Financing Competitors

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Abstract

This paper studies banks' lending to shadow banks and its impact on mortgage market competition. 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.

Keywords: Shadow Bank Funding, Warehouse Lines, Mortgage, Competition, Bank Lending

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I. Introduction

Since the financial crisis, banks have lost significant market share to shadow banks¹ in the loan origination market. By 2017, shadow banks originated \$1 trillion mortgages, about half of the entire mortgage market (Buchak et al. (2018a)). At the same time, the majority of shadow bank funding is provided by banks through warehouse lines of credit (Jiang et al. (2019)). I start this paper by documenting mortgage market competition between shadow banks and their funding providers: the banks that lend to shadow banks are themselves big mortgage originators. As shadow banks grew from 2011 to 2017, these banks lost 15 percentage-points in mortgage origination market share to shadow banks that were funded by them.

This paper studies banks' lending to their competitors and its impact on mortgage market competition. I do so using novel data from shadow bank call reports obtained through FOIA requests. I first empirically analyze the trade-off in banks' decisions to lend to shadow banks, which compete with them in the mortgage market. Based on the empirical findings, I develop a quantitative model that fully characterizes the demand and supply in both warehouse lending and mortgage markets and in which banks trade off the margins in the two markets. The model allows me to study the extent to which warehouse lending softens the competition in the mortgage market. As the potential loss in mortgage profit from increased competition rises, banks may reduce their lending to shadow banks, limiting shadow banks' expansion in regions where the competition will benefit consumers the most. I use the model to quantify the welfare implications of policies and technologies that effectively reduce banks' warehouse lending market power.

I begin by showing that warehouse lending relationships are more likely to be formed between banks and shadow banks that compete in local mortgage markets. One might imagine that warehouse lending would happen 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. I use loan-level mortgage application data to measure the geographic market overlap in mortgage origination between banks and shadow banks. A one standard deviation increase in geographic market overlap increases the likelihood of having a lending relationship by 70% of the unconditional probability; and conditional on having a lending relationship, it increases the warehouse credit line size by \$13 million. In other words, a bank is significantly more likely to form a warehouse lending relationship with a shadow bank, and to provide it with a larger credit line, if they compete in the mortgage origination market. This relationship is robust to the inclusion of bank-by-year and shadow bank-by-year fixed effects. Therefore, 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

¹The term "shadow bank" refers to non-bank (non-depository) lenders that are not subject to the same regulatory supervision as traditional banks, consistent with the definition of the Financial Stability Board. See Adrian and Ashcraft (2016), Buchak et al. (2018a).

in shadow banks' capital structure, or demand for bank funding. In fact, the results are robust to controlling for the distance between shadow banks' headquarters and banks' branch networks, a common measure for distance in relationship lending.

Next, I examine whether warehouse lending relationships are essential to shadow banks' mortgage origination. If shadow banks cannot easily substitute their current warehouse lending relationships with alternative funding sources, then individual banks have market power in warehouse lending (e.g. Sharpe (1990), Rajan (1992)). Such market power would allow banks to make strategic warehouse lending decisions.² To this end, I exploit a sharp unanticipated oil price decline that resulted in differential reduction in warehouse lending supply across banks using a Khwaja and Mian (2008) style approach. I find that shadow banks whose primary relationship banks were more exposed to the shock paid higher interest rates and received smaller warehouse lending supply were passed on to the mortgage origination market. Affected shadow banks originated fewer mortgages and raised their mortgage interest rates.

These two empirical facts suggest that banks have market power in the warehouse lending market, and the rent is larger in lending to competing shadow banks relative to non-competitors. One potential source of this additional rent comes from the information advantage that mortgage market competitors have over non-competitors in lending to shadow banks. Specifically, 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 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. As a result, if the local information advantage is sufficiently high, banks may choose to finance competing shadow banks, despite the loss in mortgage profit from the increased competition. To test this hypothesis, I construct a soft-information measure introduced by Garmaise and Moskowitz (2003). The measure captures the quality of hard information about local residential real estate captured in tax assessments. If hard information is less reliable, local banks should have a higher information advantage. I confirm that in regions where hard information is less reliable, lending to competitors is more pervasive: a shadow bank is more likely to receive, and receive larger, warehouse lines of credit from banks that have a higher geographic market overlap with itself. This evidence therefore suggests that competition and information advantage are tied together, which incentivize banks to lend to competitors.

²This leads to a possible double-marginalization problem, i.e. the exercise of market power at successive vertical layers in a supply chain, causing welfare loss. By analogy with the supply chain of non-financial products, warehouse lending can be seen as the upstream market, in which banks supply input (i.e. warehouse funding) to shadow banks; and mortgage origination can be seen as the downstream market, in which shadow banks and banks supply mortgage products to consumers.

As I argue above, an information advantage over non-competitors incentivizes banks to finance their competing shadow banks, despite the loss in mortgage profit from increased competition. On the other hand, if the loss in profits from increased mortgage market competition is high, then banks' incentives to finance competing shadow banks should be lower. I find evidence that banks reduce lending to shadow banks in counties where increased competition will lead to a larger reduction in their mortgage origination profit. Moreover, a bank's warehouse lending to specific shadow banks is much less likely if the bank has a high average market share in the shadow banks' markets. 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 county-by-year (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.

Taken together, my findings suggest a trade-off between information rent and mortgage market competition faced by banks in their warehouse lending decisions. 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.

To study the net effect of these forces on mortgage market competition, I develop a quantitative model linking warehouse lending and product market competition, in which 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.

The model fully characterizes the demand and supply in both warehouse lending and mortgage origination. Similar to Buchak et al. (2018a), banks and shadow banks compete in the mortgage origination market. Since mortgages are differentiated products, lenders have market power, which leads to economic profits. I depart from the literature by modeling shadow banks' funding from banks' warehouse lines of credit. Shadow banks' demand for warehouse funding is derived endogenously based on the profits they expect to earn from mortgage origination. Banks' lending relationships are differentiated, which gives them market power as documented in the empirical analysis, and they compete with each other to supply warehouse funding. Depending on whether they also conduct mortgage origination, banks are divided into *local banks* and *non-local banks*, which differ in their cost of monitoring shadow banks. Local banks have to account for the fact that the warehouse lines they provide will fund the competition in the mortgage origination market. The equilibrium then accounts for mortgage borrowers' optimization behavior, and the full strategic behavior of banks and shadow banks across both markets.

The model highlights several effects, which are not obvious without the model. 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 reduces banks' own incentives to compete in mortgage origination because some of the profits earned by shadow banks are funneled back to banks through warehouse lending interest rates. While these forces arise in the model, with feedback between the two markets, it is difficult to evaluate the extent to which warehouse lending softens competition. 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, where I observe the mortgage market shares, mortgage interest rates, shadow banks' funding choices, and their cost of warehouse funding.

