Mortgage Aggregation and Credit Supply*

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December 12, 2024

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Abstract

One third of U.S. mortgages are originated by small correspondent lenders and then aggregated and securitized by large aggregators. Despite the considerable size and importance of aggregators in channelling funding to the housing market, our understanding of this market remains limited. I construct a novel dataset on correspondent lender-aggregator relationships to study the causal effect of mortgage aggregation on credit supply. Exploiting the U.S. implementation of Basel III as a negative shock to aggregation, I find a significant impact on credit supply, especially to low-income borrowers. Matching frictions in the aggregation market contribute to the overall credit supply decline, while aggregators' optimal portfolio reallocation and correspondent lenders' specialization across demographic groups drive the unequal impact on low-income borrowers. My results highlight the important role of mortgage aggregation in reducing securitization frictions and expanding credit access.

JEL Codes: G2, L5

Keywords: Financial intermediation; Mortgage market structure; Mortgage servicing rights; Shock transmission

*First draft: September 2023. I would like to thank Jack Favilukis, Thomas Davidoff, Isha Agarwal, Lorenzo Garlappi, Markus Baldauf, Kai Li, Will Gornall, Elena Pikulina, Bo Bian, Alberto Teguia, Ali Lazrak, Xudong An, Richard Stanton, Erica Jiang, Cameron LaPoint, Michael Sockin, Andrey Pavlov, Deniz Anginer, Feng Liu, Guangli Lu, Xiyue Li, Dongliang Lu, Andrew MacKinlay, You Suk Kim, Artem Joukov, Sami Vähämaa and seminar and conference participants at the University of British Columbia, Simon Fraser University, Financial Management Association Annual Conference, Northern Finance Association Annual Conference, The Mortgage Market Research Conference at the Federal Reserve Bank of Philadelphia and AREUEA PhD session for useful comments. All errors are my own.

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1 Introduction

The residential mortgage market is the largest consumer credit market in the United States and vital to the nation's financial stability and economic growth. A distinctive feature of this market is the extensive use of securitization, which plays a crucial role in channelling funds to the housing market and expanding access to homeownership. Within the securitization process, a less studied yet important step is mortgage aggregation, where aggregators purchase mortgages for securitization from correspondent lenders.[1] In the U.S. mortgage market, 70% of lenders rely on this process for securitization and 30% to 50% of securitized mortgages pass through the aggregation market before being securitized through Fannie Mae, Freddie Mac, or Ginnie Mae, see Figure 1. How aggregation shapes lending is thus central for understanding shock transmission and credit distribution in the mortgage market. Despite this, our knowledge about mortgage aggregation remains limited.

In this paper, I show that the aggregation market is essential for expanding credit access. For aggregators, a significant benefit of aggregation is the acquisition of mortgage servicing rights (MSRs). Using a surprisingly punitive increase in the risk weight of MSRs under Basel III as a negative shock to aggregation, I find that a one standard deviation increase in a correspondent lender's exposure to the decrease in mortgage aggregation volume leads to a 12.5% reduction in lending. The effect is even more pronounced for low-income borrowers, who experience a 4.5% greater decline in credit supply and face worse credit access. Aggregation enables correspondent lenders to enhance their mortgage origination capacity by freeing up their balance sheets. Moreover, aggregation allows correspondent lenders to specialize in serving low-income borrowers by operating in areas with high entry costs for large aggregators. I show that matching frictions between aggregators and correspondent lenders prevent correspondent lenders from switching to other forms of funding or selling

[1] Aggregators are usually large mortgage lenders, for example, Wells Fargo and Bank of America. Correspondent lenders are usually small community banks or shadow banks, which sell their originated mortgages to non-affiliated aggregators. Examples of correspondent lenders include Hendricks County Community Bank and Odyssey Funding LLC.

directly to the agencies. These findings suggest that aggregation significantly shapes the quantity and composition of available credit in the mortgage market.

