond (1984)). To this end, I exploit variation in the quality of hard information about residential real estate values following Garmaise and Moskowitz (2003) and Granja, Matvos, and Seru (2017).

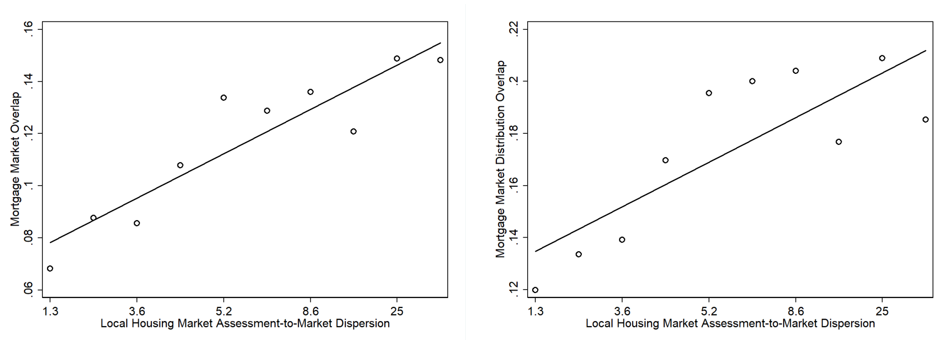
Real estate properties are assigned an assessed value by the corresponding government municipality to calculate property taxes. In most jurisdictions, the value is assessed annually. The quality of property assessments are evaluated by property tax authorities periodically. The most common measure of assessment quality is the coefficient of dispersion used by Garmaise and Moskowitz (2003). The main input for the measure is the ratio between the market value of a property recently sold and its assessed value. Suppose that the assessed value is legislated at 33% of market value. If assessments are precise, then the assessment to market value ratios should be 33% for all assessed properties. Lenders can then rely on the property assessments to closely tract the real estate market conditions. However, if the assessment to market value ratios are dispersed, e.g. some assessed values are 20% of the market value while others are 40%, then the assessed values provide little information to investors. The coefficient of dispersion, denoted by COD, measures how dispersed the assessment to market value ratios are:

$$COD = \frac{\frac{1}{N}\Sigma_i |R_i - R^{med}|}{R^{med}} \tag{3.1}$$

in which R_i is the assessment-to-market ratio for property i and R^{med} is the median assessment-to-market ratio in the county. The measure is larger when property assessments are less accurate, in which case lenders need to rely on soft information about local real estate market conditions.

Fig. 3.1 plots mortgage market overlap against the COD measure. Panel (a) plots mortgage market overlap ($\%OverlapMkt$). Panel (b) plots mortgage market distribution overlap ($MktOverlap$) that accounts for mortgage origination volume in each county. As show in this figure, the mortgage market overlap between a shadow bank and its funding provider is larger if the shadow bank originates mortgages in high COD areas.

Figure 3.1. Mortgage Market Overlap and Local Soft Information



(a) $\%OverlapMkt$ vs COD **(b)** $MktOverlap$ vs COD

I then run the following regressions to examine whether the likelihood of having a funding relationship, as well as the credit limit, increases faster with origination market overlap in areas with poorer hard information quality:

$$Pr(Lend_{i,j,t}) = \alpha+\beta_1\%MktOverlap_{i,j,t}+\beta_2\%MktOverlap_{i,j,t}\times HighCOD_{i,t}+\gamma D_{i,j,t}+\mu_{i,t}+\mu_{j,t}+\epsilon_{i,j,t}, \quad (3.2)$$

$$Limit_{i,j,t}) = \alpha + \beta_1 \% MktOverlap_{i,j,t} + \beta_2 MktOverlap_{i,j,t} \times HighCOD_{i,t} + \gamma D_{i,j,t} + \mu_{i,t} + \mu_{j,t} + \epsilon_{i,j,t}, \tag{3.3}$$

where $HighCOD_{i,t}$ is an indicator of whether the local average COD weighted by shadow banks' loan origination is above median. β_2 indicates how the importance of soft information in the real estate market amplifies the effect of origination market overlap on funding relationship formation.

Table 10 Column (1) and (2) present the linear probability regression results. The estimated coefficient on distance is negative and statistically significant, while the coefficient on its interaction with COD is not significant. Shadow banks are more likely to obtain funding from banks near their headquarters, regardless of the quality of local hard information. The coefficients on the market overlap measures are positive and statistically significant, indicating that warehouse lending relationships are more likely to be formed between banks and shadow banks with more mortgage market overlap even in markets with good-quality hard information.

Moreover importantly, consistent with the idea that competitors have information advantage in warehouse lending over non-competitions, the coefficient on the interaction of $\%OverlappedM$ and $HighCOD$ is statistically significant and positive. In regions with less reliable hard information, the likelihood of warehouse lending increases faster with mortgage origination market overlap. For shadow banks that originate mortgages in areas with above-median COD, the effect of mortgage market overlap on the likelihood of warehouse lending increases by 31%. A one standard deviation increase in

%OverlapMkt increases the likelihood of warehouse lending to shadow banks originating mortgages in high-COD areas by 1.89 percentage-points, whereas the same increase improves the likelihood of having a funding relationship with shadow banks originating mortgages in low-COD areas by 1.45 percentage-points.

Table 10 Column (3) and (4) present the intensive margin regression results. The coefficients on the market overlap measures are positive but not statistically significant, while the coefficient on their interactions with high-COD are positive and statistically significant. Conditional on having a funding relationship, there is no systematic difference between credit limits received by a shadow bank from warehouse banks with different mortgage market overlap, but the increase in such difference is significant when comparing shadow banks in high-COD areas and shadow banks in low-COD areas. If we compare shadow banks in high-COD areas to shadow banks in low-COD areas, the incremental amount of credit limit from banks with one standard deviation higher *%MktOverlap* is $7.7 million larger for shadow banks in high-COD areas.

3.3 Cost of Financing Competitors

The analysis showed that conducting mortgages in the same local markets gives banks information advantage in lending to competing shadow banks. However, financing shadow banks increases mortgage market competition, lowering banks' mortgage origination profit. I then examine whether banks attempt to use their warehouse lending market power to internalize mortgage market competition. My analysis takes two steps. I first examine banks' warehouse lending decisions across local mortgage markets. I then examine the warehouse lending relationships between banks and shadow banks.

3.3.1 In Which Markets Do Banks Finance Competitors?

If mortgages offered by banks have the same substitution pattern, a bank's market share reflects how much its demand is affected by new entrants (Berry (1994)). Intuitively, as a shadow bank enters the market, given the same substitution pattern across banks, the probability of every borrower switching to this shadow bank is identical; and the amount of demand an incumbent bank is going to lose to the entrant is proportional to its current market share. Therefore, the potential loss in mortgage profit from increased mortgage market competition arises with a bank's current mortgage market share.

I begin by comparing banks' warehouse lending across markets. Specifically, for each county that a bank originates mortgages, I add up its warehouse lending to all shadow banks in this county:

$$Limit_{i,k} = \Sigma_j \sigma_{j,k} \times Limit_{i,j},$$

where j indexes shadow banks that obtain funding from bank i, $\sigma_{j,k}$ is the share of shadow bank j's total loan origination in market k. I run the following bank-county level regressions:

$$Pr(WLend)_{i,k,t} = \alpha + \sum_b \beta_b I(MktShare_{i,k,t} \in Bin_b) + \mu_{i,t} + \mu_{k,t} + \epsilon_{i,k,t}. \quad (3.4)$$

$$WLendPerAsset_{i,k,t} = \alpha + \sum_b \beta_b I(MktShare_{i,k,t} \in Bin_b) + \mu_{i,t} + \mu_{k,t} + \epsilon_{i,k,t}. \tag{3.5}$$

$Pr(WLend_{i,k,t})$ indicates whether warehouse bank i lend to shadow banks that originate loans in market k in year t. $WLendPerAsset_{i,k,t}$ is the total credit limit extended by bank i in market k in year t scaled by its asset size. $I(MktShare_{i,k,t} \in Bin_b)$ is an indicator for whether bank i's market share in market k in year t falls within market share quantile Bin_b. Bank-by-year fixed effects and county-by-year fixed effects absorb all cross-markets and cross-banks variation. Therefore, I am comparing the warehouse lending activities of two otherwise identical warehouse banks that have different market shares within the same county. Fig. 3.2 plots β_b against the market share quantile Bin_b. Panel (a) shows the probability of lending to competing shadow banks; and Panel (b) shows the warehouse lending volume per unit of assets.

These figures show that lending to competing shadow banks is strongly negatively correlated with banks' mortgage market share. As the mortgage market share increases from less than 1% (bottom bin) to about 15% (top bin), the probability of lending to shadow banks drops by about 8 percentage points, whereas, the total warehouse lending drops by \$0.2 per dollar of assets.

Table 11 shows the regression results with the continuous mortgage market share and bank-county level controls. The result in Column (1) shows that among all counties, banks are more likely to do warehouse lending in markets where they originate mortgages. The statistically significant positive coefficient on the share of institution's total mortgage origination in the county

Figure 3.2. Mortgage Market Competition and Financing Competitors

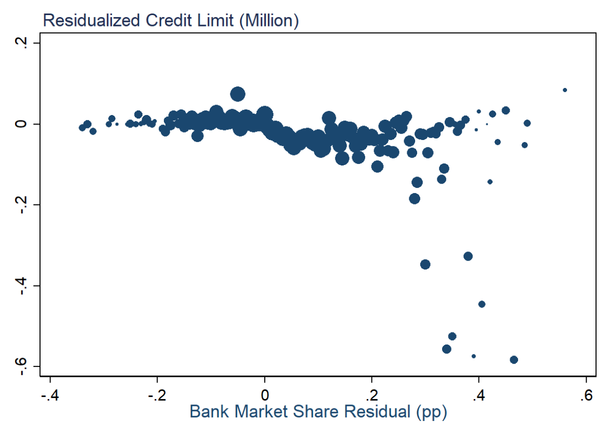


Fig. 3.2 plots in which markets banks finance competitors. The sample includes bank-county observations. The x-axes in both figures are banks' local mortgage market shares equally divided into 20 bins. The y-axes are the residualized probability of financing local competing shadow banks and the residualized total credit limits extended to local competing shadow banks, respectively, after controlling for bank-by-year fixed effects and county-by-year fixed effects.

is consistent with the results found in the previous section that banks lend to competing shadow bank to enjoy their information advantage. A bank is 1.2% more likely to do warehouse lending in a county where the share of its total mortgage origination increases by 1%.

Restricted to only counties where warehouse banks originate mortgages, banks are less likely to do warehouse lending in markets where they have higher market shares. The result in Column (2) indicates that a one percentage point increase in mortgage market share is associated with a reduction of 22 basis points in the likelihood of warehouse lending. Columns (3) shows the warehouse lending amount. As its mortgage market share increases by 10 percentage point, the amount of credit limit a bank extends to competing shadow banks in the county drops by \$0.043 per unit of assets.

3.3.2 Which Shadow Banks Do Warehouse Banks Lend to?

I then examine the idea that banks exploit market power in warehouse lending to limit competition from shadow banks, whose growth will extract more of their total market share across counties. To this end, for each pair of banks and shadow banks, I calculate the bank's average market share in markets where the shadow bank also originate mortgages:

$$MktShare_{i,j} = \Sigma_k \sigma_{i,k} \times s_{i,k} \times I(\sigma_{j,k} > 0)$$

where $\sigma_{i,k}$ is bank i's share of total mortgage origination in market k, $s_{i,k}$ is bank i's mortgage market share in market k, and $I(\sigma_{j,k} > 0)$ is an indicator that equals 1 if shadow bank j originates mortgages in market k. I test whether $MktShare_{i,j}$ is negatively correlated with the likelihood of warehouse lending as well as the size of the credit line by running the follow regressions:

$$Pr(Lend_{i,j,t}) = \alpha + \beta HighMktShare_{i,j,t} + \Gamma X_{i,j,t} + \mu_{i,t} + \mu_{j,t} + \epsilon_{i,j,t} \tag{3.6}$$

$$Limit = \alpha + \beta MktShare_{i,j,t} + \Gamma X_{i,j,t} + \mu_{i,t} + \mu_{j,t} + \epsilon_{i,j,t} \tag{3.7}$$

where $HighMktShare_{i,j,t}$ indicates whether $MktShare_{i,j,t}$ is in the top quartile, and $X_{i,j,t}$ are pairwise controls, including the logarithm of minimum distance between shadow bank i's headquarter and all branches of warehouse bank j, and mortgage origination market overlap between i and j. The shadow bank-by-year fixed effects and bank-by-year fixed effects are included to ensure identification by bank-shadow bank pairwise variation.

Table 12 reports the regression results. The likelihood of warehouse lending drops if the bank has high average market share in markets where the shadow bank originates mortgages. Conditional on headquarter distance and mortgage market overlap, the likelihood of warehouse lending drops by 38% of the unconditional mean if the bank has high mortgage market shares in the shadow bank's markets.

Moreover, banks offer smaller credit limits to shadow banks originating mortgages in markets where they have high market shares. A bank provides a $3.79 million smaller credit line to shadow banks originating mortgages in markets where its average mortgage market share is 1 percentage point higher. The results suggest that banks exploit market power in warehouse lending and reduce warehouse lending to shadow banks whose expansion would cause more losses in their mortgage profits. This suggests that a bank reduces lending to shadow banks whose growth will extract more of its total market share across markets.

These results are again robust to the inclusion of bank-by-year and shadow bank-by-year fixed effects. The results imply that banks exploit market power in warehouse lending to limit competition from shadow banks, especially in markets in which the benefits of this competition would be largest.

3.4 Shadow Bank Cost of Funding

The analysis showed that a bank reduces lending to shadow banks whose growth will extract more of its total market share across markets. I then study the implication for shadow banks' cost of funding. Specifically, I examine whether shadow banks receive more expensive funding when their potential lenders have high mortgage market shares.

I first find *potential lenders* for each shadow bank. Potential lenders of a particular shadow bank are defined as banks whose mortgage market overlap is in the top quintile. I compute the average market share of all potential lenders for each shadow bank and test whether shadow banks receive more expensive funding when their potential lenders have high mortgage market shares:

$$\hat{r}_{i,t} = \alpha + \beta MktShare_{i,t} + \Gamma X_{i,t} + \mu_t + \epsilon_{i,t}. \tag{3.8}$$

The dependent variable is shadow bank i's cost of warehouse funding in year t. $MktShare$ is the average market share of shadow bank i's potential lenders. I control for an exclusive list of shadow banks controls, including mortgage market overlap with its lenders, lagged accounting ratios, local market-adjusted mortgage portfolio compositions, and lender characteristics.

Table 13 shows the results. Shadow banks pay higher interest rates if they lend more to low income borrowers, have lower equity to asset ratios, are less profitable, and are smaller as measured by mortgage origination volume. More importantly, the coefficient on *MktShare* is positive and statistically significant, which indicates that shadow banks receive more expensive funding if they originate mortgages in markets where their potential lenders are disincentivized to lend to them due to mortgage market competition. A 1 percentage point increase in the potential lenders' mortgage market share is associated with a 30 basis-point increase in shadow banks' cost of warehouse funding.

Figure 3.3. Mortgage Market Competition and Shadow Bank Cost of Funding

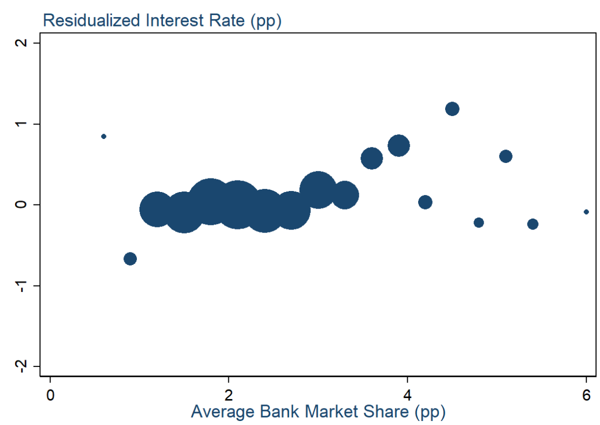


Fig. 3.2 plots residualized warehouse lending interest rate against average local bank market share.

Given the average usage of \$62 million and the average quarterly warehouse interest expense of \$1.5 million, this interest rate difference is equivalent to a 12.4% increase in warehouse interest expense.