The calibration results allow me to quantify two main forces in the warehouse lending market: the degree of (non-)substitutability between individual warehouse lenders, and the local information advantage in terms of the lower cost of warehouse lending to competing shadow banks. The result suggests a lack of substitutability between individual warehouse lenders. A one percent increase in mortgage profits from choosing a given warehouse lender only increases the probability of take-up by 3.07 percent. The low elasticity is consistent with a substantial stickiness of warehouse lending relationships, which I observe, but do not use in my calibration. The calibration result also suggests a substantial advantage of lending to competitors, which lowers their cost of lending by 74% relative to non-competitors. These results allow me to quantify banks' market power in the warehouse lending market. The lack of substitutability and local advantage grant substantial market power to banks in lending to competing shadow banks, resulting in 30% extra markups relative to noncompetitors. Local banks earn 144% markups in warehouse lending to their competing shadow banks, while non-local banks earn 110% markups.

To verify the key parameter about the degree of substitutability between individual warehouse lenders, I examine to what extent the model can quantify the transmission of bank liquidity shock following the oil price decline, which I empirically document but do not use in my calibration. About 54% of local banks and 49% of non-local banks were more exposed to the oil price shock (shocked banks) according to the classification in the reduced-form analysis. Following the oil price decline, the funding cost of shocked banks increased by 60 basis-points relative to unshocked banks.³ 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.

The model predicts that due to lack of substitutability between individual banks, shocked banks optimally raise their warehouse lending interest rates by 60 basis points following the shocks. The reduced warehouse lending competition raised the equilibrium warehouse lending interest rates charged by unshocked banks by 1 basis point. From the demand side, while 2.4% of the shadow

³The calculation is based on bank call reports.

banks that used to borrow from shocked banks switch to unshocked banks, the rest of these shadow banks stick with shocked banks, paying for higher warehouse lending interest rates. Consequently, the warehouse funding cost of shadow banks that borrowed from shocked banks increases by 59 basis points relative to shadow banks that borrowed from unshocked banks. Moreover, following the shocks, shadow banks financed by shocked banks raise their mortgage interest rates by 10 basis points, whereas shadow banks financed by unshocked banks raise their mortgage interest rates by less than 1 basis point. The predicted differences between the two groups of shadow banks are close to the difference-in-differences estimators in the empirical analysis.

Finally, in two counterfactuals I study how banks' warehouse lending market power drive the equilibrium warehouse lending and mortgage origination, and I quantify the welfare implications of policies and technologies that effectively lower banks' warehouse lending market power.

The first counterfactual analysis investigates the equilibrium consequences of mortgage market competitors' advantage in warehouse lending, by reducing non-competitors' warehouse lending costs. The reduction in non-local banks' costs of warehouse lending removes local banks' advantage, reducing local banks' markups by 74 basis points and raising non-local banks' markups by 31 percentage points. Moreover, with the same warehouse lending costs, local banks charge 7 basis-points higher warehouse lending interest rates than non-local banks, which reflects local banks' incentive to internalize mortgage market competition through warehouse lending. In the mortgage market, 4% of shadow banks, whose origination used to be limited by their relationship local banks' through vertical restraint, switch to non-local banks to obtain funding after the removal of local banks' advantage. Increased mortgage market competition from shadow banks reduces banks' mortgage markups by 7 basis points, lowering their mortgage interest rates by 0.2 basis points. Overall, a 29 basis points cost reduction in the warehouse lending market would lower the average consumer mortgage credit by 3 basis points. This reflects that about 10% of the cost savings would be passed on to consumers.

The second counterfactual analysis studies the consequences of reducing shadow banks' dependence on warehouse lending. I estimate the average warehouse loan duration to be 44 days. 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 GSE loan purchase program, for example, allowing shadow banks to sell loans in 5 days.⁴ This program would effectively reduce competitors' advantage over non-competitors in warehouse lending, and 3% of shadow banks would switch to obtain funding from non-local banks. In the mortgage market, this

⁴The GSE has put efforts to improve eMortgage adoption, which will likely shorten the warehouse duration. See, for example, "GSE Efforts to Improve eMortgage Adoption: A Follow-up to the 2016 GSE Survey Findings Report." 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 creating 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

program would increase shadow banks' markups by 40 basis points while it would decrease banks' markups 6 basis points. Overall the mortgage market would become more competitive. Shadow banks and banks would reduce their mortgage interest rates by 7 basis points and 0.2 basis points, respectively. In an average MSA with \$2.08 billion mortgage demand, consumer surplus will rise by \$8.21 million, which aggregates to a \$3.5 billion increase of the consumer surplus in the entire U.S. mortgage market. The counterfactual then shows that simple GSE interventions can help increase the competitiveness of the mortgage origination market. Further, the counterfactual suggests that the shorter warehouse duration of fintech lenders documented in Buchak et al. (2018a) provide them with a competitive advantage in mortgage lending, and directly affect competition in the mortgage market.

Related Literature

This paper 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. (2019) 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 paper provides the first systematic examination of the lending relationship between the two dominant types of lenders in the US mortgage market. Stanton et al. (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 paper 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 paper 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 et al. (2002), Berger and Udell (1995), Engelberg et al. (2012), Karolyi (2018), Paravisini et al. (2015), Schwert (2018), Bolton et al. (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 paper is also connected to recent quantitative equilibrium models of mortgage and other consumer financial product markets (e.g. Favilukis et al. (2017), Kaplan et al. (2016), Berger et al. (2018), and Eichenbaum et al. (2018)). My model follows the form of consumer demand models, such as Berry et al. (1995), and applies these modeling techniques for the purpose of answering policy questions in finance (e.g. Egan et al. (2017), 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.

The remainder of the paper proceeds as follows. I begin by discussing the data and institutional background. Then, I establish a series of empirical facts. Lastly, I develop and calibrate the quantitative model.

II. Institutional Background and Data

A. US Mortgage 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. The two main types of mortgage originators are banks (traditional banks and credit unions) and shadow banks (non-bank lenders). The primary differences between banks and shadow banks are deposit-taking and regulations. Banks take deposits and face substantially higher regulatory scrutiny than shadow banks, including capital requirements, extensive compliance and rules, and supervision from a wide set of regulators, such as the FDIC, OCC, and state regulators. While some shadow banks have better technology (known as "FinTech lenders") than banks, technology-based lending is not a distinct feature of shadow banks in general. Many shadow banks are still "brick and mortar" originators.

The nature of lenders in the mortgage market changed substantially after the financial crisis. Buchak et al. (2018a) document and provide evidence for a rapid growth of shadow banks caused by both the increasing regulatory burden faced by traditional banks and financial technological development.