There are two major challenges in testing the effect of mortgage aggregation on credit supply. The first is measurement: there is no publicly available dataset on mortgage aggregation within the securitization market dominated by Fannie Mae, Freddie Mac and Ginnie Mae. The second challenge is identification. The equilibrium aggregation amount depends on both aggregators' demand for mortgages and correspondent lenders' supply of mortgages for sale.

To address the first challenge, I construct a new dataset on aggregator-correspondent lender relationships by combining data on originated and aggregated mortgages from the Home Mortgage Disclosure Act (HMDA). Using this dataset, I examine how aggregation can influence the lending activities of correspondent lenders.

To address the second challenge, I use a difference-in-differences approach based on the implementation of the Basel III capital requirements on mortgage servicing rights (MSRs) in 2013. A mortgage servicing right is an asset that is created when the act of servicing is contractually separated from the underlying loan.[2] The servicer (i.e., financial institutions that hold MSRs) collects monthly payments from borrowers and distributes them to the relevant investors. Mortgage servicing is a scale business, where the value of MSRs generally increases with the volume of mortgages serviced. Large aggregators can absorb the fixed costs of setting up a servicing system and thus profit more by servicing larger volumes of mortgages, while smaller correspondent lenders, who typically lack such scale, often do not retain these rights. When aggregators acquire mortgages from correspondent lenders, they usually obtain the associated MSRs.

In 2013, the U.S. implementation of the Basel III Accord unexpectedly increased the risk weight of MSRs from 100% to 250% and lowered the cap on the value of MSRs

[2]See the definition in https://www.federalreserve.gov/publications/2016-capital-rules-mortgage-servicing-assets-Evolution-of-the-Mortgage-Servicing-Market-since-1998.htm

relative to a bank's common equity from 50% to 10% (Irani, Iyer, Meisenzahl, and Peydró, 2021). This unanticipated regulatory change reduced the appeal of the aggregation business for banks, as aggregation is a key method for acquiring MSRs. Using the 10% cap on MSRs relative to a bank's common equity, I construct a measure of correspondent lenders' regulatory exposure to MSRs based on their business relationships with affected aggregators. Specifically, this measure captures the *ex-ante* fraction of mortgages sold to bank aggregators whose MSR/Tier 1 capital ratio exceeded the 10% threshold before the regulation was announced.

My difference-in-differences approach compares credit supply before and after the policy change among correspondent lenders with varying levels of exposure within the same county and year. Using the correspondent Lender×County level analysis, I find that correspondent lenders with greater *ex-ante* exposure to aggregators affected by the regulatory change experience a larger decline in mortgage aggregation volume. Furthermore, this decline in aggregation leads to a reduction in mortgage originations of correspondent lenders. Specifically, a one standard deviation increase in a correspondent lender's exposure to the regulatory change results in a 12.5% decrease in their origination volume.

I further examine if the results are subject to endogenous concerns such as non-random matching between correspondent lenders and aggregators, direct impact from Basel III Accord on depository correspondent lenders, heterogeneous demand for correspondent lenders with different shock exposure. In addition, I discuss if the results can be explained by confounding events such as guarantee fee change, litigation risks and put-back risks. The above results establish that the regulatory shock affected the credit supply of individual correspondent lenders.

However, if other lenders can fill the void, aggregate credit supply need not be adversely affected. The remainder of the paper shows that aggregate credit supply does fall because it is not easy for other lenders to step in. It also shows that low-income borrowers are the most affected by the reduction in credit. To study aggregate credit supply, I extend the analysis to the county level. I construct a county-level exposure measure that reflects the ex-ante share of mortgages sold to aggregators affected by the Basel III capital requirements on MSRs. This measure allows me to explore the disruption in the aggregation market by assessing both the extensive and intensive margins of credit supply.