Chapter 4

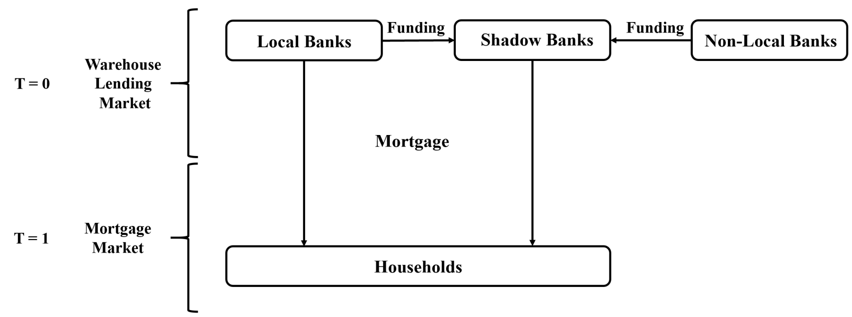
Feedback Between Funding Market and Mortgage Market: A Quantitative Framework

4.1 Introduction

My empirical analysis illustrates a trade-off between the banks' information advantages and the mortgage market competition they face in their warehouse lending decisions. On one hand, originating mortgages in the same local markets as a shadow bank provides an information advantage over other banks in warehouse lending to competing shadow banks. On the other hand, financing shadow banks increases competition in mortgage origination, lowering banks' mortgage origination profit. This trade-off implies that banks exploit market power in warehouse lending to limit shadow banks' expansion in the most profitable, least competitive mortgage origination markets. The empirical findings raise two questions. First, to what extent does this warehouse lending market structure affect mortgage market competition? Second, how would policies that effectively reduce banks' warehouse lending market power improve consumer welfare? I address these questions through a quantitative model that links warehouse lending and product market competition and in which banks trade off the costs and benefits in lending to their competing shadow banks.

4.2 Model

As the figure below illustrates, I model two interdependent markets with three groups of economic agents. The mortgage origination market mirrors Buchak et al. (2018a). Demand for mortgages arises from utility maximizing households, who choose to borrow from banks and shadow banks in a discrete choice framework. Since mortgages are differentiated products, lenders have market power, which leads to economic profits. My innovation to the previous literature develops from modeling the warehouse lending market. Shadow banks fund their mortgage origination using warehouse lines of credit, provided by competing banks. The warehouse lending market and the origination market are interconnected through two primary forces. First, shadow banks' demand for warehouse funding derives endogenously based on the profits they expect to earn from mortgage origination. Second, banks strategically choose how much funding to provide the shadow banks. Two strategic considerations affect that decision. First, the warehouse lending market is not perfectly competitive: banks are differentiated in the warehouse market, which captures the relationship lending and market power that I document in the previous chapter. Second, banks, which originate in the same market as shadow banks, have an advantage in lending to shadow banks. However, these banks also have to account for the fact that the warehouse lines they provide will fund their competition in the mortgage origination market. The equilibrium then accounts for borrower optimization behavior, and the full strategic behavior of banks and shadow banks across both markets.



In the warehouse lending market, banks, indexed by l, set the interest rates of their warehouse lines of credit to shadow banks. Depending on whether they also conduct mortgage origination, banks are divided into two types: *local banks*, which conduct mortgage origination, and *non-local banks*, which do not conduct mortgage origination. Local banks and non-local banks differ on two dimensions: the costs of monitoring shadow banks, and the competition in mortgage origination. Since local banks also originate mortgages, they compete with shadow banks in mortgage origination. Banks take into account mortgage market competition when setting the interest rates for their warehouse lines of credit. Pricing and market shares are determined endogenously.

In its search for funding, Shadow bank j faces the warehouse lending market, which comprises N_b local banks and N_o non-local banks. Individual shadow banks take warehouse lending interest rates as given and selects a bank to acquire a committed credit line.

In the mortgage market, a mass of households in need of a mortgage, indexed by i, faces the mortgage market, which comprises N_b banks and N_n

shadow banks. Individual households take mortgage pricing decisions as given.

Once shadow banks choose their funding providers, banks and shadow banks compete in mortgage origination by setting mortgage interest rates. The banks and shadow banks differ on two dimensions: convenience, modeled as a difference in quality, and costs of making mortgages. Shadow banks sell mortgages by drawing on warehouse lines of credit, the cost of which depends on the terms of the credit line. In contrast, banks sell mortgages using their own funding generated from their deposit services. For each dollar of mortgages originated by shadow banks, banks receive interest payments based on the preset rates of the warehouse lines of credit.

4.2.1 Household's Problem

Household i chooses between N_b banks and N_n shadow banks, taking mortgage rates as given. Their utility of choosing lender j is:

$$u_{i,j} = -\alpha r_j + q_j + \epsilon_{i,j}. \tag{4.1}$$

Households' utility declines in the interest rate r_j, with $\alpha > 0$ measuring the interest rate sensitivity. Borrowers also derive utility from non-price attributes, such as convenience, quality, and other services offered by the lender, which is captured by q_j and $\epsilon_{i,j}$. q_j measures average quality differences across lenders: some lenders offer better service than others, and therefore obtain more borrowers if they were to offer the same mortgage rate. $\epsilon_{i,j}$ captures horizontal differentiation, the idea that two borrowers can differ in their preferences over lenders, for example, because they already have existing accounts with a specific lender.

To aggregate preferences across borrowers into a demand function, I make a standard assumption in discrete choice demand models (Berry (1994), Berry et al. (1995)) that $\epsilon_{i,j}$ follows the extreme value distribution with a cumulative distribution function $F(\epsilon) = exp(-exp(-\epsilon))$.

4.2.2 Shadow Bank's Problem

Shadow banks originate mortgages with the quality of service q_n to households using warehouse credit obtained from banks. Shadow banks face two decisions: (1) how to set mortgage interest rates (Mortgage Market), and (2) which bank to obtain warehouse funding from (Warehouse Lending Market).

Mortgage Market: When choosing how to set interest rates in the mortgage market, the shadow bank takes its warehouse funding as given. This corresponds to the institutional setting, in which shadow banks negotiate warehouse credit lines, and then choose to draw on them over the year when they originate mortgages. Conditional on warehouse funding from bank l at interest rate ρ_l, a shadow bank's total marginal cost of mortgage lending is

$$\rho_j = \rho_n + \eta\rho_l, \tag{4.2}$$

where ρ_n represents the cost of funding common to all shadow banks, because it arises from selling mortgages to GSEs or other mortgage buyers. η captures how long the mortgages stay on shadow banks' balance sheets before being sold. Scaling ρ_l by η gives the actual warehouse lending interest expense per dollar of mortgage origination. It captures the idea that the the cost of warehouse lending only accrues while the mortgage is held by the shadow bank. When the mortgage is sold, the credit line is repaid. This normalization has two consequences: the first one is simply to correct accounting, since warehouse line prices are quoted in annual interest rates. The second one speaks to the idea that shadow banks can potentially reduce their reliance on warehouse lines, if they can speed up the time between origination and loan sale. Because warehouse costs are endogenous, and set by banks with market power, the equilibrium magnitude of changing η is unclear.

Shadow bank j sets mortgage interest rate r_j to maximize its mortgage profit

$$v_j(r_j|\rho_j) = (r_j - \rho_j)s_j(r_j|r_{j'})F, \tag{4.3}$$

where the $(r_j - \rho_j)$ represent profits per mortgage, F represent the total face value of mortgage loans in the local market, and s_j denotes lender j's mortgage market share, which is determined by households' choices given shadow bank j's mortgage interest rate and other mortgage lenders' mortgage interest rates.

Warehouse Lending Market: The profits that a shadow bank derives from lending in the origination market determine its demand for warehouse lending. Banks post interest rates on warehouse lines. Each shadow bank chooses a bank to acquire a warehouse line of credit. The empirical findings in the Chapter 2 indicate that shadow banks have a difficult time substituting across credit lines and have persistent relationships with banks. In other words, shadow banks care about more than the simple interest rate on the warehouse line. To capture these differential gains from trade as a result of differences in existing banking relationships, transaction costs, and cost-saving from other bundling services across bank-shadow bank pairs, I allow differentiation across warehouse lines. I model this as a per-dollar difference in credit line benefits derived from a certain bank credit line. Formally, $\xi_{j,l} \geq 0$ represents the idiosyncratic profit shadow bank j receives from bank l:

$$V_j(\rho_l) = \xi_{j,l} \times \underbrace{v_j^*(\rho_l)}_{\text{Mortgage Profit}} \tag{4.4}$$

This formulation also allows the warehouse line problem to be conveniently expressed as a discrete choice problem. Shadow bank j chooses bank l if its total profit from doing so is larger than choosing any other banks. Thus, the probability that bank l is chosen by shadow bank j, denoted by $s^w_{j,l}$, is:

$$s^w_{j,l} = Pr(V_j(\rho_l) \geq V_j(\rho_{l'}), \forall l') \tag{4.5}$$

I assume that $\xi_{j,l}$ is drawn from a Frechet distribution $G_k(\xi;\sigma) = e^{-(\gamma\xi)^{-\sigma}/(L+1)}$ and is i.i.d across shadow banks and banks. $\xi_{j,l}$ is normalized so that the expected value of shadow bank j's total profit is equal to its average profit: $E[\max_l V_j(\rho_l)] = \sum_l s^w_{j,l} v_j^*(\rho_l)$.

σ captures the importance of non-price differences across warehouse banks. Formally, it relates inversely to the variance of the idiosyncratic profit shocks. As σ goes to infinity, banks become perfect substitutes. In other words, shadow banks only care about the interest rate they obtain on the credit line, and do not have prior relationships with banks. Conversely, as σ moves toward zero, shadow banks effectively care little about rates charged on warehouse lines. The reliability of a specific bank, or its prior relationship become paramount. I calibrate σ to the data, to gauge the strength of this degree of substitution.

4.2.3 Bank's Problem

Banks have two types of businesses: mortgage origination and warehouse lending. They offer mortgages with the quality of service q_b to households. Banks also provide warehouse lines of credit to shadow banks. The critical insight from the first part of the paper is that mortgage originators obtain an advantage when funding shadow banks who compete with them. I model this advantage as a difference in the cost of lending (monitoring and information acquisition). Local banks, the ones with the information advantage, are indexed by b; non-local banks are indexed with o. Their cost are $c_l \in \{c_b, c_o\}$. All banks also have a common cost of funding ρ_0.

Warehouse Lending Market: Banks make warehouse lending decisions while taking into account the mortgage market competition. Since warehouse lending interest rates determine shadow banks' costs of making mortgage loans, which in turn affect banks' mortgage profit through competition, banks set interest rates of their warehouse lines of credit to maximize its total profit from both warehouse lending and mortgage origination.

Let F represent the total face value of mortgages. Let $s^w_{j,l}$ denote the choice probability that shadow bank j chooses bank l. Bank l sets its warehouse interest rate, ρ_l to maximize its total profit:

$$\underbrace{(r^*_l - \rho_0)s^*_l F}_{\text{Mortgage Profit}} + \underbrace{\eta(\rho_l - c_l)\sum_j s^w_{j,l}(\rho_l)s^*_j F}_{\text{Warehouse Lending Profit}} \tag{4.6}$$

where s^*_l, s^*_j, and r^*_l are mortgage market share of bank l, mortgage market share of shadow bank j, and bank l's optimal mortgage pricing strategy, respectively, which are all affected by ρ_l through mortgage market competition.

Mortgage Market: Only local banks originate mortgages, and internalize the competition in both markets. Recall that shadow banks take their warehouse lines of credit as given when deciding how to set mortgage rates. The same is the case for local banks. Banks set their mortgage rates, while accounting for the spillover effect on their warehouse lending profits. In other words, banks receive interest payments on each dollar of mortgages originated by shadow banks using their warehouse lines of credit. Local banks' mortgage interest rates affect shadow banks' mortgage market share through competition. Banks therefore set mortgage interest rates to maximize their total profits in mortgage origination and warehouse lending. If bank l is a non-local bank, then origination profits are zero.

Let $\mathbb{J}^j_n$ denote the set of shadow banks that have a lending relationship with bank l. Bank l sets its mortgage interest rate to maximize its total profit from warehouse lending and mortgage origination:

$$\underbrace{(r_l - \rho_0)s_l F}_{\text{Mortgage Profit}} + \underbrace{\eta(\rho_l - c_l)\sum_{j \in \mathbb{J}_n^j} s_j F}_{\text{Warehouse Lending Profit}} . \tag{4.7}$$

The first term is the mortgage origination profit. The second term is the warehouse lending profit. Formally, a bank's mortgage rate enters the profit condition in three places. It affects mortgage origination profits directly as well as through market share s_l. The effect on warehouse profits arises through shadow banks' usage of warehouse credit, s_j, which is determined through mortgage market competition. Since shadow banks pay interest on each dollar drawn from the warehouse lines, banks' mortgage pricing in turn affects their own warehouse lending profit.

4.3 Equilibrium

I focus on equilibria in which all lenders within a type are symmetric. An equilibrium is a market structure comprising the warehouse lending pricing decisions of local banks and non-local banks, $\{\rho_b, \rho_o\}$; the share of shadow banks that are financed by local banks and non-local banks, $\{S_b^w, S_o^w\}$; the mortgage pricing decisions of banks, shadow banks financed by local banks, and shadow banks financed by non-local banks, $\{r_b, r_n^b, r_n^o\}$; and the aggregate mortgage market shares of banks, shadow banks financed by local banks, and shadow banks financed by non-local banks, , $\{S_b, S_n^b, S_n^o\}$, such that:

1. Households maximize utility, taking mortgage market structure and mort-

gage pricing as given.

2. Banks and shadow banks set mortgage interest rates to maximize profits, taking shadow banks' funding choices, mortgage market structure, and the pricing decisions of other lenders as given.

3. Shadow banks choose their funding providers to maximize profits, taking warehouse lending market structure and warehouse lending price as given.

4. Warehouse lenders set warehouse lending prices to maximize profits, in anticipation of mortgage market competition and taking warehouse lending market structure and the pricing decisions of other banks as given.

To solve the model through backward induction. I first solve the mortgage market equilibrium, while taking the warehouse lending market outcome as given. I then solve the warehouse lending market equilibrium.

4.3.1 Mortgage Market Equilibrium

Household's Optimal Borrowing Decision: Households' optimal choices result in the following logistic demand function of lender j's mortgages:

$$s_j(r_j, q_j; [r_{j'}, q_{j'}]) = \frac{exp(-\alpha r_j + q_j)}{\Sigma_{j'=1} exp(-\alpha r_{j'} + q_{j'})}. \tag{4.8}$$

Intuitively, if borrowing from lender j yields higher expected utility for a household, i.e., a larger numerator, the household is more likely to borrow from lender j; if borrowing from lender j's competitors yields higher expected utility, i.e., larger denominator, the household is less likely to borrow from lender j.

Shadow Bank's Optimal Mortgage Pricing: Given shadow banks' funding choices ρ_l, the first-order condition of the shadow bank's problem results in the standard pricing equation for a shadow bank financed by bank l, denoted by r_n^l:

$$r_n^{l*} = \underbrace{\rho_n + \eta\rho_l}_{\text{Marginal Cost}} + \underbrace{\frac{1}{\alpha}\frac{1}{1-s_n}}_{Markup}. \tag{4.9}$$

Shadow banks' price can be decomposed into the marginal cost of making a loan and the markup that the lender charges over the marginal cost, which is inversely related to the price elasticity of demand. Intuitively, the more inelastic the demand is, the higher markup a lender can charge.

4.8 and 4.9 indicate that shadow banks that obtain funding from the same bank have identical market shares in equilibrium, i.e., $s_j^* = s_n^*(\rho_l)$ for all j's that obtain funding from bank l.

This expression also partially illustrates how warehousing costs spill over to the mortgage origination market. $\eta\rho_l$ illustrates how shadow banks' ability to sell loans faster directly passes to consumers in the form of lower cost. Of course, since ρ_n is the endogenous choice of the bank, banks may be able to offset this decline by charging higher rates, ρ_l.

Bank's Optimal Mortgage Pricing: Let N_n^l denote the number of shadow banks that obtain funding from bank l, ρ_l denote the warehouse lending price set by bank l, and s_n^l be the market share of any of these shadow banks. Bank l's optimal mortgage pricing strategy satisfies the following relation:

$$r_l^* = \arg\max_{r_l}(r_l - \rho_0)s_l F + \eta(\rho_l - c_b)N_n^l s_n^l F \tag{4.10}$$

The first-order condition results in the following pricing equation for bank l:

$$r_l^* = \underbrace{\rho_0}_{\text{Marginal Cost}} + \underbrace{\frac{1}{\alpha}\frac{1}{1-s_l}}_{\text{Markup in a standard pricing eqn.}} + \underbrace{\eta(\rho_l - c_b)\frac{N_n^l s_n^l}{1-s_l}}_{\text{Additional Markup}} \tag{4.11}$$

Compared to shadow banks' mortgage pricing, banks' pricing has an additional markup term arising from the warehouse lending relationships. This condition shows how warehouse lending directly distorts the competition in the mortgage origination market. Intuitively, local banks behave as if they partially collude with shadow banks in mortgage origination, since they can recover some rents from softer competition through warehouse profits. This additional markup term is determined by bank l's warehouse lending markup, $(\rho_l - c_b)$, the warehouse duration η, and the number of shadow banks financed by bank l, (N_n^l). Warehouse lending markup determines the intensive margin of bank l's stake in shadow banks' mortgage profit, whereas the latter two elements determine the extensive margin. Specifically, bank l earns $\eta(\rho_l - c_b)$ from each dollar of mortgages originated by shadow banks that obtain funding from it. Hence, the larger its warehouse lending markup $(\rho_l - c_b)$ multiplied by the warehouse loan duration η, the more it earns at per-dollar basis of shadow banks' origination; and the more shadow banks financed by bank l (N_n^l), the more shadow banks pay warehouse lending interest payments to it.