Shadow Banking Business Model: Shadow banks adopt the originate-to-distribute business model, in which access to warehouse lines of credit is crucial. The originate-to-distribute process starts with the approval of a mortgage application. Upon the approval, the shadow bank funds the mortgage using a draw from its warehouse credit line. The mortgage note serves as collateral until the debt is paid off. After the mortgage is originated, the shadow bank sells the mortgage to a loan purchaser. Post crisis, the GSEs are the main purchasers of the mortgage loans, followed by commercial banks and life insurance companies. After the sale, the proceeds are used to pay off the warehouse loan. Therefore, the duration that the mortgage is being financed by its warehouse credit depends on how quickly the shadow bank can sell it to the loan purchaser.

The total warehouse credit limit received by shadow banks was more than \$150 billion in 2017Q4, where banks provide about 90% of these warehouse funding (Jiang et al. (2019)). One important institutional detail is that in the calculation of bank regulatory risk-weighted assets, the weight on warehouse lending is the same as that on mortgage assets. Therefore, there is no regulatory benefit of engaging in one lending process over the other. Appendix A provides supplementary

institutional background of warehouse lines of credit.

B. Shadow Bank Call Reports

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 B provides greater details about sample coverage.

B.1. Sample Construction

I next 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 B 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.

B.2. Summary Statistics

The sample contains quarterly funding relationships between 184 banks and 528 shadow banks that originate mortgages in the US from 2011 to 2017.⁵ Table I 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 detailed discussion about shadow banks' balance sheet, see Jiang et al. (2019).

In terms of geographic reach of their mortgage business, the average shadow bank originates \$2

 $^{^{5}}$ 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.

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%,⁶ which varies over time with an average time-series standard deviation of 1% within a shadow bank.

To provide an example, Table II 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 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.

Warehouse Banks: Both big national banks and regional banks provide warehouse funding to shadow banks. The average asset size of warehouse banks is about \$80 billion, and the standard deviation of the size distribution is about \$300 billion.

All systematically important banks are warehouse lenders,⁷ 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 III, 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.

Moreover, warehouse banks are big originators in the US residential mortgage market, and

⁶Detailed estimation procedure can be found in Appendix B.

⁷According 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.

mortgage assets comprise 70% of their loan assets on average. They originated about 40% of total mortgages in 2011. Warehouse banks originated \$4.51 billion annually from 2011 to 2017 in 16 states on average, while some are more geographically focused than others with a standard deviation of 17 states. Warehouse banks are more concentrated in their mortgage origination activities than shadow banks. The geographic concentration index of warehouse banks is twice as large as shadow banks.⁸

Fig. 1 illustrates the warehouse lending relationships between banks and shadow banks visually in 2017 Q4. Each blue node represents a shadow bank, each green node represents a bank, and each line represents a warehouse line. Node size represents the number of warehouse lines of credit each bank or shadow bank has. Two types of warehouse lending relationships can be observed in this figure. In the center of the figure, a few banks, including both regional banks and national banks, form warehouse lending relationships with multiple shadow banks, while each of these shadow banks is also linked to several warehouse banks. As a result, a strong interconnection arises from these warehouse lending relationships; i.e., each bank forms warehouse lending relationships with very a few shadow banks that also only obtain funding from one or two such warehouse banks. Thus, interconnection between these banks and shadow banks are more restricted within individual warehouse lending relationships.

Fig. 2 zooms in on the warehouse lending relationships of the largest banks and shadow banks. Panel A shows the five warehouse banks that provided the most warehouse credit limits in 2017 Q4. Texas Capital lent to more shadow banks that did not obtain funding from the other four largest warehouse banks, whereas Bank of America, Wells Fargo, JPMorgan Chase, and UBS lent to more shadow banks that also obtained funding from one of the other four big warehouse banks, especially UBS and JPMorgan Chase, whose shadow bank borrowers were almost all linked to the other four banks. Panel B shows the five shadow banks that originated the most mortgages. All five shadow banks received warehouse funding from at least one of the big national banks in the center. Except for Caliber Home Loans, which borrowed exclusively from the national banks in center of Panel B, they also borrowed from smaller, regional warehouse banks.

III. Lending to Competitors

This section presents empirical evidence for the financing relationships between banks and shadow banks that compete in the mortgage market. I begin by laying out aggregate facts about the mortgage market competition between shadow banks and the banks that lend to them. I then examine individual warehouse lending relationships and document the clustering of warehouse lending between local competitors.

 $^{^{8}}$ The geographic concentration index is calculated as the sum of county-share squares. County-share is each originator's share of total mortgage origination in a county.

A. Aggregate Facts: Mortgage Market Competition

Aggregating total mortgage origination of different lender types over time, I find that as shadow banks grew, they directly competed with warehouse banks. Fig. 3(a) 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.⁹ 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 this period indicates that this pattern is not a mechanical result of the way market share is calculated. This plot suggests that shadow banks compete with their warehouse banks in the mortgage market. In Appendix C, I run a regression of individual bank market shares and confirm that individual warehouse banks were losing market shares to shadow banks during this sample period after controlling for bank fixed effects.

Similar market share migration patterns can be observed at the county level. Fig. 3(b) 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.

B. Warehouse Lending Clustering

Motivated by the aggregate facts, I then examine 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.

⁹See, e.g. Buchak et al. (2018a), Buchak et al. (2018b), Kim et al. (2018), Gete and Reher (2017).

B.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:

$$\% Overlap Mkt_{i,j,t} = \frac{\sum_{k} I(\sigma_{i,k,t} > 0, \sigma_{j,k,t>0})}{\sum_{k} I(\sigma_{i,k,t} > 0) + \sum_{k} I(\sigma_{j,k,t} > 0)}.$$
 (III.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:

$$MktOverlap_{i,j,t} = 1 - \frac{1}{2}\Sigma_k \left| \sigma_{i,k,t} - \sigma_{j,k,t} \right|, \qquad (\text{III.2})$$

 $MktOverlap_{i,j,t}$ 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.

B.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 IV 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. 4 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. 4. 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:

$$Pr(Lend_{i,j,t}) = \alpha + \beta \% MktOverlap_{i,j,t} + \gamma Ln(HQDistance_{i,j,t}) + \mu_{i,t} + \mu_{j,t} + \epsilon_{i,j,t}$$
(III.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 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 V 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. 4, 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. III.3 using the sub-samples. Table VI 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.

B.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 limes. 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:

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

IV. Bank Market Power in Warehouse Lending

In this section I examine whether warehouse lending relationships are essential to shadow banks' mortgage origination. If shadow banks cannot easily substitute their current warehouse lending relationships with alternative funding sources, either warehouse lines from other banks or other form of funding, then individual banks have market power in warehouse lending. This market power may affect banks' warehouse lending behavior. I begin by showing that the warehouse lending relationships are persistent. I then study whether shadow banks are able to substitute with other funding sources when their relationship banks exogenously reduce funding supply and whether such reduction in warehouse funding supply affects shadow banks' mortgage origination activities.

A. Persistent Warehouse Lending Relationship

Warehouse lending relationships between individual banks and shadow banks are persistent. Fig. 5 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%.