I examine the effect on the number of correspondent lenders providing credit and the overall credit in local markets. I find that, compared to counties with no exposure to the aggregation market, counties where 100% of originated mortgages are sold to affected aggregators see two fewer correspondent lenders after the regulatory shock and experience 10% larger decline in lending. I further show that the decline in credit supply disproportionately affects low-income borrowers. Specifically, a one standard deviation increase in county-level exposure to the aggregation market results in a 1.44% decrease in overall credit supply and a 2.16% decrease for low-income borrowers. These findings demonstrate that the Basel III capital requirements on MSRs not only reduces correspondent lender credit supply but also significantly impacts overall credit availability at the county level, with low-income borrowers disproportionately affected.

In the final part of my paper, I provide evidence that funding market frictions drive the credit supply decline. In addition, aggregation choices of aggregators and the specialization of correspondent lenders lead to unequal impacts on low-income borrowers.

I provide evidence on correspondent lenders' funding market frictions. Correspondent lenders face frictions in substituting funding between different aggregators. The relationship between correspondent lenders and aggregators is sticky; conditional on having sold to a particular aggregator in the past period, a correspondent lender has a 45% higher likelihood of maintaining that relationship in the current period. This stickiness underscores the significance of search frictions in the correspondent lender-aggregator relationships. Additionally, correspondent lenders cannot fully offset reduced aggregation volumes from one aggregator by selling to others. Lenders whose relationships with aggregators are more concentrated or who have fewer nearby aggregators experience larger reductions in origination following a decrease in aggregation volume. I also examine other choices available to correspondent lenders, such as establishing new relationships with agencies and raising deposit funding. Frictions in switching to these alternative options further lead to a decrease in funding and a decline in origination.

Next, I show that aggregators' portfolio reallocation and correspondent lender specialization lead to unequal impacts on low-income borrowers. First, I show that aggregators' behaviour shapes the origination decision of correspondent lenders. Facing high capital costs of holding mortgage servicing rights, aggregators make aggregation decisions to prioritize their own origination and reduce risk-taking in servicing. I show that aggregators reduce the aggregation for lenders with high market overlap and loans perceived as high risk. The change in aggregation preference is reflected in the origination market: correspondent lenders reduce origination more for low-income borrowers and borrowers in low-income areas.

Second, I explore the role of correspondent lenders in originating mortgages for low-income borrowers. After accounting for borrower characteristics and location, I find that low-income borrowers are more likely to apply for mortgages through correspondent lenders, indicating a preference for these lenders. Additionally, when low-income borrowers do apply, correspondent lenders are 28% less likely to reject their applications than other lenders while maintaining similar default rates. They are also less likely to reject applications due to incomplete submissions or unverifiable information, suggesting that correspondent lenders may have access to soft information or offer better origination services to low-income borrowers.

Taken together, my results imply that aggregation significantly shapes the credit supply of correspondent lenders. It is crucial for policymakers to consider the role of the aggregation market in affecting credit access, particularly for low-income borrowers.

The rest of the paper proceeds as follows. Section 2 connects my paper to the related literature. Section 3 briefly describes institutional features of the mortgage servicing industry and data used in the empirical analysis. Section 4 describes my empirical strategy and introduces the measure construction. Section 5 presents my main findings on mortgage aggregation and credit supply. Section 6 and 7 discuss the forces that drive the reduced credit access. Section 8 presents the robustness tests. Section 9 concludes.

2 Related Literature

My paper contributes to the literature on the relationships between financial institutions in over-the-counter financial markets. While the over-the-counter markets for federal funds, interbank lending, corporate bond, credit default swaps, municipal bonds, asset-backed securities, and currencies have been widely studied,[3] the over-the-counter market for mortgages, specifically the aggregation market, has received less attention. Using data on all private-label, fixed-rate mortgages before the financial crisis, Stanton, Walden, and Wallace (2014, 2018) construct an aggregation network and highlight the financial fragility in the U.S. mortgage market due to the interconnectedness of mortgage lenders. Focusing on Ginnie Mae loans, Benson, Kim, and Pence (2023) analyze the impact of mortgage issuer composition on credit supply through the aggregation market. Building on this literature, my paper is among the first to construct mortgage correspondent lender-aggregator relationships after the financial crisis and analyze how this structure influences the impacts of banking regulations on lending.