In bank l's mortgage pricing strategy, in addition to its own mortgage origination profit, it also considers the impact of its mortgage interest rate on its shadow bank borrowers' usage of warehouse funding. A lower mortgage interest rate affects the demand for shadow banks' mortgages s_n^l through mortgage market competition. Since shadow banks use warehouse funding to finance their mortgage origination, this in turn, affects shadow banks' usage of funding and thus affects bank l's warehouse lending profit. Therefore, banks charge higher mortgage interest rates than they would if there were no warehouse lending relationships between shadow banks and them.

4.3.2 Warehouse Lending Market Equilibrium

Shadow Bank's Optimal Funding Choice: Since in the model each shadow bank chooses one lender, its profit maximization problem conveniently becomes a discrete choice problem. Given the distribution of idiosyncratic profits, shadow banks' optimal funding choices result in the following probability of choosing a given bank:

$$s_{j,l}^w(\rho_l; \{\rho_{l'}\}) = \frac{v_{j,l}^\sigma}{\sum_{l'} v_{j,l'}^\sigma}. \tag{4.12}$$

Given these choice probabilities, the expected profit of shadow bank j

can be expressed as:

$$E\Pi_j = (\frac{1}{L+1}\sum_l v_{j,l}^{\sigma})^{\frac{1}{\sigma}}. \tag{4.13}$$

As banks become better substitutes, σ increases, and expected profits are closer to the origination profits. Since shadow banks have identical equilibrium mortgage pricing and mortgage market shares if they obtain funding from the same bank, shadow banks' mortgage profits are functions of their funding choices:

$$v_{j,l} = v_l = \frac{s_n^l}{\alpha(1-s_n^l)}F, \ \ \forall\ j, \tag{4.14}$$

where s_n^l is the market share of any shadow bank that obtains funding from warehouse lender l.

Hence, $s_{j,l}^w = s_l^w$ for all j. The number of shadow banks that are financed by bank l, denoted by N_n^l, is

$$N_n^l(\rho_l; \{\rho_{l'}\}) = s_l^w N_n \tag{4.15}$$

where

$$s_l^w = \frac{(\frac{s_n^l}{\alpha(1-s_n^l)})^{\sigma}}{\sum_{l'}(\frac{s_n^{l'}}{\alpha(1-s_n^{l'})})^{\sigma}}. \tag{4.16}$$

Bank's Optimal Warehouse Lending Pricing: I derive shadow banks' demand for warehouse lending in Eqn. 4.12. Banks' compete in the warehouse market by setting warehouse rates resulting in the following first-order condition of Eqn. 4.6:

$$\rho_l = c_l + [s_n^{l*} + \underbrace{(\eta N_n s_l^w)^{-1}(\frac{\partial r_l^*}{\partial \rho_l} s_l^* + (r_l - \rho_0)\frac{\partial s_l^*}{\partial \rho_l})}_{\text{Internalizing Origination}}] \times [-\frac{\partial s_n^{l*}}{\partial \rho_l}(1 + \frac{\sigma(1 - s_l^w)}{(1 - s_n^{l*})})]^{-1}, \tag{4.17}$$

where $\frac{\partial s_n^{l*}}{\partial \rho_l}$, $\frac{\partial r_{l*}}{\partial \rho_l}$, and $\frac{\partial s_{l*}}{\partial \rho_l}$ are the effect of ρ_l on the mortgage market equilibrium market share of any shadow bank financed by bank l, on bank l's equilibrium mortgage pricing, and on bank l's mortgage market equilibrium market share, respectively. Recall that c_l reflects the cost advantage of local banks in lending, which they partially pass through to consumers (note that several quantities on the RHS are equilibrium functions, which also depend on the costs). Second, the additional term "Internalizing Origination" reflects local banks' warehouse lending pricing, which indicates local banks' incentives to internalize the cost of mortgage market competition.

4.4 Calibration

The model highlights several effects, which are not obvious. For example, warehouse lending restrains competition in mortgage origination in several ways. First, banks can restrict warehouse lending to lower shadow banks' ability to compete. Second, warehouse lending decreases banks' own incentives to compete hard in mortgage origination. Some of the profits that are earned by shadow banks are funneled back to banks through warehouse lending interest rates. While these forces arise in the model, it is difficult to evaluate the extent to which warehouse lending softens competition, and in which types of markets. To evaluate the quantitative extent of these forces, I calibrate the model using the conforming mortgage market data and the data of shadow banks' warehouse lines of credit, which I was able to obtain from the FOIA requests. After presenting the results, I show that the calibrated model matches up with data on dimensions, which were not used for the calibration, such as the actual duration of mortgage warehousing, and the consequences of the oil shock to banks in Chapter 2.

I aggregate data to the CBSA-Year level and calibrate to observed data in the mean CBSA-Year from 2012 to 2017. In the data, I observe the geographic distribution of banks' and shadow banks' mortgage origination activities as well as the warehouse lending relationships between banks and shadow banks. Using these two pieces of information, for each CBSA I classify shadow banks into *local bank-financed* and *non-local bank-financed*, based on whether their major funding providers sell mortgages in the same CBSA-Year. With this classification, I obtain the aggregate mortgage market share of banks, local bank-financed shadow banks, and non-local bank-financed shadow banks, $\{S_b, S_n^b, S_n^o\}$, the mortgage pricing of each type $\{r_b, r_n^b, r_n^o\}$, the average warehouse lending interest rates paid by local bank-financed shadow banks and non-local bank-financed shadow banks, $\{\rho_b, \rho_o\}$, the aggregate warehouse lending market share of local banks and non-local banks, $\{S_b^w, S_o^w\}$, the mortgage market size, F, and the number of each type, $\{N_n, N_b, N_o\}$.

I calibrate the model to obtain model primitives, the households' price sensitivity α, the quality of each type of mortgage lenders, $\{q_b, q_n\}$, the common component of shadow bank funding costs ρ_n, the warehouse duration η, the variance of the idiosyncratic profits terms in shadow banks' funding demand σ, and the marginal cost of warehouse lending of local banks and non-local banks, $\{c_b, c_o\}$.

I make the following normalization. I measure funding costs as yield spreads to the ten-year treasury y and normalize banks' funding cost to be zero: $\tilde{\rho}_0 = \rho_0 - y = 0$. Moreover, I measure mortgage lending quality relative to banks, i.e. $q_b = 0$, similar to setting the share of outside good in Berry (1994) and Berry et al. (1995).

Calibration: Mortgage Origination

I have nine parameters to calibrate, and nine equations governing the behavior of households and lenders. I therefore calibrate the model solving a system of nine non-linear equations. I can solve for all but one parameter (α) in closed form. To provide intuition on how different parameters are identified I walk through the calibration step by step, assuming a consistent estimate of (α) in hand. I conclude by showing the equation that implicitly pins down alpha.

Given α, I can calibrate shadow banks' quality relative to banks to match the optimal household's decision. I derive q_n as a function of observed mortgage interest rates, mortgage market shares, and α:

$$q_n = \alpha(r_n^b - r_b) - ln(\frac{s_b}{s_n^b}) \tag{4.18}$$

The idea is simple, a lender charges higher rates than other lenders, for a given market share, if it is offering a better product. Otherwise borrowers would not be willing to pay higher rates. A similar intuition applies to market shares: for fixed mortgage rates, a lender with a higher market share must be offering a better product.

After calibrating mortgage demand parameters, I can recover the effective marginal costs of lending for local-bank-financed shadow banks and non-local bank-financed shadow banks, using their pricing decisions:

$$\tilde{\rho}_n^b = (r_n^b - y) - \frac{1}{\alpha}\frac{1}{1 - s_n^b} \tag{4.19}$$

$$\tilde{\rho}_n^o = (r_n^o - y) - \frac{1}{\alpha}\frac{1}{1 - s_n^o} \tag{4.20}$$

Intuitively, for a given mark-up, a lender with higher costs will charge higher rates. Because warehouse lending rates by local and non-local shadow banks differ, they imply differences in the costs of lending. The effective marginal lending from the model comprises two components, the overall cos of lending to shadow banks, and the warehouse cost. Recall that the effective warehouse cost depends on the length of warehousing, i.e. the time between a loan's origination and sale, η.

Given the average warehouse lending interest rates paid by local bank-financed shadow banks and non-local bank-financed shadow banks in the data, I calibrate η to match the following two marginal cost relations simultaneously. Because shadow bank warehousing time is independent of local and non-local borrowing, as:

$$\eta = \frac{\tilde{\rho}_n^b - \tilde{\rho}_n^o}{(\rho_b - y) - (\rho_o - y)} \tag{4.21}$$

Since shadow banks' marginal cost of mortgage lending is the sum of a common component ρ_n and the warehouse lending interest rates scaled by η, I then calibrate ρ_n to match the calibrated $\tilde{\rho}_n^b$ and the calibrated η:

$$\rho_n - y = \tilde{\rho}_n^b - \eta(\rho_b - y) \tag{4.22}$$

Calibration: Warehouse Lending Market

Next, I calibrate the warehouse lending market parameters. Using local banks' optimal mortgage pricing decisions, I calibrate local banks' marginal cost of warehouse lending. I observe the warehouse lending interest rate charged by local banks ρ_b, the mortgage price set by local banks r_b, local banks' mortgage market shares s_b, and the share of shadow banks financed by local banks s_b^w along with their mortgage market share s_n^b. I calibrate c_b by inverting the first-order condition of the local bank's problem in the mortgage market characterized in 4.11:

$$\tilde{c}_b = (\rho_b - y) - [(r_b - y) - \frac{1}{\alpha}\frac{1}{1-s_b}]\frac{1-s_b}{\eta N_n s_b^w s_n^b} \tag{4.23}$$

I then calibrate the degree of substitutability of warehouse lenders, captured by the variance of shadow banks' idiosyncratic profits σ, using shadow banks' optimal funding choices. From Eqn. 4.16, I derive an expression for σ as a function of observed shadow bank funding choices and their mortgage market shares:

$$\sigma = \frac{ln(s_b^w) - ln(s_o^w)}{ln(\frac{s_n^b}{\alpha(1-s_n^b)}F) - ln(\frac{s_n^o}{\alpha(1-s_n^o)}F)} = \frac{ln(s_b^w) - ln(s_o^w)}{ln(\frac{s_n^b}{1-s_n^b}) - ln(\frac{s_n^o}{1-s_n^o})} \tag{4.24}$$

Intuitively, if warehouse lenders were perfect substitutes, shadow banks would choose the cheapest funding source. As lenders become differentiated, shadow banks trade off the warehouse interest rate with non-interest rate characteristics of a warehouse bank. A larger difference between the observed warehouse lending market share ratio and the observed mortgage profit ratio (between local bank-financed and non-local bank-financed shadow banks) indicates that warehouse lenders are more differentiated.

With the calibrated σ, I calibrate non-local banks' marginal cost of warehouse lending to match non-local banks' optimal warehouse lending pricing decisions in 4.17:

$$\tilde{c}_o = (\rho_o - y) - s_n^o[-\frac{\partial s_n^o}{\partial \rho_o}(1 + \frac{\sigma(1 - s_o^w)}{(1 - s_n^o)})]^{-1} \tag{4.25}$$

As before, mark-ups are determined by demand elasticity, but here, the demand elasticity is derived from the profit condition of shadow banks, which I can compute because I have calibrated the other parameters.

To provide intuition, I walked through the calibration assuming I had a consistent estimate of α in hand. In fact, α is determined by the implicit equation, which matches local banks' mortgage pricing in Eqn. 4.23 and warehouse lending pricing simultaneously:

$$\tilde{c}_b = (\rho_b - y) - [s_n^b + (\eta N_n s_b^w)^{-1}(\frac{\partial r_b}{\partial \rho_b} s_b + (r_b - \rho_0)\frac{\partial s_b}{\partial \rho_b})] \times [-\frac{\partial s_n^b}{\partial \rho_b}(1 + \frac{\sigma(1 - s_b^w)}{(1 - s_n^b)})]^{-1} \tag{4.26}$$

4.4.1 Results

The calibration results are shown in Table 14. In the mortgage market, the calibrated household price sensitivity is 0.6, which is close to the estimation in the literature that implies that borrowers are quite price elastic, with a demand elasticity of 2.5 (Buchak et al. (2018b), DeFusco and Paciorek (2017)). This elasticity implies markups of 75%. My estimates suggest that borrowers prefer banking services to shadow banks. A borrower may prefer obtaining a mortgage from her bank because of lower search cost, easy payment and other bunching banking services. This is again consistent with the literature (Buchak et al. (2018b).

In the warehouse lending market, two economic forces are essential in shaping this funding market structure: the degree of (non-)substitutability between individual warehouse lenders, and the local information advantage in terms of lower cost of warehouse lending to competing shadow banks. The result suggests that shadow banks have a difficult time substituting between individual warehouse lenders. The estimated degree of substitutability is 3.07 suggesting that a one percent increase in mortgage profit from choosing a given warehouse lender only increases the probability of this warehouse lender being selected by 3.07 percent. Intuitively, if banks were perfect substitutes, a sufficiently small increase in the mortgage profit of choosing a warehouse lender would lead to a large shift in warehouse funding demand for this warehouse lender. The low elasticity indicates that shadow banks obtain substantial profits from choosing a particular bank, making them less sensitive to warehouse lending interest rates. This result is consistent with a substantial stickiness of warehouse lending relationships. In the next section, I formally link the estimate to the stickiness estimates empirically document in Chapter 2 but not used in my calibration.

Moreover, the calibration result also suggests a substantial advantage of lending to competitors, reflected in local banks' lower marginal cost of warehouse lending relative to non-local banks. The cost of warehouse lending to competitors is 74% lower than the cost of warehouse lending to non-competitors. With an average shadow bank funding demand of $8.5 billion and the estimated warehouse duration of 0.12, lending to competitors costs $7.4 million less than lending to non-competitors. Taken together, the calibration results quantify banks' market power in the warehouse lending market.

One potential effect, which lessens the power of banks in this market is shadow banks' ability to sell loans quickly. If shadow banks can sell loans instantaneously, then the impact of warehouse market power is limited because warehouse cost become small relative to overall funding costs. One the other hand, if warehousing the loan takes a significant amount of time, then warehouse loans climb in importance. The calibrated warehouse parameter $\eta = 0.12$, suggests that the average loan is warehouse funded for 44-day. Even though time to sale was not used to calibrate the model, this estimate is very close to the observed average time-to-sale of mortgages that were originated by shadow banks and were sold to the GSEs over the same time period, which was about 47 days.

The lack of substitutability and local advantage grant substantial market power to banks in leading to competing shadow banks, resulting in 30% extra markups relative to non-competitors. Local banks earn 144% markups in warehouse lending to their competing shadow banks, while non-local banks earn 110% markups.

4.4.2 Verification of Model Parameters

To better understand the accuracy of my model and the calibration results, I compare my model predictions to the findings on changes in warehouse lending relationships following bank net worth shocks that I examine in Section **??**. Recall that banks with large balance sheet exposure to the O&G industry experienced significant net worth declines following a sharp fall in oil prices from the second quarter of 2014 to the first quarter of 2015. Following the oil price decline, more exposed banks reduced warehouse lending amount and were more likely to terminate a warehouse lending relationship (Table 4).

Despite not being calibrated to this shock, the model is able to match the data, both qualitatively and quantitatively. On the qualitative side, viewed through the lens of my model, these changes reflect an increase in the funding cost of more exposed banks relative to less exposed banks. Banks optimally charge higher warehouse lending interest rates in response to the increase in their funding cost, which lowered the probability of shadow banks obtaining funding from these banks. The lack of substitutability between individual banks makes some shadow banks stay with the more exposed banks after the oil price shock, despite the increased warehouse lending interest rates charged by these banks. Subsequently, shadow banks financed by more exposed banks raise their mortgage interest rates by a larger amount than other shadow banks, lowering their mortgage origination market share in equilibrium.