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:

$$Pr(Lend_{i,j,t}) = \alpha + \beta_0 PastLend_{i,j,t} + \beta_1 PastLend_{i,j,t} \times Bank_{j,t} + \mu_{i,t} + \mu_{j,t} + \epsilon_{i,j,t}.$$
(IV.1)

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 VII 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.

B. 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).

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 et al. (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 et al. (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.¹⁰ 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 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.¹¹ 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, 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.

B.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 control group over time in Fig. 6(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.

 $^{^{10}}$ 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.

¹¹DealScan covers between half and 3-quarters of the volume for outstanding commercial and industrial loans in the US.

I run the following difference-in-differences regression:

$$\hat{r}_{i,t} = \alpha + \beta HighOilShock_i \times Post_t + \gamma Post_t + \Gamma X_{i,t} + \mu_i + \epsilon_{i,t},$$
(IV.2)

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 VIII 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.

A simple plot in Fig. 6(b) 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:

$$Ln(Limit)_{i,t} = \alpha + \beta Termination_i \times Post_t + \gamma Post_t + \Gamma X_{i,t} + \mu_i + \epsilon_{i,t},$$
(IV.3)

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 VIII 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.

B.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:

$$ln(Origin_{i,k,t}) = \alpha + \beta HighOilShock_i \times Post_t + \mu_i + \mu_{k,t} + \epsilon_{i,k,t}.$$
 (IV.4)

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 IX Column (1) and (2) show the average reduction in mortgage origination in the twoyear 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. 7 (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.

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:

$$r_j = \alpha + \beta_1 LT V_j + \beta_2 DT I_j + \beta_3 FICO_j + \epsilon_j, \qquad (IV.5)$$

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,

$$R_{i,k,t} = \frac{1}{N_{i,k,t}} \sum_{j \in \mathbb{J}_i} \epsilon_j + \hat{\alpha}_t + \hat{\beta}_{1,t} \times \overline{LTV}_t + \hat{\beta}_{2,t} \overline{DTI}_t + \hat{\beta}_{3,t} \overline{FICO}_t,$$
(IV.6)

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:

$$R_{i,k,t} = \alpha + \beta HighOilShock_i \times Post_t + \mu_i + \mu_{k,t} + \epsilon_{i,k,t}.$$
 (IV.7)

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 IX 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. 7 (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.

V. Trade-off in Banks' Warehouse Lending Decisions

The two facts documented above suggest that banks have market power in warehouse lending, the rent of which is larger in lending to competing shadow banks relative to non-competitors. This section analyzes the benefits and costs in financing competing shadow banks and study how banks exploit market power in warehouse lending decisions.

On one hand, 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 noncompetitors. 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. On the other hand, 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.

A. 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 et al. (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:

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

in which R_i is the assessment-to-market ratio for property *i* and R^{med} is the median assessmentto-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.

I first divide shadow banks into the high-COD group and the low-COD group based on the local average COD in markets where they originate mortgages. Fig. 8 plots the percentage of lending relationships in each market overlap bin for the high-COD group and the low-COD group, respectively. About 25-percent of the lending relationships of in the high-COD group are formed between banks and shadow banks whose mortgage market overlap is in the top 5%, whereas about only 10% of the lending relationships in the low-COD group are formed in the top mortgage market

overlap bin. Within the sub-sample of banks and shadow banks that have the top 5% mortgage market overlap, mortgage market overlap is still a key determinant of lending relationships in the high-COD group but does not drive lending relationships in the low-COD group. In particular, as shown in Panel (b), the number of lending relationships are nearly evenly distributed across mortgage market overlap bins in the low-COD group, while significantly more lending relationships are formed between banks and shadow banks with more mortgage market overlap.

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:

$$\begin{aligned} Pr(Lend_{i,j,t}) &= \alpha + \beta_1 \% M kt Overlap_{i,j,t} + \beta_2 M kt Overlap_{i,j,t} \times High COD_{i,t} + \gamma D_{i,j,t} + \mu_{i,t} + \mu_{j,t} + \epsilon_{i,j,t}, \\ (V.2) \\ Limit_{i,j,t}) &= \alpha + \beta_1 \% M kt Overlap_{i,j,t} + \beta_2 M kt Overlap_{i,j,t} \times High COD_{i,t} + \gamma D_{i,j,t} + \mu_{i,t} + \mu_{j,t} + \epsilon_{i,j,t}, \\ (V.3) \end{aligned}$$

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 X 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 X 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.

B. Cost: Increased Mortgage Market Competition

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.

B.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:

$$Pr(WLend)_{i,k,t} = \alpha + \sum_{b} \beta_b I(MktShare_{i,k,t} \in Bin_b) + \mu_{i,t} + \mu_{k,t} + \epsilon_{i,k,t}.$$
 (V.4)

$$WLendPerAsset_{i,k,t} = \alpha + \sum_{b} \beta_b I(MktShare_{i,k,t} \in Bin_b) + \mu_{i,t} + \mu_{k,t} + \epsilon_{i,k,t}.$$
 (V.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. 9 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 XI shows the regression results with the continuous mortgage market share and bankcounty 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 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.

B.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:

$$Pr(Lend_{i,j,t}) = \alpha + \beta HighMktShare_{i,j,t} + \Gamma X_{i,j,t} + \mu_{i,t} + \mu_{j,t} + \epsilon_{i,j,t}$$
(V.6)

$$Limit = \alpha + \beta MktShare_{i,j,t} + \Gamma X_{i,j,t} + \mu_{i,t} + \mu_{j,t} + \epsilon_{i,j,t}$$
(V.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 XII 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.

C. 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:

$$\hat{r}_{i,t} = \alpha + \beta M kt Share_{i,t} + \Gamma X_{i,t} + \mu_t + \epsilon_{i,t}.$$
(V.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 XIII 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. 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.

VI. Effect on Mortgage Market Competition: A Quantitative Model

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.

A. Model Description

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 Section IV. Second, banks, which originate in the same market as shadow banks, have an advantage in lending to shadow banks (Section V). 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.

A.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:

$$u_{i,j} = -\alpha r_j + q_j + \epsilon_{i,j}.\tag{VI.1}$$

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 $F(\epsilon) = exp(-exp(-\epsilon))$.

A.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

$$\rho_j = \rho_n + \eta \rho_l, \tag{VI.2}$$

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

$$v_j(r_j|\rho_j) = (r_j - \rho_j)s_j(r_j|r_{j'})F,$$
 (VI.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 Section IV 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 costsaving 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:

$$V_{j}(\rho_{l}) = \xi_{j,l} \times \underbrace{v_{j}^{*}(\rho_{l})}_{\text{Mortgage Profit}}$$
(VI.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 $s_{j,l}^w$, is:

$$s_{j,l}^w = Pr(V_j(\rho_l) \ge V_j(\rho_{l'}), \forall l') \tag{VI.5}$$

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: $E[\max_l V_j(\rho_l)] = \sum_l s_{j,l}^w v_j^*(\rho_l)$.