My paper also relates to the extensive literature on shock transmission through financial intermediation.[4] Financial or regulatory shocks propagate through the supply chain, lending relationships, and international trade (Acemoglu and Tahbaz-Salehi, 2020; Craig and Ma, 2022; Xu, 2022). The strength and timing of shock transmission depend on

[3] See, e.g. Bech and Atalay (2010); James, Marsh, and Sarno (2012); Afonso, Kovner, and Schoar (2013); Peltonen, Scheicher, and Vuillemey (2014); Hollifield, Neklyudov, and Spatt (2017); Li and Schürhoff (2019); Friewald and Nagler (2019); Craig and Ma (2022); Huber (2023)

[4] See, e.g. Chodorow-Reich (2014); Xu (2022); Acemoglu and Tahbaz-Salehi (2020); Craig and Ma (2022)

the relationships between firms and financial institutions and vary by market. In the mortgage market, previous research has examined how securitization shocks transmit to the housing market and the real economy.[5] However, previous shocks often abstract from the structure of the mortgage aggregation market. Using Basel III capital requirements on mortgage servicing rights as a natural experiment, my paper investigates how a regulatory shock transmits through the mortgage aggregation market. Related to the literature that examines the regulatory impact of post-financial crisis banking reforms,[6] my paper underscores an important consideration for policymakers: overlooking the mortgage aggregation market could lead to underestimating the impact of regulation due to the close links between mortgage servicing rights, aggregation, and the strategic behaviour of market participants in origination and aggregation.

Finally, my paper contributes to the literature on the development of the U.S. mortgage market after the Global Financial Crisis. This literature has highlighted two major trends during this period: first, the rise of shadow banks in mortgage origination, servicing, and the issuance of mortgage-backed securities;[7] and second, the decline in low-income credit and small mortgages, particularly in the FHA market.[8]. Among these papers, Buchak, Chau, and Jørring (2023); Hamdi, Jiang, Lewis, Padi, and Pal (2023) and Agarwal, Hu, Roman, and Zheng (2023) use the same banking regulation shock to study the transfer of mortgage servicing rights on mortgage market. My paper differs from these papers in at least three ways: first, my paper emphasizes the complementarity between mortgage servicing and mortgage aggregation and studies the frictions in the

[5]See, e.g. Mian and Sufi (2009); Piskorski, Seru, and Vig (2010); Mian and Sufi (2014); Loutskina and Strahan (2015); Gete and Reher (2021); Mian and Sufi (2022)

[6]See, e.g. Kashyap, Stein, and Hanson (2010); Cosimano and Hakura (2011); Bichsel, Lambertini, Mukherjee, and Wunderli (2022); Auer, Matyunina, and Ongena (2022)

[7]See, e.g. Buchak, Matvos, Piskorski, and Seru (2018); Fuster, Plosser, Schnabl, and Vickery (2019); Jiang, Matvos, Piskorski, and Seru (2020); Gete and Reher (2021); Buchak, Chau, and Jørring (2023); Hamdi, Jiang, Lewis, Padi, and Pal (2023); Chu, Zhang, and Zhang (2023); Blank, Highfield, and Yerkes (2022); Benson, Kim, and Pence (2023); D'Acunto and Rossi (2022); DeFusco, Johnson, and Mondragon (2020); Agarwal, Hu, Roman, and Zheng (2023)

[8]See, e.g. Frame, Gerardi, Mayer, Xu, and Zhao (2024); Bhutta, Laufer, and Ringo (2017); D'Acunto and Rossi (2022)

aggregation market instead of servicing transfer market; second, my paper highlights the information asymmetry between participants in the aggregation market, while Hamdi, Jiang, Lewis, Padi, and Pal (2023) and Buchak, Chau, and Jørring (2023) focus on the agency conflicts between originators, servicers and investors and Agarwal, Hu, Roman, and Zheng (2023) points out the key funding model difference between banks and shadow banks with mortgage servicing rights; third, my paper shows how aggregation, as a funding source could impact credit supply to home purchase, while these papers examine the transfer of mortgage servicing rights on refinance, foreclosures and monetary policy transmission, respectively.