These qualitative predictions are in line with the findings from Section **??**. As predicted by the model, the rise of banks' funding cost was passed on to their relationship shadow banks, increasing their relationship shadow banks' warehouse funding cost (Table 8). Moreover, shadow banks, whose relationship banks were more exposed to the oil shock, raised their mortgage interest rates relative to other shadow banks, which in turn lowered their mortgage origination volume (Table 9).

I next examine the extent to which the model can quantify the transmission of bank shocks following the oil price decline. I find the fraction of banks that were more exposed to the oil price shock as defined in Section **??** and calculate the change of their funding cost following the oil price decline relative to less exposed banks. The change in funding cost is calculated using banks' interest expenses and amount of debt outstanding from their quarterly call reports. About 54% of local banks and 49% of non-local banks were more exposed to the oil price shock based on the classification from Section **??**. Following the oil price decline, the funding cost of more exposed banks (shocked banks) increased by 60 basis-points relative to that of less exposed banks (unshocked banks). I impose these shocks to banks in my model and find the new equilibrium warehouse lending market structure as well as the new equilibrium mortgage interest rates and mortgage market shares of different types of originators.

Table 15 shows the model predictions. Panel A shows the model predicted warehouse lending market equilibrium before and after the shocks. Due to the lack of substitutability between individual banks, shocked local banks optimally increase their warehouse lending interest rates 61 basis points following the shocks, while shocked non-local banks increase their rates by 60 basis points. In response to reduced warehouse lending competition the unshocked banks also increased warehouse lending interest rates, but by only 1 basis point. Despite the substantial increase in warehouse rates, only 2.4% of the shadow banks switch to unshocked banks. The rest of these shadow banks stick with the shocked banks, paying higher warehouse lending interest rates.

Consequently, the average warehouse funding cost of shadow banks that borrowed from shocked banks before the shocks increases more than that of shadow banks that borrowed from unshocked banks. In Panel B of Table 15, I calculate the average warehouse funding cost of shadow banks that borrowed from shocked banks and unshocked banks before the shocks. Shadow banks that borrowed from shocked banks before the shocks pay 60-bps higher interest rate on their warehouse funding, while shadow banks that borrowed from unshocked banks before the shocks pay 1-bps higher interest rate on their warehouse funding. Therefore, the difference between the warehouse funding cost changes of the two groups of shadow banks is 59 basis points. This number is very close to the difference-in-differences estimator reported in Column (1) of Table 8.

Moreover, Panel C reports the equilibrium mortgage interest rates before and after the shocks. I calculate the average mortgage interest rates set by shadow banks that borrowed from shocked banks and unshocked banks before the shocks. Following the shocks, the average mortgage interest rate of shadow banks that borrowed from shocked banks rises by 10 basis points, whereas the average mortgage interest rate of shadow banks that borrowed from unshocked banks rises by less than 1 basis points. The difference between the mortgage interest rate changes of the two groups of shadow banks is about 10 basis points. This number is close to the difference-in-differences estimator reported in Column (4) of Table 9.

Despite not using the data from the oil shocks in the calibration, the model is able to predict, both qualitatively and quantitatively, the consequences of the oil price shock in the warehouse lending market as well as the effects on shadow banks' mortgage origination activities.

4.5 Counterfactual Analysis

I use the calibrated model to study two counterfactuals. The model links warehouse lending and product market competition, in which banks trade off the costs and benefits in lending to their competing shadow banks. The lack of substitutability and local advantage grant substantial market power to banks in lending to competing shadow banks. I study two counterfactuals to better understand how these two forces drive the equilibrium warehouse lending and mortgage origination.

The first counterfactual investigates the equilibrium consequences of mortgage market competitors' advantage in warehouse lending: the information advantage. Specifically, how this advantage of some warehouse lenders shapes the financing arrangements in the warehouse market, and its impact on their competition in the mortgage market. The second counterfactual studies the consequences of reducing shadow banks' dependence on warehouse lending, which I study through the lens of an improved GSE loan purchase program.

4.5.1 Competitors' Advantage in Warehouse Lending

In the first counterfactual analysis, I study how the advantage derived from lending to competing shadow banks affects the financing relationships between banks and shadow banks and its impact on their competition in the mortgage market. Specifically, to what extent does lending to competitors' advantage in warehouse lending affect local banks' warehouse lending as well as mortgage origination behaviors? How much does it soften mortgage market competition?

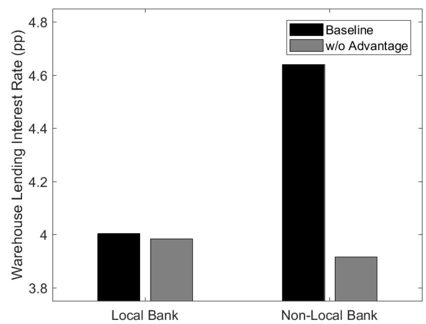
The model estimates that local banks have a 73 basis points lower warehouse lending cost than non-local banks. I remove local banks' advantage by reducing non-local banks' warehouse lending cost (c_o) to that of local banks. $c_o = c_b$. I solve the model for new set of equilibrium prices and quantities, which flow through to lenders' profits and borrowers' surplus. Fig. 4.1 shows the results.

The direct consequences can be seen in the warehouse market (Panel (a)-(c)). As expected, if non-local banks become as efficient as local banks, the former gain, while the latter lose. The lower cost of non-local banks lending passes through to lower warehouse lending interest rates, which reduce by 72bp, and increase their markups by 31pp. At the same time, increased competition from non-local banks lowers local banks' warehouse rates by 2bp and decrease their markups by 74bp. After removing local banks' advantage, the warehouse lending interest rate charged by local banks is 7bp higher than that charged by non-local banks, because local banks take into account the mortgage market competition when making warehouse lending pricing decisions, while non-local banks do not. Despite a large decline in warehouse rates, only 4% of the shadow banks will switch to non-local banks to obtain funding due to the lack of substitutability between individual warehouse banks.

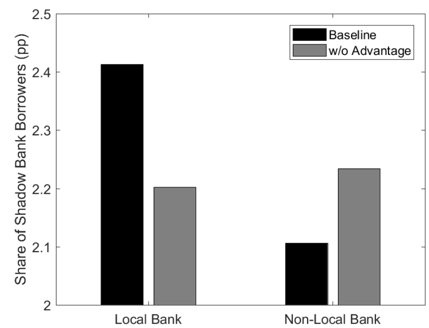
Panel (d)-(f) show the mortgage market outcomes. Each figure shows three groups of lenders: shadow banks financed by non-local banks (Non-Local Financed), shadow banks financed by local banks (Local-Financed), and banks. The non-local financed shadow banks directly benefit from the reduction in non-local banks' warehouse lending interest rates and lower their mortgage interest rates by 8 basis points. Besides, 4% of the shadow banks that

Figure 4.1. Counterfactual - Competitors' Advantage in Warehouse Lending

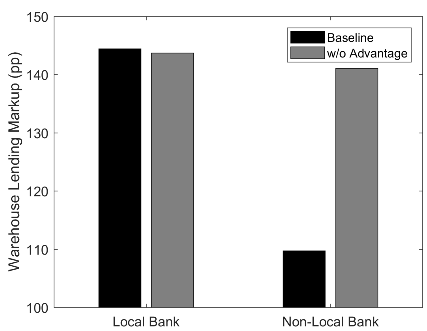
Figure 4.1 plots the impact of mortgage market competitors' advantage in warehouse lending. Panel (a)-(c) show warehouse lending market outcomes. Panel (d)-(f) show mortgage market outcomes.



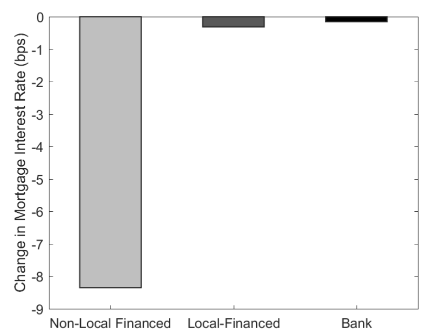
(a) Warehouse Lending Interest Rate



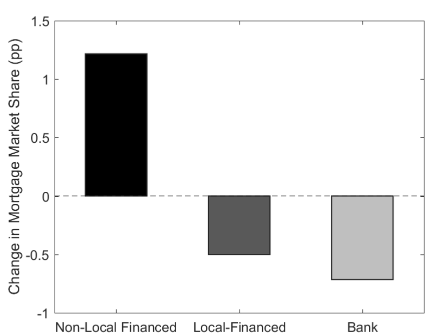
(b) Share of Shadow Bank Borrowers



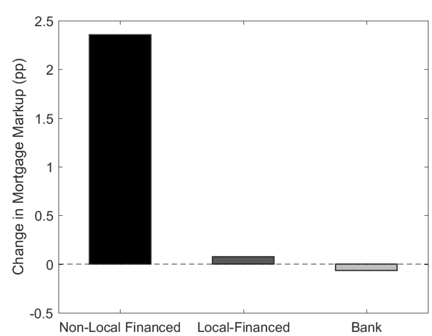
(c) Warehouse Lending Markup



(d) Mortgage Interest Rate



(e) Mortgage Market Share



(f) Mortgage Markup

switch to non-local banks to obtain funding also benefit from the cost reduction. Consequently, the local-financed shadow banks will reduce their mortgage interest rates by 0.3 basis points on average. Increased mortgage market competition from shadow banks will reduce banks' mortgage markups by 7 basis points, lowering their mortgage interest rates by 0.2 basis points. From the demand side, the market share of the non-local financed shadow banks will increase by 1.2 percentage points, where 0.5% borrowers will be gained from the local-financed shadow banks and 0.7% borrowers will be gained from banks.

Overall, a 29 basis points cost reduction in the warehouse lending market will lower the average consumer mortgage credit by 3 basis points. This reflects that about 10% cost savings will be passed on to consumers.

4.5.2 More efficient GSE loan purchase program

The second counterfactual studies the consequences of reducing shadow banks' dependence on warehouse lending by shortening the warehouse loan duration. I estimate the average warehouse loan duration of 44 days, which means that shadow banks pay off each credit drawdown from their warehouse lines of credit in 44 days on average. If shadow banks could sell loans faster, they could originate more mortgages with less warehouse funding. The practical implementation of this counterfactual would be a more efficient loan purchase program that the GSE has been developing. For example, the GSE has put efforts to improve eMortgage adoption, which will likely shorten the warehouse loan duration.[1] Moreover, Fannie Mae and Freddie Mac have been working on creating data standardization of information provided by the mortgage originators through the Uniform Mortgage Data Program.[2] Such reform may boost operational efficiency.

I use the model to quantify the welfare implications of a more efficient GSE loan purchase program. I allow η, which determines the warehouse duration, to vary between 0 to 0.5. $\eta = 0$ describes the situation where the GSE purchase mortgages right after they are originated by shadow banks. A larger η indicates a longer warehouse duration. $\eta = 0.5$ corresponds to a six-month warehouse duration. Each η generates an equilibrium warehouse lending pricing, mortgage interest rates, and mortgage market shares of different types of lenders.

The model shows that a speedier GSE loan purchase program will reduce warehouse lending relationships between local banks and shadow banks, leading to a less integrated local mortgage market and increasing mortgage market competition. In particular, given a specific warehouse lending interest

[1] "GSE Efforts to Improve eMortgage Adoption: A Follow-up to the 2016 GSE Survey Findings Report"

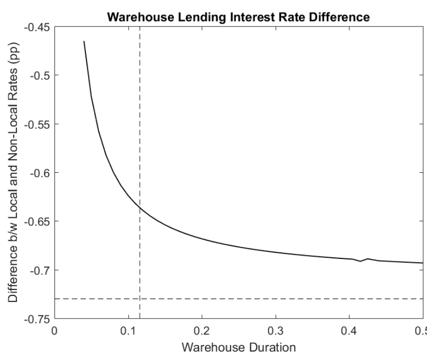
[2] Some other efforts made to improve the transaction speed can be found in the following initiatives: "GSE Reform: Creating a Sustainable, More Vibrant Secondary Mortgage Market;" "GSE Plan Would Encourage Warehouse Lines of Credit;" "The Changing Dynamics of the Mortgage Servicing Landscape." In addition, Fannie Mae and Freddie Mac have been working on create data standardization of information provided by the mortgage originators through the Uniform Mortgage Data Program. Such reform may boost operational efficiency. (See, for example, https://fas.org/sgp/crs/misc/R45828.pdf; https://www.fhfa.gov/Media/Blog/Pages/standardizing-mortgage-data-through-the-UMDP.aspx)

rate, shortened warehouse duration will effectively reduce warehouse lenders' stake in shadow banks' mortgage profits. As shown in banks' optimal mortgage pricing strategy (Eqn. 4.11), banks gain mortgage market power from their stake in shadow banks' mortgage profit through warehouse lending relationships. Shortened warehouse duration will reduce banks' market power in local mortgage markets, leading to lower mortgage interest rates charged by banks in equilibrium. In the warehouse lending market, local banks take into account mortgage market competition in their warehouse lending decision-making. As warehouse duration is shortened, shadow banks' total funding cost will become less sensitive to the warehouse lending interest rate, and thus local banks will need to increase their warehouse lending interest rates by a larger amount to affect shadow banks' mortgage pricing. Therefore, local banks' warehouse lending interest rates will rise relative to non-local banks' as warehouse duration becomes shorter. Consequently, some shadow banks that obtain funding from local banks will switch to non-local banks, reducing warehouse lending relationships between local banks and shadow banks. This reduces local banks' stake in shadow banks' mortgage profit at the extensive margin, which will further increase the mortgage market competition.

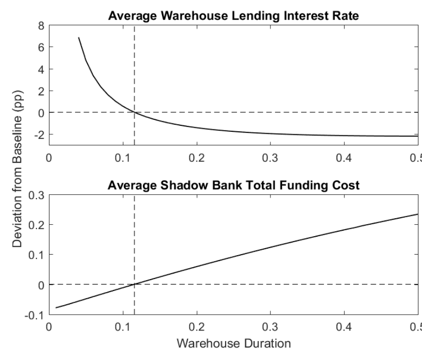
Fig. 4.2 quantifies this intuition. Panel (a)-(c) show warehouse lending market outcomes. Panel (a) shows local banks' warehouse lending interest rate relative to non-local banks' as warehouse duration changes. The horizontal reference line shows the difference between local banks' cost of warehouse lending and non-local banks' cost of warehouse lending, $c_b - c_o$. The distance between

Figure 4.2. Counterfactual - Warehouse Duration

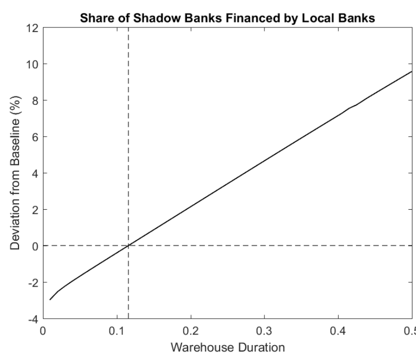
Figure 4.2 plots the impact of changing the warehouse duration. The x-axis is warehouse duration. The vertical dashed line indicates the baseline. Panel (a) shows local banks' warehouse lending interest rates relative to non-locals'. Panel (b) shows shadow banks' funding cost, $\rho_n + \eta\rho_l$, and compares it with the average warehouse lending interest rate. Panel (c) shows the share of shadow banks financed by local banks. Panel (d) shows mortgage interest rates. Panel (e) shows mortgage markup. Panel (f) shows consumer surplus in average MSA with \$2.08 billion mortgage demand.