 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.

A.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 $s_{j,l}^w$ 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:

$$\underbrace{(r_l^* - \rho_0)s_l^*F}_{\text{Mortgage Profit}} + \underbrace{\eta(\rho_l - c_l)\sum_{j} s_{j,l}^w(\rho_l)s_j^*F}_{\text{Warehouse Lending Profit}}$$
(VI.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}_n^j 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:

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

B. 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, 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 mortgage 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.

B.1. Mortgage Market Equilibrium

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

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

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

VI.8 and VI.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:

$$r_{l}^{*} = \arg \max_{r_{l}} (r_{l} - \rho_{0}) s_{l} F + \eta (\rho_{l} - c_{b}) N_{n}^{l} s_{n}^{l} F$$
(VI.10)
The first-order condition results in the following pricing equation for bank l:

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

B.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:

$$s_{j,l}^{w}(\rho_{l}; \{\rho_{l'}\}) = \frac{v_{j,l}^{\sigma}}{\sum_{l'} v_{j,l'}^{\sigma}}.$$
 (VI.12)

Given these choice probabilities, the expected profit of shadow bank j can be expressed as:

$$E\Pi_{j} = \left(\frac{1}{L+1} \sum_{l} v_{j,l}^{\sigma}\right)^{\frac{1}{\sigma}}.$$
 (VI.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:

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

$$N_n^l(\rho_l; \{\rho_{l'}\}) = s_l^w N_n \tag{VI.15}$$

where

$$s_{l}^{w} = \frac{\left(\frac{s_{n}^{l}}{\alpha(1-s_{n}^{l})}\right)^{\sigma}}{\sum_{l'} \left(\frac{s_{n}^{l'}}{\alpha(1-s_{n}^{l'})}\right)^{\sigma}}.$$
 (VI.16)

Bank's Optimal Warehouse Lending Pricing: I derive shadow banks' demand for warehouse lending in Eqn. VI.12. Banks' compete in the warehouse market by setting warehouse rates resulting in the following first-order condition of Eqn. VI.6:

$$\rho_l = c_l + [s_n^{l*} + \underbrace{(\eta N_n s_l^w)^{-1} (\frac{\partial r_l^*}{\partial \rho_l} s_l^* + (r_l - \rho_0) \frac{\partial s_l^*}{\partial \rho_l})]}_{\text{Internalizing Origination}} \times [-\frac{\partial s_n^{l*}}{\partial \rho_l} (1 + \frac{\sigma(1 - s_l^w)}{(1 - s_n^{l*})})]^{-1}, \quad (\text{VI.17})$$

where $\frac{\partial s_{l^*}^{l_*}}{\partial \rho_l}$, $\frac{\partial r_{l*}}{\partial \rho_l}$, 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.

C. 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 Section IV.

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 :

$$q_n = \alpha (r_n^b - r_b) - \ln(\frac{s_b}{s_n^b})$$
(VI.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:

$$\tilde{\rho}_{n}^{b} = (r_{n}^{b} - y) - \frac{1}{\alpha} \frac{1}{1 - s_{n}^{b}}$$
(VI.19)

$$\tilde{\rho}_{n}^{o} = (r_{n}^{o} - y) - \frac{1}{\alpha} \frac{1}{1 - s_{n}^{o}}$$
(VI.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:

$$\eta = \frac{\tilde{\rho}_n^b - \tilde{\rho}_n^o}{(\rho_b - y) - (\rho_o - y)} \tag{VI.21}$$

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 :

$$\rho_n - y = \tilde{\rho}_n^b - \eta(\rho_b - y) \tag{VI.22}$$

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 VI.11:

$$\tilde{c}_b = (\rho_b - y) - [(r_b - y) - \frac{1}{\alpha} \frac{1}{1 - s_b}] \frac{1 - s_b}{\eta N_n s_b^w s_n^b}$$
(VI.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. VI.16, I derive an expression for σ as a function of observed shadow bank funding choices and their mortgage market shares:

$$\sigma = \frac{\ln(s_b^w) - \ln(s_o^w)}{\ln(\frac{s_b^h}{\alpha(1 - s_n^b)}F) - \ln(\frac{s_o^n}{\alpha(1 - s_n^o)}F)} = \frac{\ln(s_b^w) - \ln(s_o^w)}{\ln(\frac{s_n^b}{1 - s_n^b}) - \ln(\frac{s_n^o}{1 - s_n^o})}$$
(VI.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 VI.17:

$$\tilde{c}_o = (\rho_o - y) - s_n^o \left[-\frac{\partial s_n^o}{\partial \rho_o} \left(1 + \frac{\sigma(1 - s_o^w)}{(1 - s_n^o)} \right) \right]^{-1}$$
(VI.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. VI.23 and warehouse lending pricing simultaneously:

$$\tilde{c}_{b} = (\rho_{b} - y) - [s_{n}^{b} + (\eta N_{n} s_{b}^{w})^{-1} (\frac{\partial r_{b}}{\partial \rho_{b}} s_{b} + (r_{b} - \rho_{0}) \frac{\partial s_{b}}{\partial \rho_{b}})] \times [-\frac{\partial s_{n}^{b}}{\partial \rho_{b}} (1 + \frac{\sigma(1 - s_{b}^{w})}{(1 - s_{n}^{b})})]^{-1}$$
(VI.26)

D. Results

The calibration results are shown in Table XIV. 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 Section IV 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.

E. 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 IV. 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 A4).

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 IV. 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 VIII). 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 IX).

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 IV 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 IV. 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 XV 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 XV, 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 VIII.

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 IX.

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.

F. 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.

F.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. 10 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 nonlocal 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 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.

F.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.¹² 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.¹³ 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 rate, shortened warehouse duration will effectively reduce warehouse lenders' stake in shadow banks' mortgage profits. As shown in banks' optimal mortgage pricing strategy (Eqn. VI.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. 11 quantifies this intuition. Panel (a)-(c) show warehouse lending market outcomes. Panel

¹² "GSE Efforts to Improve eMortgage Adoption: A Follow-up to the 2016 GSE Survey Findings Report"

¹³Some 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)

(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 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.¹⁴ 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

 $^{^{14}}$ 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.

times of fintech lenders documented in Buchak et al. (2018a) provide them with a competitive advantage in mortgage lending, and directly affect competition in the mortgage market.

VII. Conclusion

This paper characterizes a novel connection between banks and shadow banks through warehouse lending relationships. Using shadow bank call reports obtained through FOIA requests, I show that individual banks form persistent lending relationships with their competing shadow banks in the local mortgage market, and individual banks are not perfectly substitutable, giving banks warehouse lending market power. Through a set of empirical analyses, I provide evidence for a trade-off between information advantage and mortgage market competition faced by warehouse banks in their warehouse lending decisions. On one hand, conducting mortgages in the same local markets gives banks an information advantage in lending to their competing shadow banks over non-competitors. On the other hand, financing shadow banks increases mortgage market competition, lowering banks' mortgage origination profit. Banks trade off these sources of rents and exploit their warehouse lending market power to limit shadow banks' expansion in markets where the competition will benefit mortgage borrowers the most.