In addition, this paper is closest to Benson, Kim, and Pence (2023) and Frame, Gerardi, Mayer, Xu, and Zhao (2024). Both focus on the FHA mortgage market; the former examines the impact of the exit of large aggregators on credit standards and interest rates, while the latter investigates the decline in credit access for low-income borrowers in the FHA market due to litigation risks faced by large banks. My paper expands on these studies by examining both the conventional and FHA markets and introducing a new contributing factor—the decline in aggregation—as a driver of reduced credit access for low-income borrowers. This paper also identifies how aggregation market matching frictions contribute to the decline in mortgage lending to disadvantaged borrower groups, complementing other research on supply-side frictions in the credit market.[9]

[9] See, e.g. Frame, Gerardi, Mayer, Xu, and Zhao (2024); Jiang, Yu, and Zhang (2022); Cespedes, Jiang, Parra, and Zhang (2024); Huang, Linck, Mayer, and Parsons (2024); Frame, Huang, Mayer, and Sunderam (2021); Hurtado and Sakong (2022)

3 Institutional Background and Data

3.1 Mortgage Market Structure

Mortgage lending generally occurs through the retail, wholesale, or correspondent lending channels.[10] In the retail channel, lenders handle the entire origination process directly with consumers and track mortgage applications throughout the closing process. In the wholesale channel, mortgage brokers, working as independent contractors, collaborate with multiple mortgage lenders to offer mortgage products to consumers. However, they do not make credit decisions nor fund the mortgages. In the correspondent lending channel, correspondent lenders fund their mortgage originations and independently manage the origination process. These lenders sell the originated mortgages to wholesale lenders (aggregators) based on pre-arranged pricing commitments. They can also sell mortgages to wholesale lenders through loan exchange platforms, such as Optimal Blue.

In this paper, I focus on the correspondent lending channel, highlighting mortgage aggregation behaviour in the U.S. mortgage market. Figure 2 illustrates the flow of funds when a mortgage is originated and then sold to aggregators and securitizers. In the diagram, both aggregators and correspondent lenders can originate mortgages. Without direct relationships with securitizers, correspondent lenders sell mortgages to aggregators to secure funding for originating new loans. Aggregators, in turn, sell most of these mortgages to securitizers. Figure 4 shows the fraction of purchasers of aggregated mortgages. Over 80% of the mortgages that aggregators purchase are sold to agencies, with only a small fraction remaining on their balance sheets within the same year. This percentage is similar to the fraction of originated mortgages that remain on their balance sheets during the current year.[11]

[10] https://files.consumerfinance.gov/f/2012/01/Mortgage-Origination-Examination-Procedures.pdf

[11] One caveat of the Home Mortgage Disclosure Act (HMDA) data is that it only reports the action of mortgages in the current year. If a mortgage is originated in the current year and sold in the next year, it is recorded as unsold in HMDA. It is possible that the unsold mortgages will be sold next year.

The costs associated with establishing business relationships with agencies have contributed to the rise of correspondent lenders. To form a business relationship with Fannie Mae, Freddie Mac, or Ginnie Mae, lenders must undergo a lengthy application process–typically over 21 weeks–meet strict eligibility requirements and maintain financial stability. By selling to large aggregators with direct relationships with these government-sponsored enterprises (GSEs), correspondent lenders avoid the need to comply with these agency requirements themselves. Government-sponsored enterprises also avoid the costs of establishing relationships with small lenders and the accompanying counterparty risks and reputation risks.