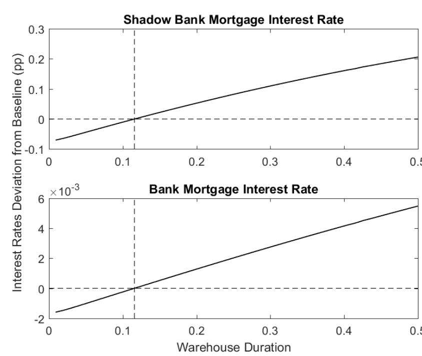
(a) Local Relative to Non-Local



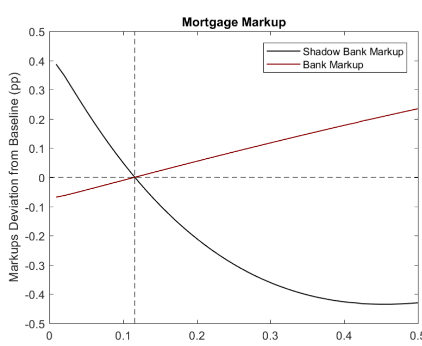
(b) Shadow Bank Funding Cost



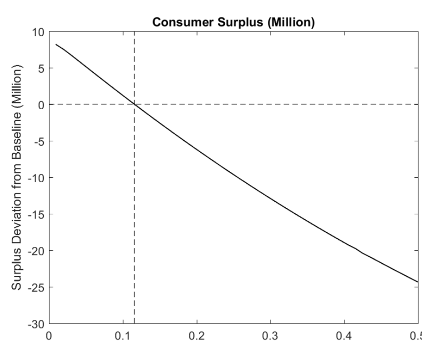
(c) Share Financed by Local Banks



(d) Mortgage Interest Rate



(e) Mortgage Markup



(f) Consumer Surplus

the plot and this reference reflects the additional warehouse lending interest rates local banks charge to internalize mortgage market competition. As warehouse loan duration becomes shorter, this additional warehouse lending interest rate will be enlarged. If shadow banks are able to sell the mortgages in less than 15 days, i.e. $\eta < 0.04$, this additional warehouse lending interest rate will be larger than 26 basis points. As warehouse loan duration increases to 0.5, i.e. six months, this additional warehouse lending interest rate will drop to 3.5 basis points. Panel (b) compares changes in shadow banks' funding cost ($\rho_n + \eta\rho_l,\ \rho_l \in \{\rho_b, \rho_o\}$) and changes in average warehouse lending interest rate. Shortened warehouse duration effectively reduces shadow banks' dependence on banks' warehouse funding. If warehouse duration is less than 15 days, shadow banks' funding cost will reduce by 6 basis points, despite of the 7pp increase in the average warehouse lending interest rate. Panel (c) shows share of shadow banks that obtain funding from local banks. Since shadow banks' funding cost becomes less sensitive to warehouse lending interest rates as warehouse duration is shortened, shortened warehouse duration effectively reduces local banks' advantage over non-local banks in warehouse lending. If warehouse duration becomes less than 5 days, 3% of the shadow banks will switch to non-local banks to obtain funding. In contrast, if warehouse duration becomes longer and reaches half a year, shadow banks will become very sensitive to warehouse lending interest rates. About 10% of the shadow banks will switch to local banks to obtain funding.

Panel (d)-(f) show mortgage market outcomes. Panel (d) shows mortgage interest rates by lender type. If warehouse duration is shortened to be less than 15 days, the reduced funding cost will allow shadow banks to lower their mortgage interest rates by 7 basis points. As discussed above, shortened warehouse duration reduces local banks' stake in shadow banks' mortgage profit at both the extensive margin and the intensive margin. As a result, banks will reduce their mortgage interest rates by 0.2 basis points. Panel (e) further quantifies this intuition by showing mortgage markups. Banks' mortgage markup increases with shadow banks' warehouse duration almost linearly with a slope of 0.6. Shortening warehouse duration by 30 days will reduce banks' markup by 6 basis points. In contrast, shadow banks' markup will rise by 40 basis points if warehouse duration is shortened by 30 days. As warehouse duration reaches six months, shadow banks' markup will decline by 40 basis points. Finally, Panel (f) shows consumer surplus.[3] In an average MSA with $2.08 billion mortgage demand, consumer surplus will rise by $8.21 million if warehouse duration is shortened by 40 days. If warehouse duration reaches six months, consumer surplus will drop by more than $20 million.

The counterfactual shows that simple GSE interventions can help increase the competitiveness of the mortgage origination market. Further, the counterfactual suggests that the shorter warehouse times of fintech lenders documented in Buchak et al. (2018a) provide them with a competitive ad-

[3]Following Buchak et al. (2018b), I compute consumer surplus as a lifetime present-value dollar equivalent measure of expected utility, which is integrated over consumer specific preference shocks, while assuming a subjective discount rate of 4% over a period of 10 years.

vantage in mortgage lending, and directly affect competition in the mortgage market.

Table 1
Summary Statistics

This table reports summary statistics of HMDA-matched shadow banks and warehouse banks. Panel A shows shadow banks' summary statistics. Panel B shows banks' summary statistics. The sample period is from 2011 to 2017. Balance sheets are observed at quarterly frequency. Mortgage origination activity is observed at annual frequency.

Panel A: Shadow Bank 2011Q1 — 2017Q4

	N	Mean	Median	Stdev.
Asset (Billion)	6487	0.47	0.07	1.51
Mortgage (%)	6487	68.08	76.67	24.87
Warehouse Debt Facility(%)	6487	60.87	69.95	25
Mortgage Origination (Billion)	1,893	2.10	0.74	5.35
# States of Origination	1893	22.46	19	16.01
Geographic Concentration	1893	0.1	0.06	0.12
#Credit Lines	6487	3.62	3	2.19
Credit Limit (Million)	22272	111.06	40	609.16
Lender Share Stdev	5874	0.14	0.12	0.11
Usage (Million)	22272	61.55	18.11	428.36
Lender Share Stdev	5800	0.2	0.16	0.15
Estimated Interest Rate Spread	5171	0.03	0.03	0.02
Time Series Stdev Number of Shadow Banks	333	0.01	0.01	0.01
Number of Shadow Bank	416			

Panel B: Bank Summary Statistics 2011Q1 — 2017Q4

	N	Mean	Median	Stdev.
Asset (Billion)	3,067	80.93	2.39	304.23
Total Loan (%)	3,067	0.68	0.69	0.12
Mortgage (%)	3,067	0.47	0.48	0.17
Mortgage Origination (Billion)	768	4.51	0.19	19.65
# States of Origination	768	15.62	8.00	16.92
Geographic Concentration	768	0.21	0.15	0.20
Number of Bank	207			

Table 2
Quicken Loans Warehouse Line of Credit Providers

This table reports the warehouse funding sources of Quicken Loans in 2017 Q4. Quicken Loans is a shadow bank, which by the end of 2017 became the largest residential mortgage originator in the United States in terms of mortgage origination volume.

Provider	Limit ($ Billion)	Used ($ Billion)
Bank of America	1	0.64
Credit Suisse First Boston	2.2	0.45
Fannie Mae	2.5	2.03
Freddie Mac	1	0.33
Fifth Third Bank	0.18	0.18
JP Morgan Chase	1.75	1.58
Morgan Stanley	0.75	0.29
Rock Holdings	0.3	0
Royal Bank of Canada	0.65	0.52
USB	1	0.27
Various	2.26	2.29
Total	13.59	8.55

Table 3
Top 10 Line of Credit Providers in 2017 Q4

This table lists the ten banks that provided most warehouse credit to shadow banks in 2017 Q4. Column A reports lender name. Column B reports total line of credit limit extended to shadow banks. Column C reports the number of shadow banks that receive funding from them. Column D reports the average size of shadow banks they finance.

Bank	Total Limit (Billion)	No. Borrowers	Ave. Borrower Size (Billion)
JPMorgan Chase	12.90	49	2.42
Bank of America	12.17	53	1.97
Texas Capital Bancshares, Inc	9.34	127	0.84
UBS Group AG	7.06	28	2.13
Wells Fargo	6.83	56	0.94
Barclays	6.00	21	3.96
Morgan Stanley	4.43	11	5.56
TIAA	3.79	36	1.41
Comerica Incorporated	3.77	66.00	0.18
Citigroup Inc.	3.77	13	3.41
U.S. Bancorp	3.43	27	0.93

Table 4
Pairwise Measures Summary Statistics

Table 4 presents descriptive statistics of pairwise measures for matched pairs and unmatched pairs, respectively. The sample contains all possible pairs between warehouse banks and shadow banks. A bank is included in the data set if it conducts warehouse lending business and lends to at least one shadow bank in a particular year. Min. Distance is the minimum distance between the shadow bank's headquarter and all branches of a particular warehouse bank. %Overlapped Markets is the percentage of total markets overlapped: $\%OverlapMkt_{i,j,t} = \frac{\Sigma_k I(\sigma_{i,k,t}>0, \sigma_{j,k,t>0})}{\Sigma_k I(\sigma_{i,k,t}>0)+\Sigma_k I(\sigma_{j,k,t}>0)}$. Market Overlap measures geographic market distribution overlap: $MktOverlap_{i,j,t} = 1 - \frac{1}{2}\Sigma_k\left|\sigma_{i,k,t} - \sigma_{j,k,t}\right|$, where $\sigma_{i,k,t} = \frac{LoanVolume_{i,k,t}}{\Sigma_k LoanVolume_{i,k,t}}$ is the share of institution i's total loan origination in market k in year t. $MktOverlap_{i,j,t}$ ranges from 0 to 1, where 1 means that bank i's origination activities shares exactly the same distribution with shadow bank j's origination activities across markets defined at county level.

Panel A: Matched Pairs

	N	Mean	Stdev	25th	Median	75th
Min. Distance	6,735	942.27	1115.12	4.69	509.07	1,614.93
%Overlapped Markets	6,735	0.11	0.12	0.02	0.07	0.17
Market Overlap	6,735	0.17	0.17	0.02	0.10	0.30

Panel B: Unmatched Pairs

	N	Mean	Stdev	25th	Median	75th
Min. Distance	248,783	1546.59	1177.60	583.45	1,328.98	2,431.19
%Overlapped Markets	248,783	0.05	0.07	0.00	0.02	0.07
Market Overlap	248,783	0.06	0.10	0.00	0.01	0.07

Table 5
Lending to Competitors

Table 5 reports the results of the following regression specification:

$$Pr(Lend_{i,j,t}) = \alpha + \beta\% MktOverlapi,j,t + \gamma Ln(HQDistance_{i,j,t}) + \mu_{i,t} + \mu_{j,t} + \epsilon_{i,j,t}$$

In Panel A, the dependent variable takes the value of 100 if shadow bank i obtains funding from warehouse bank j in year t and zero otherwise. In Panel B, the dependent variable is the warehouse lines of credit limit in millions shadow bank i receives from warehouse bank j in year t. $D_{i,j,t}$ is measured by the logarithm of minimum distance between shadow bank i's headquarter and all branches of warehouse bank j. $MktOverlap_{i,j,t}$ is measured by share of counties where both shadow bank i and warehouse bank j originate mortgage loans out of total number of counties where either shadow bank i or warehouse bank j originates loans in Column (1) and (2), and is measured by *Market Overlap*, i.e. $1 - \frac{1}{2}\Sigma_k \left|\sigma_{i,k,t} - \sigma_{j,k,t}\right|$, in Column (3) and (4). Standard errors are clustered at shadow banks and banks. I present the standard errors in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Extensive Margin

	Pr(Lending Relationship) (pp)			
	(1)	(2)	(3)	(4)
Ln(HQ Distance)	-0.866***	-0.869***	-0.613***	-0.633***
	(0.178)	(0.171)	(0.167)	(0.153)
% Overlapped Market	18.572***	21.689***		
	(3.930)	(5.174)		
Market Overlap			18.197***	19.790***
			(2.804)	(3.373)
Bank×Year FE		x		x
Shadow Bank×Year FE		x		x
Num of Observations	255,517	255,517	255,517	255,517
R2	0.028	0.114	0.032	0.116

Panel B: Intensive Margin

	Credit Limit (Million)			
	(1)	(2)	(3)	(4)
Ln(HQ Distance)	-1.229	0.524	0.881	1.246
	(2.029)	(1.102)	(2.562)	(1.300)
% Overlapped Market	363.316***	111.710***		
	(93.584)	(41.979)		
Market Overlap			248.160***	69.316**
			(72.207)	(27.388)
Bank×Year FE		x		x
Shadow Bank×Year FE		x		x
Num of Observations	6,726	5,906	6,726	5,906
R2	0.172	0.791	0.153	0.790

Table 6
Lending to Competitors: Sub-Sample Robustness

Table 6 shows the sub-sample analysis of lending relationship sorting. I estimate Eqn. 2.3 using sub-samples constructed based on geographic dispersion, mortgage origination volume, asset size, respectively. Standard errors are clustered at shadow banks and banks. I present the standard errors in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: % Overlapped Markets

	Pr(Lending Relationship) (pp)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Concentrated	Dispersed	Small (Origin. Vol.)	Big (Origin. Vol.)	Small (Asset)	Big (Asset)
Ln(HQ Distance)	-1.343***	-0.811***	-1.482***	-0.657***	-1.494***	-0.611***
	(0.267)	(0.169)	(0.235)	(0.212)	(0.245)	(0.159)
% Overlapped Markets	8.184**	31.026***	11.553*	26.873***	15.387***	21.320***
	(4.074)	(7.586)	(6.463)	(6.483)	(5.574)	(7.600)
Bank×Year FE	x	x	x	x	x	x
Shadow Bank×Year FE	x	x	x	x	x	x
Observations	64,646	64,446	64,220	64,269	48,763	80,198
R2	0.114	0.132	0.095	0.151	0.085	0.135

Panel B: Market Overlap

	Pr(Lending Relationship) (pp)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Concentrated	Dispersed	Small (Origin. Vol.)	Big (Origin. Vol.)	Small (Asset)	Big (Asset)
Ln(HQ Distance)	-0.964***	-0.599***	-1.263***	-0.402**	-1.047***	-0.395**
	(0.231)	(0.169)	(0.252)	(0.189)	(0.232)	(0.155)
Market Overlap	13.420***	24.710***	12.981***	24.230***	21.864***	20.188***
	(3.890)	(5.107)	(4.395)	(5.333)	(4.833)	(5.401)
Bank×Year FE	x	x	x	x	x	x
Shadow Bank×Year FE	x	x	x	x	x	x
Observations	64,646	64,446	64,220	64,269	48,763	80,198
R2	0.117	0.131	0.097	0.152	0.093	0.136

Table 7
Persistent Lending Relationships

Table 7 reports the coefficients from the following regressions:

$$\begin{aligned} Pr(Lend_{i,j,t}) =& \alpha + \beta_0 PastLend_{i,j,t} + \beta_1 PastLend_{i,j,t} \times LenderType_{j,t} + \beta_2 X_{i,t} \\ &+ \beta_3 X_{i,t} \times LenderType_{j,t} + \epsilon_{i,j,t} \end{aligned}$$

The dependent variable takes the value of 100 if shadow bank i obtains funding from lender j in year t and 0 otherwise. $PastLend_{i,j,t}$ indicates whether shadow bank i borrowed from lender j in year $t-1$. $LenderType_{j,t}$ takes value of 1 if lender j is a bank and 0 otherwise. $X_{i,t}$ are shadow bank controls, including lagged equity to asset ratio (*Lagged ETA*), and negative net income to asset growth indicator(*Negative* Δ*NITA*) that takes the value of 1 if shadow bank i's net income to asset ratio in year t is lower than that in year $t-1$. Standard errors are clustered at shadow banks and banks. I present the standard errors in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Pr(Lending) (pp)			
	(1)	(2)	(3)	(4))
Past Lending	85.530***	76.530***	76.910***	21.774***
	(1.162)	(3.940)	(3.858)	(6.218)
Bank×Past Lending		10.008**	10.113**	10.887*
		(4.058)	(3.978)	(6.468)
Ln(Asset)			0.005	0.009
			(0.007)	(0.009)
Bank×Ln(Asset)			0.025**	0.012
			(0.012)	(0.011)
Lagged ETA			0.057	0.102
			(0.062)	(0.080)
Bank×Lagged ETA			-0.424***	-0.553***
			(0.122)	(0.184)
Negative ΔNITA			0.021	0.017
			(0.021)	(0.015)
Bank×Negative Δ NITA			-0.052	-0.051*
			(0.032)	(0.028)
Lender×Year FE	x	x	x	
Borrower×Year	x	x		
Lender×Shadow Bank FE				x
Year FE			x	x
Observations	685,920	685,920	582,936	579,004
R2	0.629	0.630	0.704	0.822

Table 8
Exogenous Credit Reduction and Shadow Bank Borrowing

Table 8 shows the effect of exogenous reduction in bank credit supply on shadow banks' borrowing. Columns (1) and (2) report the effect on shadow banks' cost of funding. The dependent variable is the interest rate spread in percentage points. *HighOilShock* is an indicator for high O&G exposure banks, which equals 1 if a bank lender was severely exposed to the oil shock. *Post* is 1 for quarters after 2014Q2. Shadow bank controls include lagged net income to asset ratio, lagged equity to asset ratio, and lagged operating cash flow to asset ratio. Columns (3) and (4) report the effect on shadow banks' credit limits. The dependent variable is the logarithm of total credit limit. *Post* is 1 for quarters after the termination. *HighOilShock* is an indicator for the funding relationship terminations due to the oil price shock. Shadow bank controls include net income to total asset and the logarithm of total assets. Bank controls include the logarithm of total assets, loan delinquency rate, change in tier 1 capital ratio. Local controls include change in local income per capita, and change in local unemployment rate. Standard errors are clustered at shadow bank level. I present the standard errors in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Interest Rate(pp)		Ln(Limit)	
	(1)	(2)	(3)	(4)
Post	-0.924***	-1.295***	0.366***	0.287***
	(0.259)	(0.367)	(0.070)	(0.075)
High Oil Shock× Post	0.599*	0.885**	-0.302*	-0.259*
	(0.325)	(0.386)	(0.181)	(0.149)
Shadow Bank FE	x	x		
Shadow Bank Controls		x		x
Shadow Bank × Cohort FE			x	x
Observation	837	747	1,823	1,783