I then rationalize the empirical findings in a quantitative model. 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 model allows me to quantify two primary forces in the warehouse lending market: the degree of (non-)substitutability between individual warehouse lenders, and the local information advantage in terms of a lower cost of warehouse lending to the competing shadow banks. The calibration result suggests a lack of substitutability between individual warehouse lenders. A one percent increase in mortgage profits from choosing a given warehouse lender only increases the probability of take-up by 3.07 percent. The calibration result also suggests a substantial advantage of lending to competitors, which lowers their cost of lending by 74% relative to non-competitors. The lack of substitutability and local advantage grant substantial market power to banks in lending to the competing shadow banks, resulting in 30% extra mark-up relative to non-competitors.

Finally, 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 reduction in non-local banks' cost of warehouse lending would remove local banks' advantage, reducing local banks' markups by 74 basis points and raising non-local banks' markups by 31 percentage points. About 4% of the shadow banks, whose origination used to be limited by their relationship local banks through vertical restraint, switch to non-local banks to obtain funding after the removal of local banks' advantage. Increased mortgage market competition from shadow banks reduces banks' mortgage markups by 7 basis points, lowering their mortgage interest rates by 0.2 basis points. Overall, a 29 basis points cost reduction in the warehouse lending market would lower the average consumer mortgage credit by 3 basis points. This reflects that about 10% cost savings would be passed on to consumers.

The second counterfactual quantifies the welfare implications of a more efficient GSE loan purchase program. I estimate the average warehouse loan duration of 44 days. If shadow banks could sell loans in less than 5 days, they could originate more mortgages with less warehouse funding. This program would effectively reduce competitors' advantage over non-competitors in warehouse lending, and 3% of the shadow banks would switch to non-local banks to obtain funding. In the mortgage market, this program would increase shadow banks' markups by 40 basis points while it would decrease banks' markups by 6 basis points. Overall the mortgage market would become more competitive. Shadow banks and banks reduce their mortgage interest rates by 7 basis points and 0.2 basis points, respectively. In an average MSA with \$2.08 billion mortgage demand, consumer surplus will rise by \$8.21 million.

Another meaningful counterfactual is how bank regulations change banks' incentives to finance their competitors, affecting the interconnectedness between banks and shadow banks. In the baseline case, banks are not constrained, and thus they make independent decisions for each local market. As banks become constrained, they will solve their constrained optimization problems to allocate resources between mortgage origination, warehouse lending to local shadow banks, and warehouse lending to non-local shadow banks. Since banks have an advantage in lending to the competing shadow banks over non-competitors, regulatory constraints may lead to more integration through warehouse lending relationships between banks and shadow banks within local mortgage markets.

Remaining questions that this paper does not address include: To what extent do other considerations, such as risk management and regulatory arbitrage, affect banks' warehouse lending decisions? Why don't we observe banks and shadow banks merging? In other words, why do independent shadow banks exist? These could be interesting avenues for future research.

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Figure 1. Warehouse Lending Between Banks and Shadow Banks

Fig.1 plots the warehouse lending relationships between banks and shadow banks in 2017. Each blue node represents a shadow bank. Each green node represents a bank. Each line represents a warehouse line. Node size represents the number of warehouse lines of credit each bank or shadow bank has in 2017.



Figure 2. Warehouse Lending Relationships of Largest Banks and Shadow Banks

Fig.2 plots the warehouse lending relationships of the largest banks and shadow banks in 2017. Panel A shows the five warehouse banks that provided the most warehouse credit limits. Panel B shows the five shadow banks that originated most mortgages. Each blue node represents a shadow bank. Each green node represents a bank. Each line represents a warehouse line. Node size represents the number of warehouse lines of credit each bank or shadow bank has in 2017.



(a) Top 5 Warehouse Banks



(b) Top 5 Shadow Banks

Figure 3. Mortgage Market Share Migration

Fig. 3 plots the aggregate market share from 2011 by lender type. Blue solid line represents the market share of warehouse banks. Red dashed line represents the market share of non-warehouse banks. Green dotted line represents the market share of shadow banks from 2009 to 2017. Panel (a) plots warehouse bank market share growth against shadow bank growth from 2011 to 2017. Panel (b) plots non-warehouse bank market share growth against shadow bank growth from 2011 to 2017. Mortgage origination market shares are calculated using HMDA data.



(a) Aggregate Mortgage Market Share by Lender Type



(b) County-Level Market Share Growth from 2011 to 2017

Figure 4. Lending to Competitors



Figure 5. Persistent Lending Relationships

Fig. 5 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.





Figure 6 shows the effect of exogenous credit reduction on shadow bank borrowing. Panel (a) 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. Panel (b) 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.



Figure 7. Exogenous Credit Reduction and Shadow Bank Mortgage Origination

Figure 7 shows the event study for shadow bank mortgage origination. Panel (a) plots the difference-in-differences coefficients of Eqn. IV.4, where the dependent variable is the log of mortgage origination at the county-year level calculated using HMDA. Panel (b) plots the difference-in-differences coefficients of Eqn. IV.7, 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.



Figure 8. Soft Information and Financing Competitors

Fig. 8 plots the share of total credit lines (as a percentage of total credit lines between banks and shadow banks during the sample period) in each mortgage origination overlap bin for high-COD regions and low-COD regions, respectively. Panel (a) is the full-sample plot. Panel (b) focuses on the subsample of bank-shadow bank pairs whose market overlap is in the top 5% group.





Fig. 9 shows the correlation between the cost of increased competition in mortgage origination and financing competing shadow banks. Panel (a) and (b) plot 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. Panel (c) plots which shadow banks banks lend to. The sample contains pairwise observations between banks and shadow banks. The x-axis is the bank's average market share in the shadow bank's markets equally divided into 10 bins. The y-axis is the residualized probability of having a lending relationship after controlling for bank-by-year fixed effects and shadow bank-by-year fixed effects as well as market overlap.



(c) Probability of Lending Relationships

Figure 10. Counterfactual - Competitors' Advantage in Warehouse Lending

Figure 10 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.



Figure 11. Counterfactual - Warehouse Duration

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 Figure 11 plots the impact of changing the warehouse duration. The x-axis is warehouse duration. The vertical dashed line indicates the baseline. Panel (a) shows mortgage markup. Panel (f) shows consumer surplus in average MSA with \$2.08 billion mortgage demand.



Table I 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.