Table 9
Exogenous Credit Reduction and Shadow Bank Mortgage Supply

Table 9 shows the result of regression 2.8 and 2.11. Column (1) and (2) show log mortgage origination volume. The regressions are on the county-year level. The *Post* is 1 if it is in year 2015 or 2016 and 0 if it is in year 2012 or 2013. Column (3) and (4) show residualized mortgage interest rates after controlling for LTV, DTI, and FICO. The regressions are on the zip-quarter level. The *Post* is 1 if it is after 2014Q2 and 0 if it is before 2014Q2. $HighOilShock$ is an indicator of whether the share of shadow bank i's total funding obtained from high O&G exposure banks is above the sample median in 2013. Standard errors are computed by clustered bootstrap, which is clustered by shadow banks and counties (zip codes). I present the standard errors in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Ln(Mortgage Origination Volume)		Mortgage Interest Rate	
	(1)	(2)	(3)	(4)
HighOilShock×Post	-0.171***	-0.176***	0.142***	0.108***
	(0.015)	(0.015)	(0.015)	(0.013)
Shadow Bank FE	x	x	x	x
County (Zip) FE	x		x	
Year (Q) FE	x		x	
County (Zip)×Year (Q) FE		x		x
Observation	113,614	112,809	78,361	77,086
R2	0.511	0.526	0.388	0.586

Table 10
Soft Information and Warehouse Lending

Table 10 reports the coefficients from the following two regressions:

$$Y = \alpha + \beta_1 MktOverlap_{i,j,t} + \beta_2 MktOverlap_{i,j,t} \times COD_{i,t} + \gamma D_{i,j,t} + \mu_{i,t} + \mu_{j,t} + \epsilon_{i,j,t}$$

The dependent variable in Columns (1) and (2) takes the value of one if shadow bank i obtains funding from warehouse bank j in year t and zero otherwise, and in Columns (3) and (4) is the limit in million on the credit line extended by bank i to shadow bank j in year t. $D_{i,j,t}$ is measured by the logarithm of minimum distance between shadow bank i's headquarter and all branches of warehouse bank j. $MktOverlap_{i,j,t}$ is measured by share of counties where both shadow bank i and warehouse bank j originate mortgage loans out of total number of counties where either shadow bank i or warehouse bank j originates loans in Column (1) and (3), and is measured by *Market Overlap*, i.e. $1 - \frac{1}{2}\Sigma_k \left|\sigma_{i,k,t} - \sigma_{j,k,t}\right|$, in Column (2) and (4). $COD_{i,t}$ is the local average coefficient of dispersion weighted by shadow banks' loan origination. Standard errors are clusterd at shadow banks and banks. I present the standard errors in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respecti vely.

	Pr(Lending Relation)		Credit Limit (Million)	
	(1)	(2)	(3)	(4)
Ln(HQ Distance)	-0.905***	-0.666***	-0.105	0.288
	(0.092)	(0.087)	(1.159)	(1.325)
Ln(HQ Distance)×High COD	0.039	0.036	1.111	1.733
	(0.104)	(0.108)	(1.014)	(1.061)
%Overlapped Market	18.818***		76.116	
	(2.578)		(45.846)	
%Overlapped Market×High COD	5.762**		64.562*	
	(2.858)		(38.748)	
Market Overlap		18.444***		38.851
		(2.105)		(24.182)
Market Overlap×High COD		2.781		59.404**
		(2.396)		(23.255)
Bank×Year Fixed Effects	x	x	x	x
Shadow Bank×Year Fixed Effects	x	x	x	x
Num of Observations	246,442	246,442	5,745	5,745
R2	0.116	0.118	0.791	0.789

Table 11
In Which Markets Do Banks Finance Competitors?

Table 11 examines in which markets banks do warehouse lending. The sample consists of bank-market observations. The dependent variable in Panel A is $Pr(WarehouseLending)$, which takes the value of one if warehouse bank i lend to shadow banks that originate loans in market k in year t and zero otherwise. The dependent variable in Panel B is $WarehouseLending/Asset$, which is total warehouse credit limit extended by warehouse bank i in market k in year t scaled by bank i's total asset size. The independent variables are *%Bank Total Origin.*, which is the share of bank i's total loan origination in market k in year t, and *Local Market Share*, which is bank i's market share in k in year t. Markets are defined by counties. Bank-by-year fixed effects and county-by-year fixed effects are included. In column (1), the sample includes all counties. In columns (2)-(3), only counties where bank i has positive loan origination volume are included in the sample. Standard errors are clustered at county and bank level. I present the standard errors in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Pr(Warehouse Lending)		Warehouse Lending/Asset
	(1)	(2)	(3)
	All Counties	Origination Counties	Origination Counties
% Bank Total Origin.	118.501***	27.238***	4.253***
	(15.467)	(6.305)	(1.420)
Local Market Share		-22.063*	-0.427***
		(12.644)	(0.150)
Bank×Year FE	x	x	x
County×Year FE	x	x	x
Observations	2,282,592	201,904	199,742
R2	0.550	0.618	0.256

Table 12
Which Shadow Banks Do Warehouse Banks Lend to?

Table 12 reports regression results about the internalization of cost of competition. The dependent variable in the first two columns is the probability of shadow bank i obtaining a credit line from bank j. The dependent variable in the last two columns is the credit line limit conditional on having a lending relationship. *Ln(HQ Distance)* is measured by the logarithm of minimum distance between shadow bank i's headquarter and all branches of warehouse bank j. *Bank Market Share* is bank j's market share in markets where shadow bank i presents, weighted by bank j's origination share (of bank j's total origination). *%Overlapped Markets* and *Market Overlap* are the two mortgage market overlap measures introduced before. Standard errors are clusterd at shadow banks and banks. I present the standard errors in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Pr(Warehouse Lending)		Credit Limit (Million)	
	(1)	(2)	(3)	(4)
Ln(HQ Distance)	-0.896***	-0.652***	0.080	0.875
	(0.166)	(0.147)	(1.041)	(1.227)
Bank Market Share	-1.000**	-0.590	-378.740**	-367.576**
	(0.476)	(0.401)	(164.607)	(158.760)
%Overlapped Markets	22.524***		116.274***	
	(5.310)		(43.232)	
Market Overlap		19.921***		73.275**
		(3.380)		(28.524)
Bank×Year Fixed Effects	x	x	x	x
Shadow Bank×Year Fixed Effects	x	x	x	x
Observations	255,517	255,517	5,906	5,906
R2	0.115	0.116	0.792	0.790

Table 13
Shadow Bank Cost of Funding

Table 13 shows the implications for shadow bank cost of funding. regression results about the internalization of competition cost. Standard errors are clustered at shadow banks. I present the standard errors in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Shadow Bank Cost of Funding (pp)			
	(1)	(2)	(3)	(4)
Ave. Market Share of Local W.Banks	30.387***	30.207***	24.203**	24.583**
	(10.333)	(10.315)	(10.627)	(10.434)
Market Similarity			-1.683**	-1.476**
			(0.696)	(0.731)
Selected Shadow Bank Controls				
Local-Adj Low Income Share	2.542**	2.411**	2.367**	2.338*
	(1.198)	(1.200)	(1.195)	(1.201)
Lagged Equity/Asset	-1.682**	-1.441*	-1.549**	-1.433*
	(0.714)	(0.751)	(0.720)	(0.753)
Lagged Net Income/Asset	-10.076***	-10.808***	-10.818***	-11.284***
	(3.385)	(3.485)	(3.459)	(3.510)
Ln(Origin)	-0.263***	-0.212***	-0.235***	-0.215***
	(0.057)	(0.079)	(0.062)	(0.078)
Other Shadow Bank Controls	x	x	x	x
Lender Controls		x		x
Observations	1,194	1,191	1,194	1,191
R2	0.095	0.096	0.103	0.102

Table 14
Model Calibration

Table 14 reports the calibrated parameters. Top panel shows the mortgage market parameters. Bottom panel shows the warehouse lending market parameters.

Parameter	Description	Value
	Mortgage Market Parameters	
α	Mortgage borrower price sensitivity	0.60
q_n	Shadow banks' service quality relative to banks'	-1.01
ρ_n^b	The total funding cost of shadow banks financed by local banks	0.09
ρ_n^o	The total funding cost of shadow banks financed by non-local banks	0.13
$\tilde{\rho}_n$	Common component of shadow banks' funding costs relative to banks'	-0.37
η	Warehouse duration of shadow bank mortgages	0.12
	Warehouse Lending Market Parameters	
σ	Variance of shadow bank idiosyncratic taste shocks	3.07
$\tilde{c}_o$	Non-local banks' marginal cost of warehouse lending	0.99
$\tilde{c}_b$	Local banks' marginal cost of warehouse lending	0.26

Table 15
Verification of Model Parameters

Table 15 shows the verification of model parameters prediction. I impose a 60-bps increase in the funding cost of 54% local banks and 49% non-local banks and find the model prediction before and after the shocks. Panel A shows the warehouse lending market equilibrium before and after the shocks. Affected banks are banks that experience a funding cost increase, while unaffected banks are banks that do not experience a funding cost change. Panel B shows the average warehouse funding costs of shadow banks that borrowed from affected banks and unaffected banks, respectively, before the shocks. Panel C shows the average mortgage interest rates set by shadow banks that borrowed from affected banks and unaffected banks, respectively, before the shocks.

Panel A: Warehouse Lending Market Equilibrium

	Local Banks		Non-Local Banks	
	(1) Shocked	(2) Unshocked	(3) Shocked	(4) Unshocked
Warehouse Lending Interest Rate (ρ_b)				
Pre-Shock (pp)	5.17	5.17	5.97	5.97
Post-Shock (pp)	5.78	5.18	6.57	5.98
Share of Shadow Bank Borrowers (S_b^w)				
Pre-Shock (pp)	21.4	18.3	29.6	30.8
Post-Shock (pp)	20.9	18.3	28.9	31.9

Panel B: Average Shadow Bank Cost of Funding by Lender Type

	(1) Pre-Shock	(2) Post-Shock	(3) Difference
Shocked Bank (pp)	5.63	6.23	0.60
Unshocked Bank (pp)	5.67	5.68	0.01

Panel C: Average Shadow Bank Mortgage Interest Rates

	(1) Pre-Shock	(2) Post-Shock	(3) Difference
Shadow Banks Financed by Shocked Banks (pp)	2.31	2.41	0.10
Shadow Banks Financed by Unshocked Banks (pp)	2.32	2.32	0.00

Appendices

Appendix A

Institutional Background

To obtain a warehouse line of credit, shadow banks sign a warehouse lending contract with its lender. The contract specifies the total committed line of credit limit, interest rate, rules of usage, commitment period, and covenants. For example, in the 30-page warehouse line of credit agreement between Bayport Mortgage and First Tennessee Bank signed in 2004 [1], the committed line is $20 million dollars. The interest rate is set to be one month LIBOR rate plus 2.75%. Each advance is required to be repaid on the earlier of 45 days from the funding date, the purchase date for the mortgage loans, the earliest date on which the loan becomes past due 60 days or more, or the termination of the agreement. Also, the credit can only be used for *eligible* mortgages that satisfy certain specific requirements set by the bank. In this example, First Tennessee Bank provides a table of mortgage loan grades based on combined loan to value ratio (CLTV) and FICO score and requires that

> "No more than 5% of a warehouse line may be used to warehouse loans graded 5; no more than 15% of a warehouse line may be used to warehouse the combined total of all loans graded 4 or 5;

[1] https://www.sec.gov/Archives/edgar/data/1095996/000119312504134234/dex102.htm

> ......; loans which fall below the minimum grade 5 FICO criterion or which fall above the maximum grade 5 CLTV criterion may not be warehoused."

Moreover, covenants about firm net worth, liquidity and leverage ratio are imposed, the violation of which leads to a termination of the agreement.

Appendix B

Data

B.1 Shadow Bank and Warehouse Bank Data

I construct a novel data set about the warehouse credit providers of shadow banks in the US residential mortgage origination market from 2011 to 2017. I collect the data from the shadow bank call report filings to state regulators. Pursuant to the S.A.F.E. Mortgage Licensing Act of 2008, non-depository mortgage originators that hold a state license or state registration to conduct mortgage origination are required to complete a call report on a quarterly basis since 2011. To access the call report data, I submitted FOIA requests to all states and finally obtained the data from Washington state and Massachusetts state.

The data set contains 544 shadow banks that originated 79.7% of total shadow bank mortgage loans from 2012 to 2017. Fig. D.2a compares my sample coverage to total loan origination by years. Except for 2011, about 80% (77.6% 81.5%) of total shadow bank mortgage origination in each year is covered by my sample. Since the call reports were not enforced in Massachusetts in 2011, my sample coverage in 2011 is not as comprehensive as in later years. Even so, my sample still covers more than 40% of total shadow bank origination in 2011. Fig. D.2b compares my sample to the entire shadow bank population recorded by HMDA. The data set contains most shadow banks on the right tail of the entire shadow bank size distribution. I obtain data on 171 out of 240 largest shadow lenders identified in Buchak et al (2018), where all shadow banks among the top 10 mortgage lenders in 2017 are included. Small local shadow banks in states other than Washington and Massachusetts are underrepresented in our data set. 464 small local shadow banks recorded in HMDA in 2017 are missing from our sample. The average loan origination volume of these missing small local shadow banks is $371 million in 2017.

To identify each lender, I manually assigned bank regulatory call report ID and the holding company ID by searching line of provider names on the FDIC BankFind website. For banks whose names are not unique, I attempt to identify them by checking on the websites of all possible banks under the same name listed on the FDIC BankFind to find the one that has a warehouse lending business division. For line of credit providers that are not banks, I searched their information online to categorize them. Using this data set, I identify quarterly funding relationships between 544 shadow banks and 399 funding providers from 2011 to 2017, where 222(202) providers are banks (identified-banks).

While the shadow bank call reports collect data on credit limits and remaining credit limits, I do not observe the interest rate on individual lines of credit. To provide insight on pricing, I estimate the average interest rate a shadow bank pays on all of its credit lines. In particular, since I observe the debt outstanding and the warehouse interest expense from the balance sheet and income statement, I am able to back out the average interest rate on a shadow bank's debt by estimating $\tilde{r}_{i,t}$ in the following equation:

$$WarehouseExpense_{i,q} = (1+r_{i,t}^{daily}+Qave\_Libor_{i,q})^{90}\times LineUsage_{i,q} - LineUsage_{i,q}$$

where $WarehouseExpense_{i,q}$ is shadow bank i's total warehouse interest expense in quarter q, $Qave\_Libor_{i,q}$ is the quarterly average overnight LIBOR rate in quarter q, and $LineUsage$ is the sum of shadow bank i's usage of all credit lines in quarter q. This pricing model is close to the actual expression of interest rate in a warehouse lending agreement[1].

Lastly, I merge the shadow bank funding provider data set with the Home Mortgage Disclosure Act (HMDA) database to obtain loan-level and area-level mortgage lending activities for the shadow banks and the warehouse banks. While each shadow bank is identified by a unique ID in the National Mortgage License System (NMLS ID), which is used as an identifier in both of the shadow bank call reports and the HMDA database, the NMLS ID is not disclosed in the public portion of the HMDA database. To link the two data sets, I construct a crosswalk table between the HMDA institution ID and the NMLS ID using NMLS Consumer Access platform, where consumers can search for shadow bank registration information using company name and address.

[1] A few number of warehouse lending agreements can be found on the SEC website; e.g. https://www.sec.gov/Archives/edgar/data/1095996/000119312504134234/dex102.htm

B.2 Other Data

I obtain data on loan origination and loan purchases from HMDA. HMDA records the vast majority of residential mortgage applications in the United States. It provides loan-level loan origination activity details by both depository and non-depository institutions. The public portion reports the application outcome, the loan type and purpose, the loan amount, the applicant's address, race, and income. HMDA records whether the originator sells the loan within one year to a third party, where the purchaser type, e.g. GSE or a bank, is reported. In addition to loan origination activities, HMDA also collects the same set of information on loan purchases. While it does not collect information about the purchaser of each loan sold or the information about the seller of each loan purchased, I map the two data sets on an exclusive group of loan and borrower characteristics to identify the bank that purchases each loan sold by a shadow bank as well the seller of each loan purchased by a bank.

I obtain data on the geographical coordinates and location of each branch of every warehouse bank from the Summary of Deposits (SOD) database provided by the FDIC. I assign latitudes and longitudes to each branch address by geocoding branch addresses via Google Geocoding whenever geographical coordinate data are missing. Data on shadow banks' headquarter addresses are obtained from the HMDA. I geocode the headquarter addresses to get latitudes and longitudes. I compute the minimum and the average geographical distance between the branch networks of each warehouse bank and each shadow bank's headquarter. To do so for each shadow bank-bank pair, I first calculate the geodetic distance between each branch and the shadow bank's headquarter. I then find the minimum and the average of all pair-wise distances.

Appendix C

Additional Analysis

C.1 Product Market Competition

To examine whether warehouse banks are the ones losing market shares as shadow banks grow, I run the following regressions for all banks:

$$\Delta MktShare_i = \alpha + \beta I(Warehouse_i) + \Gamma X_i + \epsilon_i, \tag{C.1}$$

$$MktShare_{i,t} = \alpha + \Sigma_t \beta_t I(Warehouse_i) \times I(Year = t) + \Sigma_t (X_i \times I(Year = t))' \Gamma_t + \mu_i + \mu_t + \epsilon_{i,t} \tag{C.2}$$

In the first cross-sectional specification, the dependent variable, $\Delta MktShare_i = \frac{LoanOrigin_{i,2017}}{AllOrigin_{i,2017}} - \frac{LoanOrigin_{i,2011}}{AllOrigin_{i,2017}}$, is bank i's change of market share from 2011 to 2017, and the independent variable of interest, $I(Warehouse_i)$, is an indicator that takes the value of 1 if bank i is a warehouse bank and 0 otherwise. Examining market share changes allows me to analyze changes in lending separately from changes in overall market size. In the second panel specification, the dependent variable is bank i's market share in year t, and the independent variables of interest are the terms of interaction between $I(Warehouse)$ and year. In both specifications, X_i are bank and local controls.

The results in Table 2 confirm that as shadow banks grow, warehouse banks' market shares decline more than non-warehouse banks' market shares on average after controlling for bank characteristics and local economic conditions. On average, warehouse banks' market share drops by 5.6-bps more than non-warehouse banks' market share from 2011 to 2017. Columns (3) excludes the largest four banks, indicating that the effect is not only driven by the big originators.

Furthermore, shadow banks and their warehouse banks originate mortgages in the same local markets. To document the extent to which shadow bank is funded by banks that directly compete in the same geographic market, I calculate the percentage of total shadow bank origination being funded by banks that originate mortgages in the same geographic market. Table 1 reports the quantities by different geographic market definition. In Column (1), a geographic market is defined as a CBSA. From 2012 to 2017, 92% of shadow bank origination on average is funded by banks originating loans in the same CBSA. With a tighter definition of geographic market, Column (2) shows that 91% of total shadow bank origination is funded by banks originating loans in the same county from 2012 to 2017.

C.2 Oil Shock

I begin with analyzing the impact of the oil price decline on bank warehouse lending. Fig. D.4 plot the loan delinquency rate, change of tier 1 capital, and warehouse lending amount for high O&G exposure banks and low O&G exposure banks, respectively. Since I do not directly observe the performance of O&G loans as a separate group, I plot the delinquency rate on all commercial and industrial loans (C&I loans) that include O&G loans and the delinquency rate on non-C&I loans that do not include O&G loans. As shown in Fig. D.4(a), the average delinquency rates on C&I loans for the two groups diverge after the oil price shock. The high O&G exposure banks experienced a rising delinquency rate on their C&I loans, while the average C&I loan delinquency rate stayed constant among the low O&G exposure banks. Such pattern is not observed in the non-C&I loans. As shown in Fig. D.4(b), the average delinquency rates on non-C&I loans in the two groups of banks follow each other closely. The increased delinquency rate reduced the net worth of the high O&G exposure banks. Fig. D.4(c) shows that the high O&G exposure banks had smaller growth in tier 1 capital relative to the low O&G exposure banks after the oil price shock. Finally Fig. D.4(d) shows that the high O&G exposure banks cut warehouse lending to shadow banks after the oil price shock.

To formally test the bank lending channel, I run the following regressions:

$$Ln(Limit)_{i,j,t} = \alpha + \beta HighOilShock_{i,j} \times Post_t + \gamma Post_t + \Gamma X_{i,t} + \mu_{i,j} + \epsilon_{i,j,t} \quad \text{(C.3)}$$

$$\Delta Ln(Limit)_{i,j} = \alpha + \beta HighOilShock_{i,j} + \mu_i + \epsilon_{i,j} \quad \text{(C.4)}$$

where $HighOilShock_{i,j}$ is an indicator of high O&G exposure banks, which equals 1 if a bank lender was severely exposed to the oil shock,in both specifications. The first specification is estimated using a panel data set from 2013Q2 to 2016Q2, where $Post_t$ is 1 for quarters after 2014Q2 and $X_{i,t}$ are shadow bank controls, including net income to total asset, change in local income per capita, and change in local unemployment rate. The second fixed effects specification follows Khwaja and Mian (2008), where $\Delta Ln(Limit)_{i,j}$ is the difference between quarterly average $ln(Limit)$ before and after the oil shock. In particular, I require a continuous bank-shadow bank funding relationship during the pre-shock period and extending into the post-shock period. I further test the extensive margin by estimating a linear probability model:

$$Termination_{i,j} = \alpha + \beta HighOilShock_{i,j} + \mu_i + \epsilon_{i,j} \tag{C.5}$$

where $Termination_{i,j}$ indicates whether the credit line extended by bank i to shadow bank j is terminated in two years since the second quarter of 2014.

The shadow bank fixed effects subsume any general changes in the shadow bank's credit demand that is common across warehouse lenders. This addresses the concern that the effects of the oil price decline might induce correlated shadow bank demand for warehouse credit and bank lending supply shocks. Using the fixed effects specification, I compare how the intensive and extensive margin on the same shadow bank's borrowing from one bank changes relative to another more affected bank. To the extent this within shadow bank variation fully absorbs shadow bank-specific credit demand changes, the estimated differences in borrowing growth and likelihood in termination can be plausibly attributed to differences in warehouse banks' exposure to the oil price shock.

Table 4 reports the regression results. The difference-in-differences result in Column (1) is consistent with the fixed effect specification result in

Column (2), both of which suggest that following the oil price shock, high-O&G exposure banks reduce their warehouse lending. The difference between the credit limit extended by high O&G exposure banks and the credit limit extended by low O&G exposure banks to the same shadow bank drops by 14.5%, which is statistically significant. Results in Column (3) and (4) indicate that high-O&G exposure banks are more likely to terminate funding relationships with shadow banks than low-O&G banks in the two-year window following the oil price shock. For the average shadow bank, the likelihood of a funding relationship with a high-O&G exposure bank being terminated is 21.3% higher than the likelihood of a funding relationship with a low-O&G exposure bank being terminated. The effect is statistically significant.

Appendix D

Appendix Figures and Tables

Figure D.1

Numbers used to plot this figure are calculated using lines of credit information obtained from the RMLA section of the shadow bank call reports in 2017 Q4.

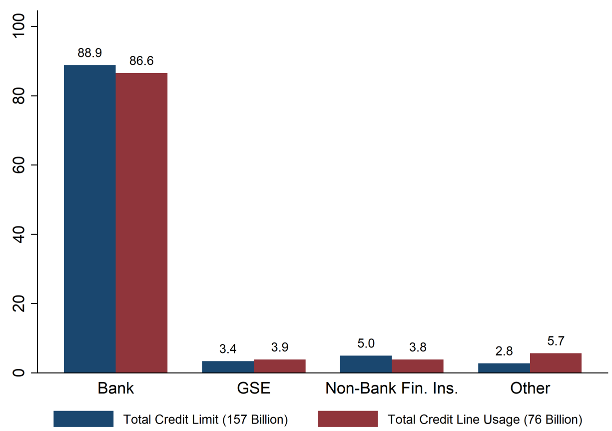


Table 1
Shadow Bank Mortgage Origination Funded by Local Competitors

This table reports the percentage of total shadow bank origination being funded by banks that originate mortgages in the same geographic market. In Panel A, a geographic market is defined at CBSA level. In Panel B, a geographic market is defined at county level.

Panel A: CBSA

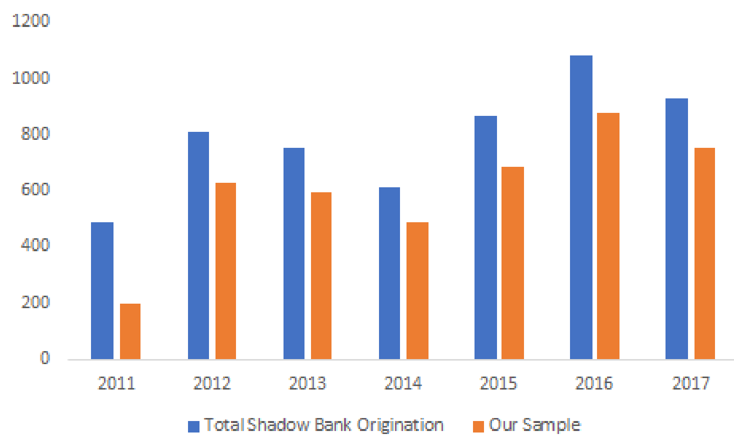
Year	N	Value-weighted Mean	Mean	Stdev	p25	Median	p75
2012	610	0.92	0.59	0.18	0.46	0.6	0.72
2013	611	0.93	0.63	0.16	0.52	0.64	0.76
2014	609	0.91	0.65	0.16	0.54	0.67	0.77
2015	608	0.94	0.66	0.15	0.57	0.67	0.78
2016	608	0.92	0.67	0.14	0.58	0.68	0.78
2017	610	0.92	0.7	0.15	0.61	0.72	0.81

Panel B: County

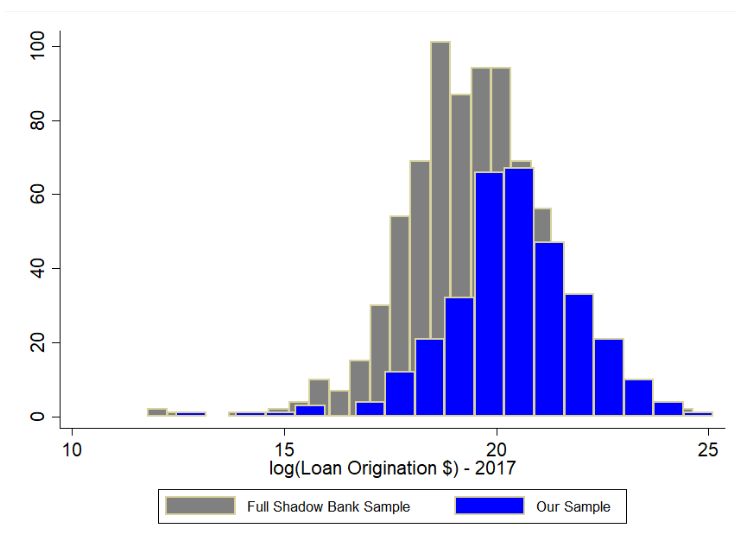
Year	N	Value-weighted Mean	Mean	Stdev	p25	Median	p75
2012	2,972	0.91	0.5	0.2	0.35	0.51	0.65
2013	2,983	0.92	0.55	0.19	0.42	0.56	0.69
2014	2,910	0.90	0.54	0.21	0.4	0.57	0.7
2015	2,947	0.93	0.56	0.2	0.44	0.58	0.71
2016	2,939	0.91	0.56	0.2	0.44	0.59	0.72
2017	2,950	0.90	0.59	0.21	0.47	0.63	0.74

Figure D.2. Sample Coverage

This figure compares my sample coverage to total shadow bank loan origination recorded by HMDA. Panel A plots the total loan origination covered by year. Panel B plots the histograms of the size of shadow banks in my sample as well as in shadow banks in HMDA.



(a) Sample Coverage by Year



(b) Sample Size Distribution in 2017 Dollar

Table 2
Warehouse Lending and Bank Market Share Decline

Table 2 reports the coefficients in the following models:

$$\Delta MktShare_i = \alpha + \beta I(Warehouse_i) + \Gamma X_i + \epsilon_i$$
$$MktShare_{i,t} = \alpha + \Sigma_t \beta_t I(Warehouse_i) \times I(Year = t) + \Sigma_t (X_i \times I(Year = t))' \Gamma_t + \mu_i + \mu_t + \epsilon_{i,t}$$

In the first cross-sectional specification, the dependent variable is the change in market share from 2011 to 2017, and the independent variable of interest is $I(Warehouse_i)$, an indicator that equals 1 if the bank does warehouse lending during my sample period and 0 otherwise. Columns (1) to (3) report the cross-sectional regression results. In the second panel specification, the dependent variable is bank i's market share in year t, and the independent variables of interest are the terms of interaction between $I(Warehouse)$ and year. Column (4) reports the panel regression results. In both specifications, X_i are bank and local controls, including ln(asset) in 2011, residential real estate share of asset in 2011, change in tier 1 capital ratio from 2011 to 2017, change in county income per capita from 2011 to 2017, change in county unemployment rate from 2011 to 2017, average county mortgage default rate from 2009 to 2011, and county demographics in 2011. All local controls are weighted by bank's loan origination in 2011. Columns (1), (2) and (4) report results using all banks; and Column (3) report results without the biggest four banks, Bank of America, Wells Fargo, Citigroup, and JPMorgan Chase. Standard errors are clustered at shadow bank level in Column (4). I present the standard errors in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	(1) ΔMktShare (bps	(2) ΔMktShare (bps)	(3) ΔMktShare (bps)	(4) Market Share (bps)
Warehouse Bank	-12.579***	-5.559***	-0.729**	
	(1.859)	(2.046)	(0.303)	
Baseline: Warehouse Bank×Year 2011				
Year=2012				-0.738
				(0.798)
Year=2013				-1.568
				(1.384)
Year=2014				-3.638
				(2.245)
Year=2015				-4.146*
				(2.344)
Year=2016				-4.907*
				(2.605)
Year=2017				-5.408*
				(3.073)
Bank Controls		x	x	x
Local Controls		x	x	x
Bank FE				x
Year FE				x
N	2,127	2,127	2,123	17,789
R2	0.021	0.054	0.017	0.048
Mean	-0.6	-0.6	0.06	1.54
Std Dev	20.0	20.0	2.9	23.41

Table 3
Lending Relationship and Geographical Proximity

Table 3 reports the coefficients from a linear probability model:
$Pr(Lend_{i,j,t}) = \alpha + \beta Distance_{i,j,t} + \Gamma X_{j,t} + \mu_{i,t} + \epsilon_{i,j,t}$
The dependent variable takes the value of one if shadow bank i obtains funding from warehouse bank j in year t and zero otherwise. *Distance* is measured by the logarithm of minimum distance between shadow bank i's headquarter and all branches of warehouse bank j in Column (1) and (2) and is measured by the logarithm of average pairwise distance between shadow bank i's loan origination counties and bank j's branch network in Column (3). In Column (4) I include both distance measures. Standard errors are clusterd at shadow banks and banks. I present the standard errors in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Pr(Lending Relationship)			
	(1)	(2)	(3)	(4)
Ln(HQ Distance)	-0.010***	-0.011***		-0.010***
	(0.001)	(0.002)		(0.002)
Ln(Pairwise Distance)			-0.028***	-0.006*
			(0.004)	(0.004)
Bank Controls				
Ln(Asset)	0.006***			
	(0.001)			
Market Dispersion	0.011			
	(0.007)			
Share of Asset				
Residential Mortgage	0.089***			
	(0.023)			
Loan to Nondep. Financial Ins.	0.393***			
	(0.135)			
C&I Loan	0.095***			
	(0.034)			
Core Deposit	0.063*			
	(0.035)			
Tier 1 Capital Ratio	0.027			
	(0.051)			
Bank×Year Fixed Effects	No	Yes	Yes	Yes
Shadow Bank×Year Fixed Effects	Yes	Yes	Yes	Yes
Num of Observations	247,574	247,682	246,422	246,421
R2	0.056	0.111	0.105	0.111

Table 4
Oil Shock and Warehouse Lending Reduction

Table 4 shows the effect of the oil shock on banks' warehouse lending. Column (1) is estimated using a panel data set from 2013Q2 to 2016Q2, where *Post* is 1 for quarters after 2014Q2. In Column (2), the dependent variable is the difference between quarterly average $ln(Limit)$ before and after the oil shock. In Column (3) and (4), the dependent variable is an indicator for termination, which takes the value of one if the credit line is terminated in two years since the second quarter of 2014. In all four columns, $HighOilShock$ is an indicator of high O&G exposure banks, which equals 1 if a bank lender was severely exposed to the oil shock. Shadow bank controls include net income to total asset and the logarithm of total assets. Bank controls include the logarithm of total assets, loan delinquency rate, change in tier 1 capital ratio. Local controls include change in local income per capita, and change in local unemployment rate. Standard errors are clustered at lending relationships in Column (1) and clustered at shadow banks in Column (2)-(4). I present the standard errors in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	(1) Ln(Limit)	(2) Δ Ln(Limit)	(3) I(Termination)	(4) I(Termination)
High Oil Shock		-0.120**	0.182***	0.213***
		(0.058)	(0.052)	(0.053)
Post Shock	0.275***			
	(0.075)			
High Oil Shock×Post	-0.145*			
	(0.084)			
Net Income/Asset	-1.049**		-2.525**	
	(0.498)		(1.142)	
Local Controls	x		x	
Bank Controls			x	x
Shadow Bank Fixed Effects		x		x
Credit Line Fixed Effects	x			
Number of Observations	5,987	495	482	660
R2	0.009	0.008	0.062	0.060

Table 5
Do Shadow Banks Enter High-Interest Rate Counties?