	Ν	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			

	Ν	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			

Panel B:	Bank Sum	mary Statist	ics 2011Q1	-2017Q4

Table II 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 IIITop 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 Credit Limit (Billion)	Number of Borrowers	Average 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 IV Pairwise Measures Summary Statistics

Table IV 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 warehouse bank. 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: $\% OverlapMkt_{i,j,t} = \frac{\sum_k I(\sigma_{i,k,t} > 0, \sigma_{j,k,t} > 0)}{\sum_k I(\sigma_{i,k,t} > 0) + \sum_k I(\sigma_{i,k,t} > 0)}$. Market Overlap measures geographic market distribution overlap: $MktOverlap_{i,j,t} = 1 - \frac{1}{2}\sum_k |\sigma_{i,k,t} - \sigma_{j,k,t}|$, where $\sigma_{i,k,t} = \frac{LoanVolume_{i,k,t}}{\sum_k LoanVolume_{i,k,t}}$ 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						
	Ν	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: Ur	matched Pairs			
	Ν	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 VLending to Competitors

Table V 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. $1 - \frac{1}{2}\Sigma_k |\sigma_{i,k,t} - \sigma_{j,k,t}|$, 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 Rel	ationship) (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		х		x
Shadow Bank×Year FE		х		х
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 Limi	t (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		х		х
Shadow Bank×Year FE		х		х
Num of Observations	6,726	$5,\!906$	6,726	$5,\!906$
R2	0.172	0.791	0.153	0.790

Table VI Lending to Competitors: Sub-Sample Robustness

Table VI shows the sub-sample analysis of lending relationship sorting. I estimate Eqn. III.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: % O	verlapped Marke	ts		
			Pr(Lending Relat	tionship) (pp)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Concentrated	Dispersed	Small (Origin. Vol.)	Big (Origin. Vol.)	Small (Asset)	$\underset{(Asset)}{\operatorname{Big}}$
Ln(HQ Distance)	-1.343^{***}	-0.811^{***}	-1.482^{***}	-0.657^{***}	-1.494^{***}	-0.611^{***}
% Overlapped Markets	(0.207) 8.184** (4.074)	(0.109) 31.026^{***} (7.586)	(6.253) 11.553* (6.463)	(6.212) 26.873^{***} (6.483)	(5.243) 15.387^{***} (5.574)	(0.139) 21.320*** (7.600)
Bank×Year FE	х	x	x	x	x	x
Shadow Bank \times Year FE	х	x	х	х	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: I	Market Overlap			
			Pr(Lending Relat	tionship) (pp)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Concentrated	Dispersed	Small (Origin. Vol.)	Big (Origin. Vol.)	Small (Asset)	$\begin{array}{c} \operatorname{Big} \\ (\operatorname{Asset}) \end{array}$
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	х	х	x	х	х	х
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 VII Persistent Lending Relationships

Table VII reports the coefficients from the following regressions:

$Pr(Lend_{i,j,t}) = \alpha + \beta_0 PastLend_{i,j,t} + \beta_1 PastLend_{i,j,t} \times LenderType_{j,t} + \beta_2 X_{i,t} + \beta_3 X_{i,t} \times LenderType_{j,t} + \epsilon_{i,j,t} + \beta_1 PastLend_{i,j,t} \times LenderType_{j,t} + \beta_2 X_{i,t} + \beta_3 X_{i,t} \times LenderType_{j,t} + \beta_1 PastLend_{i,j,t} \times LenderType_{j,t} + \beta_2 X_{i,t} + \beta_3 X_{i,t} \times LenderType_{j,t} + \beta_1 PastLend_{i,j,t} \times LenderType_{j,t} + \beta_2 X_{i,t} + \beta_3 X_{i,t} \times LenderType_{j,t} + \beta_1 PastLend_{i,j,t} \times LenderType_{j,t} + \beta_2 X_{i,t} \times LenderType_{j,t} + \beta_3 X_{i,t} \times LenderType_{j,t} + \beta_3 X_{i,t} \times LenderType_{j,t} + \beta_4 X_{i,t} \times LenderType_{j,t} \times LenderT$

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 $\Delta NITA$) 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.

		$\Pr(\text{Lending}) (pp)$			
	(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)	
$Bank \times Ln(Asset)$			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 Δ NITA			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	х	х			
Lender×Shadow Bank FE				х	
Year FE			х	х	
Observations	685,920	685,920	582,936	579,004	
R2	0.629	0.630	0.704	0.822	

Table VIII Exogenous Credit Reduction and Shadow Bank Borrowing

Table VIII 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)		$\operatorname{Ln}(\operatorname{Limit})$	
	(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	х		
Shadow Bank Controls		х		x
Shadow Bank \times Cohort FE			х	х
Observation	837	747	1,823	1,783

Table IX Exogenous Credit Reduction and Shadow Bank Mortgage Supply

Table IX shows the result of regression IV.4 and IV.7. 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 l	Interest Rate
	(1)	(2)	(3)	(4)
HighOilShock×Post	-0.171^{***} (0.015)	-0.176^{***} (0.015)	$\begin{array}{c} 0.142^{***} \\ (0.015) \end{array}$	$\begin{array}{c} 0.108^{***} \\ (0.013) \end{array}$
Shadow Bank FE	x	х	x	x
County (Zip Code) FE	х		х	
Year (Quarter) FE	х		x	
County (Zip Code)×Year (Quarter) FE		х		х
Observation	$113,\!614$	112,809	78,361	77,086
R2	0.511	0.526	0.388	0.586
Table X Soft Information and Warehouse Lending

Table X reports the coefficients from the following two regressions:

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

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. $1 - \frac{1}{2}\Sigma_k |\sigma_{i,k,t} - \sigma_{j,k,t}|$, 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, respectively.

	Pr(Lending Relation)		Credit Lin	nit (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	х	x	х	x
Shadow Bank×Year Fixed Effects	х	х	х	х
Num of Observations	246,442	246,442	5,745	5,745
R2	0.116	0.118	0.791	0.789

Table XI In Which Markets Do Banks Finance Competitors?

Table XI 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(Warehou	se Lending)	Warehouse Lending/Asset
	(1)	(2)	(3)
	All Counties	Origination Counties	Origination Counties
% Bank Total Origin.	118.501^{***} (15.467)	27.238*** (6.305)	4.253^{***} (1.420)
Local Market Share	×	-22.063^{*} (12.644)	-0.427*** (0.150)
$Bank \times Year FE$	х	х	x
County×Year FE Observations R2	x = 2,282,592 = 0.550	x 201,904 0.618	$x \\ 199,742 \\ 0.256$

Table XIIWhich Shadow Banks Do Warehouse Banks Lend to?

Table XII 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 Lim	it (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	х	x	x	x
Shadow Bank×Year Fixed Effects	х	х	х	х
Observations	255,517	255,517	$5,\!906$	$5,\!906$
R2	0.115	0.116	0.792	0.790

Table XIII Shadow Bank Cost of Funding

Table XIII 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-Adjusted Portfolio 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)
$\operatorname{Ln}(\operatorname{Origin})$	-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		х		х
Observations	$1,\!194$	$1,\!191$	1,194	1,191
R2	0.095	0.096	0.103	0.102

Table XIV Model Calibration

Table XIV reports the calibrated parameters.	Top panel	shows the	mortgage marke	et parameters.	Bottom panel
shows the warehouse lending market parameters	s.				

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
$\tilde{ ho}_n$	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 XV Verification of Model Parameters

Table XV 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: V	Warehouse Lendin	g Market Equilibriu	m	
	Loca	l Banks	Non-Lo	ocal 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) Unshocked Bank (pp)	5.63 5.67	$6.23 \\ 5.68$	$\begin{array}{c} 0.60\\ 0.01 \end{array}$	

Panel C: Average Shadow Bank Mortgage Interest Rates				
	(1) Pre-Shock	(2) Post-Shock	(3) Difference	
Shadow Banks Financed by Shocked Banks (pp) Shadow Banks Financed by Unshocked Banks (pp)	2.31 2.32	$2.41 \\ 2.32$	$\begin{array}{c} 0.10\\ 0.00 \end{array}$	

APPENDIX

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 ¹⁵, 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;; 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.

 $^{^{15} \}rm https://www.sec.gov/Archives/edgar/data/1095996/000119312504134234/dex102.htm$

Appendix B. Data

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. A2a 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. A2b 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:

$$Warehouse Expense_{i,q} = (1 + r_{i,t}^{daily} + Qave_Libor_{i,q})^{90} \times LineUsage_{i,q} - LineUsage_{i,q} - LineUsage_{i,q} + LineUsage_{i,q} - LineUsage_{i,q} + LineUsage_{i,q} - LineUsage_{i,q} + LineUsag$$

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 agreement¹⁶.

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.

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,

 $^{^{16}\}mathrm{A}$ 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

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

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:

$$\Delta MktShare_i = \alpha + \beta I(Warehouse_i) + \Gamma X_i + \epsilon_i, \tag{C1}$$

$$MktShare_{i,t} = \alpha + \Sigma_t \beta_t I(Warehouse_i) \times I(Year = t) + \Sigma_t (X_i \times I(Year = t))' \Gamma_t + \mu_i + \mu_t + \epsilon_{i,t} \quad (C2)$$

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 A2 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 A1 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.

Oil Shock

I begin with analyzing the impact of the oil price decline on bank warehouse lending. Fig. A4 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. A4(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. A4(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. A4(c) shows that the high O&G exposure banks had smaller growth in tier 1 capital relative to the low 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:

$$Ln(Limit)_{i,j,t} = \alpha + \beta HighOilShock_{i,j} \times Post_t + \gamma Post_t + \Gamma X_{i,t} + \mu_{i,j} + \epsilon_{i,j,t}$$
(C3)

$$\Delta Ln(Limit)_{i,j} = \alpha + \beta HighOilShock_{i,j} + \mu_i + \epsilon_{i,j} \tag{C4}$$

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:

$$Termination_{i,j} = \alpha + \beta HighOilShock_{i,j} + \mu_i + \epsilon_{i,j}$$
(C5)

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 A4 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 Figures and Tables

Figure A1

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.



Figure A2. 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.





(b) Sample Size Distribution in 2017 Dollar

Figure A3. Heterogeneity in Financing Competing Shadow Banks

Fig. A3 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 A4. 2014 Oil Price Shock

Fig. A4 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 (b) Change of Non-C&I Loan Delinquent Charge-off Rate from 2014Q2

and Charge-off Rate from 2014Q2



(c) Change of Warehouse Bank Tier 1 Cap- (d) Total Warehouse Lending Changes from ital from 2014Q22014Q2

Table A1 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	Ν	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
		Р	anel B: Count	y			
Year	Ν	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

0.56

0.56

0.59

0.2

0.2

0.21

0.44

0.44

0.47

0.58

0.59

0.63

0.71

0.72

0.74

2015

2016

2017

2,947

2,939

2,950

0.93

0.91

0.90

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Table A2 Warehouse Lending and Bank Market Share Decline

Table A2 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)	(2)	(3)	(4)
	$\Delta MktShare$ (bps	$\Delta MktShare (bps)$	Δ MktShare (bps)	Market Share (bps)
Warehouse Bank	-12.579^{***} (1.859)	-5.559^{***} (2.046)	-0.729** (0.303)	
Baseline: Warehouse Bank×Year 2011				
Year=2012				-0.738
Year=2013				(0.798) -1.568 (1,384)
Year=2014				(1.364) -3.638 (2.245)
Year=2015				(2.245) -4.146*
Year=2016				(2.344) -4.907*
Year=2017				(2.605) -5.408* (3.073)
Bank Controls		x	x	x
Local Controls Bank FE Year FE		х	х	x x 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

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Table A3 Lending Relationship and Geographical Proximity

Table A3 reports the coefficients from a linear probability model:

Table A3 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)			
Residential Mortgage Share of Asset	0.089***			
	(0.023)			
Loan to Nondepository Financial Ins. Share of Asset	0.393***			
	(0.135)			
C&I Loan Share of Asset	0.095***			
	(0.034)			
Core Deposit Share	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 A4Oil Shock and Warehouse Lending Reduction

Table A4 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)	(2)	(3)	(4)
	Ln(Limit)	Δ Ln(Limit)	I(Termination)	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		х	
Bank Controls			х	х
Shadow Bank Fixed Effects		х		х
Credit Line Fixed Effects	х			
Number of Observations	5,987	495	482	660
R2	0.009	0.008	0.062	0.060

Table A5Do Shadow Banks Enter High-Interest Rate Counties?

Table A5 reports results of the following regression:

$$\Delta ShadowMktShare_{k} = \alpha + \beta_{1}R_{k}^{2009} + \beta_{2}WbMktShare_{k}^{2009} + \beta_{3}R_{k}^{2009} \times WbMktShare_{k}^{2009} + \epsilon_{k}R_{k}^{2009} + \epsilon_{k$$

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^{*} (0.256)	0.457^{*} (0.256)	0.768^{***} (0.297)	0.772^{***} (0.297)	0.787^{**} (0.345)	0.770^{**} (0.344)	
Warehouse Bank Market Share in 2009			0.870^{***} (0.265)	0.745^{***} (0.265)			
Rate Res.×Wb. Mkt. Share in 2009			-0.506^{**} (0.242)	-0.480^{**} (0.241)			
High Wb. Mkt. Share in 2009					4.027^{***} (0.520)	3.979^{***} (0.517)	
Rate Res.×High Wb. Mkt. Share in 2009					(0.526) -0.859^{*} (0.508)	-0.769 (0.506)	
County Controls		x		x		x	
Num. of Observations R2	$3,124 \\ 0.001$	$3,124 \\ 0.012$	$3,124 \\ 0.007$	$3,124 \\ 0.017$	$3,124 \\ 0.024$	$3,124 \\ 0.034$	