Table 5 reports results of the following regression:

$$\Delta ShadowMktShare_k = \alpha + \beta_1 R_k^{2009} + \beta_2 WbMktShare_k^{2009} + \beta_3 R_k^{2009} \times WbMktShare_k^{2009} + \epsilon_k$$

where $\Delta ShadowMktShare_k$ is shadow bank market share growth from 2010 to 2017 in county k, R_k^{2009} is the average mortgage interest rate residual in county k in 2009, and $WbMktShare_k^{2009}$ is warehouse bank market share in county k in 2009. R_k^{2009} and $WbMktShare_k^{2009}$ are standardized, so coefficients can be interpreted as percent change in shadow bank market share for a one standard deviation change in the independent variable. I present the standard errors in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Shadow Bank Market Share Growth from 2010 to 2017					
	(1)	(2)	(3)	(4)	(5)	(6)
Mortgage Rate Residual in 2009	0.434*	0.457*	0.768***	0.772***	0.787**	0.770**
	(0.256)	(0.256)	(0.297)	(0.297)	(0.345)	(0.344)
Warehouse Bank Market Share in 2009			0.870***	0.745***		
			(0.265)	(0.265)		
Rate Res.×Wb. Mkt. Share in 2009			-0.506**	-0.480**		
			(0.242)	(0.241)		
High Wb. Mkt. Share in 2009					4.027***	3.979***
					(0.520)	(0.517)
Rate Res.×High Wb. Mkt. Share in 2009					-0.859*	-0.769
					(0.508)	(0.506)
County Controls		x		x		x
Num. of Observations	3,124	3,124	3,124	3,124	3,124	3,124
R2	0.001	0.012	0.007	0.017	0.024	0.034

Figure D.3. Heterogeneity in Financing Competing Shadow Banks

Fig. D.3 visualizes the geographic distribution of the percentage of shadow bank origination being financed by local bank competitors in 2017. A geographic market is defined as a county.

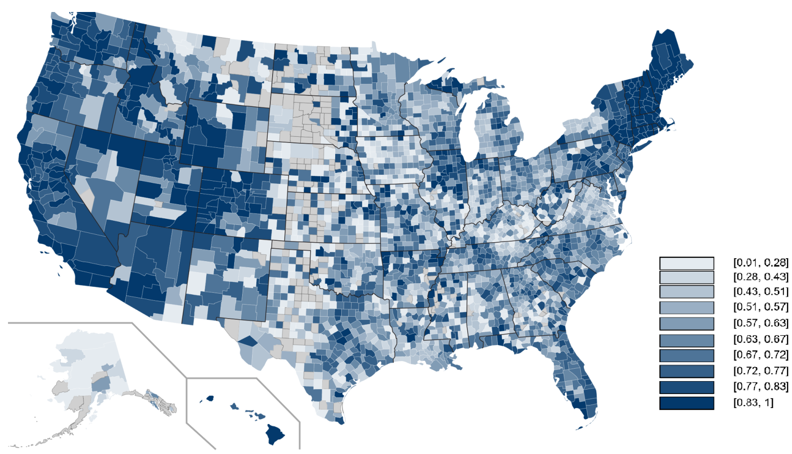
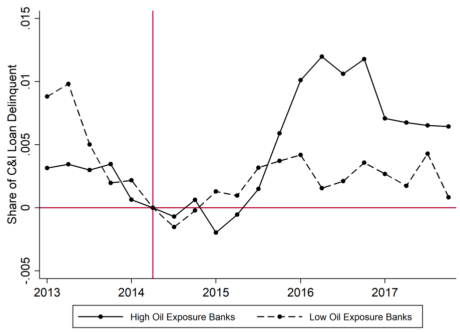
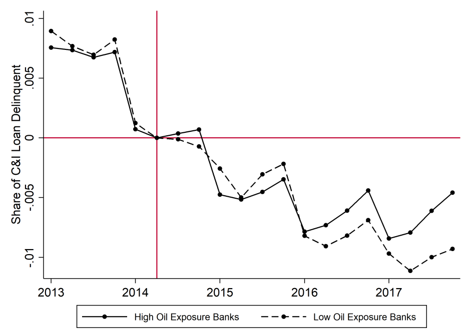


Figure D.4. 2014 Oil Price Shock

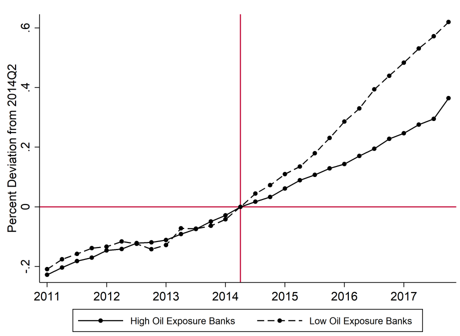
Fig. D.4 plot the delinquency rate of commercial and industrial loans, change of tier 1 capital, and warehouse lending amount for high O&G exposure banks and low O&G exposure banks, respectively.



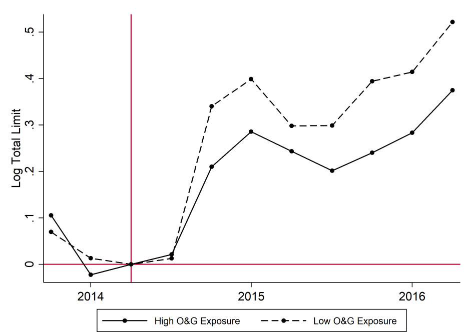
(a) Change of C&I Loan Delinquent and Charge-off Rate from 2014Q2



(b) Change of Non-C&I Loan Delinquent and Charge-off Rate from 2014Q2



(c) Change of Warehouse Bank Tier 1 Capital from 2014Q2



(d) Total Warehouse Lending Changes from 2014Q2

Bibliography

Adelino, Manuel, Kristopher Gerardi, and Barney Hartman-Glaser, 2019, Are lemons sold first? dynamic signaling in the mortgage market, *Journal of Financial Economics* 132, 1–25.

Adrian, Tobias, and Adam B Ashcraft, 2016, Shadow banking: a review of the literature, in *Banking crises*, 282–315 (Springer).

Benetton, Matteo, 2018, Leverage regulation and market structure: An empirical model of the uk mortgage market, *Available at SSRN 3247956* .

Berger, Allen N, and Gregory F Udell, 1995, Relationship lending and lines of credit in small firm finance, *Journal of business* 351–381.

Berger, David W, Konstantin Milbradt, Fabrice Tourre, and Joseph Vavra, 2018, Mortgage prepayment and path-dependent effects of monetary policy, Technical report, National Bureau of Economic Research.

Berry, Steven, James Levinsohn, and Ariel Pakes, 1995, Automobile prices in market equilibrium, *Econometrica: Journal of the Econometric Society* 841–890.

Berry, Steven T, 1994, Estimating discrete-choice models of product differentiation, *The RAND Journal of Economics* 242–262.

Bhutta, Neil, 2012, Gse activity and mortgage supply in lower-income and minority neighborhoods: The effect of the affordable housing goals, *The Journal of Real Estate Finance and Economics* 45, 238–261.

Bidder, Rhys M, John R Krainer, and Adam H Shapiro, 2018, De-leveraging or de-risking? how banks cope with loss, Federal Reserve Bank of San Francisco.

Bolton, Patrick, Xavier Freixas, Leonardo Gambacorta, and Paolo Emilio Mistrulli, 2016, Relationship and transaction lending in a crisis, *The Review of Financial Studies* 29, 2643–2676.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 2018a, Fintech, regulatory arbitrage, and the rise of shadow banks, *Journal of Financial Economics* 130, 453–483.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 2018b, The limits of shadow banks, Technical report, National Bureau of Economic Research.

Cestone, Giacinta, and Lucy White, 2003, Anticompetitive financial contracting: The design of financial claims, *The Journal of Finance* 58, 2109–2141.

Cetorelli, Nicola, 2004, Real effects of bank competition, *Journal of Money, Credit and Banking* 543–558.

Cetorelli, Nicola, and Philip E Strahan, 2006, Finance as a barrier to entry: Bank competition and industry structure in local us markets, *The Journal of Finance* 61, 437–461.

Chakraborty, Indraneel, Itay Goldstein, and Andrew MacKinlay, 2019, Monetary stimulus and bank lending, *Journal of Financial Economics* .

Chava, Sudheer, and Amiyatosh Purnanandam, 2011, The effect of banking crisis on bank-dependent borrowers, *Journal of Financial Economics* 99, 116–135.

DeFusco, Anthony A, and Andrew Paciorek, 2017, The interest rate elasticity of mortgage demand: Evidence from bunching at the conforming loan limit, *American Economic Journal: Economic Policy* 9, 210–40.

Demyanyk, Yuliya, and Elena Loutskina, 2016, Mortgage companies and regulatory arbitrage, *Journal of Financial Economics* 122, 328–351.

Di Maggio, Marco, Amir Kermani, and Christopher Palmer, 2016, How quantitative easing works: Evidence on the refinancing channel, *Journal of Monetary Economics* 81, 111–132.

Diamond, Douglas W, 1984, Financial intermediation and delegated monitoring, *The review of economic studies* 51, 393–414.

Dixit, Avinash, 1983, Vertical integration in a monopolistically competitive industry, *International Journal of Industrial Organization* 1, 63–78.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, 2019, How monetary policy shaped the housing boom, Technical report, National Bureau of Economic Research.

Egan, Mark, Ali Hortaçsu, and Gregor Matvos, 2017a, Deposit competition and financial fragility: Evidence from the us banking sector, *American Economic Review* 107, 169–216.

Egan, Mark, Stefan Lewellen, and Adi Sunderam, 2017b, The cross section of bank value, Technical report, National Bureau of Economic Research.

Eichenbaum, Martin, Sergio Rebelo, and Arlene Wong, 2018, State dependent effects of monetary policy: The refinancing channel, Technical report, National Bureau of Economic Research.

Elenev, Vadim, Tim Landvoigt, and Stijn Van Nieuwerburgh, 2016, Phasing out the gses, *Journal of Monetary Economics* 81, 111–132.

Engel, Kathleen C, and Patricia A McCoy, 2016, *The subprime virus: Reckless credit, regulatory failure, and next steps* (Oxford University Press).

Engelberg, Joseph, Pengjie Gao, and Christopher A Parsons, 2012, Friends with money, *Journal of Financial Economics* 103, 169–188.

Favilukis, Jack, Sydney C Ludvigson, and Stijn Van Nieuwerburgh, 2017, The macroeconomic effects of housing wealth, housing finance, and limited risk sharing in general equilibrium, *Journal of Political Economy* 125, 140–223.

Fisman, Raymond, Daniel Paravisini, and Vikrant Vig, 2017, Cultural proximity and loan outcomes, *American Economic Review* 107, 457–92.

Fuster, Andreas, Matthew Plosser, Philipp Schnabl, and James Vickery, 2019, The role of technology in mortgage lending, *The Review of Financial Studies* 32, 1854–1899.

Gan, Jie, 2007, The real effects of asset market bubbles: Loan-and firm-level evidence of a lending channel, *The Review of Financial Studies* 20, 1941–1973.

Garmaise, Mark J, and Tobias J Moskowitz, 2003, Confronting information asymmetries: Evidence from real estate markets, *The Review of Financial Studies* 17, 405–437.

Gete, Pedro, and Michael Reher, 2017, Nonbanks and lending standards in mortgage markets. the spillovers from liquidity regulation .

Granja, Joao, Gregor Matvos, and Amit Seru, 2017, Selling failed banks, *The Journal of Finance* 72, 1723–1784.

Hou, Zhenbo, Jodie Keane, J Kennan, and D Willem te Velde, 2015, The oil price shock of 2014: Drivers, impacts and policy implications, *Overseas Development Institute W orking Paper* 415.

Hubbard, R Glenn, Kenneth N Kuttner, and Darius N Palia, 2002, Are there bank effects in borrowers' costs of funds? evidence from a matched sample of borrowers and banks, *The Journal of Business* 75, 559–581.

Hurst, Erik, Benjamin J Keys, Amit Seru, and Joseph Vavra, 2016, Regional redistribution through the us mortgage market, *American Economic Review* 106, 2982–3028.

Irani, Rustom M, Rajkamal Iyer, Ralf R Meisenzahl, and Jose-Luis Peydro, 2018, The rise of shadow banking: Evidence from capital regulation .

Iyer, Rajkamal, and Jose-Luis Peydro, 2011, Interbank contagion at work: Evidence from a natural experiment, *The Review of Financial Studies* 24, 1337–1377.

Jiang, Erica, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 2020, Banking without deposits: Evidence from shadow bank call reports, Technical report, National Bureau of Economic Research.

Kaplan, Greg, Kurt Mitman, and Giovanni L Violante, 2016, Non-durable consumption and housing net worth in the great recession: Evidence from easily accessible data, Technical report, National Bureau of Economic Research.

Karolyi, Stephen Adam, 2018, Personal lending relationships, *The Journal of Finance* 73, 5–49.

Keys, Benjamin J, Tomasz Piskorski, Amit Seru, and Vikrant Vig, 2012, Mortgage financing in the housing boom and bust, in *Housing and the Financial Crisis*, 143–204 (University of Chicago Press).

Khwaja, Asim Ijaz, and Atif Mian, 2008, Tracing the impact of bank liquidity shocks: Evidence from an emerging market, *American Economic Review* 98, 1413–42.

Kim, You Suk, Steven M Laufer, Richard Stanton, Nancy Wallace, and Karen Pence, 2018, Liquidity crises in the mortgage market, *Brookings Papers on Economic Activity* 2018, 347–428.

Loutskina, Elena, and Philip E Strahan, 2009, Securitization and the declining impact of bank finance on loan supply: Evidence from mortgage originations, *The Journal of Finance* 64, 861–889.

Mathewson, G Frank, and Ralph A Winter, 1984, An economic theory of vertical restraints, *The RAND Journal of Economics* 27–38.

Nadauld, Taylor D, and Shane M Sherlund, 2013, The impact of securitization on the expansion of subprime credit, *Journal of Financial Economics* 107, 454–476.

Paravisini, Daniel, 2008, Local bank financial constraints and firm access to external finance, *The Journal of Finance* 63, 2161–2193.

Paravisini, Daniel, Veronica Rappoport, and Philipp Schnabl, 2015, Specialization in bank lending: Evidence from exporting firms, Technical report, National Bureau of Economic Research.

Petersen, Mitchell A, and Raghuram G Rajan, 1994, The benefits of lending relationships: Evidence from small business data, *The journal of finance* 49, 3–37.

Petersen, Mitchell A, and Raghuram G Rajan, 1995, The effect of credit market competition on lending relationships, *The Quarterly Journal of Economics* 110, 407–443.

Petersen, Mitchell A, and Raghuram G Rajan, 2002, Does distance still matter? the information revolution in small business lending, *The journal of Finance* 57, 2533–2570.

Robles-Garcia, Claudia, 2019, Competition and incentives in mortgage markets: The role of brokers .

Saidi, Farzad, and Daniel Streitz, 2018, Bank concentration and product market competition, *Work. Pap., Stockh. Sch. Econ., Stockholm Google Scholar Article Location* .

Schnabl, Philipp, 2012, The international transmission of bank liquidity shocks: Evidence from an emerging market, *The Journal of Finance* 67, 897–932.

Schwert, Michael, 2018, Bank capital and lending relationships, *The Journal of Finance* 73, 787–830.

Stanton, Richard, Johan Walden, and Nancy Wallace, 2014, The industrial organization of the us residential mortgage market, *Annu. Rev. Financ. Econ.* 6, 259–288.

Stein, Jeremy C, 2002, Information production and capital allocation: Decentralized versus hierarchical firms, *The journal of finance* 57, 1891–1921.

Williams, Emily, and Stefan Lewellen, 2020, Did technology contribute to the housing boom? evidence from mers .

Wong, Arlene, 2019, Refinancing and the transmission of monetary policy to consumption, *American Economic Review* .

Xiao, Kairong, 2018, Monetary transmission through shadow banks .

Vita

Permanent address: xueweijiang0313@gmail.com

This dissertation was typed by the author.