The system became even more attractive with the separation of mortgage servicing from origination in the 1980s. Under pressure to increase earnings and liquidate the assets of failed institutions with mortgage operations, the mortgage industry disintegrated and developed a market for trading servicing rights. Among industry practitioners, mortgage servicing is considered a scale business, with the value of mortgage servicing rights positively correlated with the volume of underlying loans serviced. Large lenders accumulate mortgage servicing rights to benefit from economies of scale, while smaller lenders prefer to sell mortgages with the servicing rights released, receiving a servicing premium upfront. This arrangement benefits both aggregators and correspondent lenders: aggregators leverage economies of scale in servicing, while correspondent lenders face lower entry barriers since they can focus solely on origination.

Following the Global Financial Crisis, failed shadow banks, such as Countrywide, sold their correspondent lending and servicing businesses to large banks. Coupled with the volume discounts on guarantee fees provided by Fannie Mae and Freddie Mac,[12] large banks like Wells Fargo, Bank of America, and JPMorgan Chase accumulated significant servicing

[12] Fannie Mae and Freddie Mac offered bulk discounts when large banks delivered a high volume of mortgages for securitization. Pricing was based on bilateral negotiations and aimed to increase liquidity in the to-be-announced (TBA) market and mitigate operational risks from small lenders. However, this practice was criticized for creating unequal participation in the securitization market.

portfolios and expanded their aggregation businesses. Although the aggregation business declined after Fannie Mae and Freddie Mac adopted guarantee fee parity to increase market competition in 2011, it remains an active segment of the mortgage market.

3.2 Data Sources

In this section, I describe the data sources. I use Home Mortgage Disclosure Act (HMDA) data, Fannie Mae and Freddie Mac Single Family Loan Level Data, Attom Real Estate Transaction data, and bank and shadow bank call reports. I describe the data sources below.

Home Mortgage Disclosure Act (HMDA): I observe the mortgage origination and aggregation activity of lenders using the HMDA dataset. HMDA is the most comprehensive information source of the U.S. mortgage market, covering around 90% of the origination. It requires financial institutions that meet minimum asset and loan origination thresholds to disclose information about the applications for, originations and purchase of covered mortgages, including home purchases and refinances for each calendar year. The dataset contains a rich set of characteristics about the lender, borrower, and mortgage at the application level. I observe the loan characteristics, such as loan amount, location of collateral, and borrower characteristics, such as income, race, and ethnicity. For lenders, I observe their name and address, as well as a unique lender identifier. HMDA defines originators as entities that independently make the underwriting and funding decisions of newly originated mortgages. If a lender does not make underwriting decisions, e.g. a mortgage originated through the wholesale channel via brokers, then the origination is attributed to the wholesale lender.[13] HMDA also reports the covered loans purchased by the covered financial institutions after closing.

Fannie Mae and Freddie Mac Single Family Loan Level Data: I observe the key mortgage contract terms and loan performance using the Fannie Mae and Freddie Mac

[13] https://www.consumerfinance.gov/rules-policy/regulations/1003/4/#a

Single Family Loan Level Dataset. The dataset includes long-term, fixed-rate, conforming mortgages sold to Fannie Mae and Freddie Mac and provides key mortgage contract terms such as loan-to-value ratio (LTV), debt-to-income ratio and FICO score. It also includes the seller name, servicer name, first payment date and geographical information of the property. In addition, it tracks the loan performance at the monthly level. This dataset supplements HMDA data by offering mortgage risk measures and loan performance.

Attom Real Estate Transaction Data: Attom Real Estate Transaction data provides transaction information for the U.S. dating back to the early 1990s, covering over 2,750 counties. The dataset includes details such as transaction price, transaction date, housing characteristics, and the exact location of the property. It also provides basic mortgage information, such as loan amount, loan-to-value ratio, and lender name.

Call report data: I obtain the bank call reports data from Wharton Research Data Services (WRDS), which contains balance sheets and income statements for banks and savings banks. I get credit union call reports data from the National Credit Union Administration. Finally, I acquire shadow bank call reports data by submitting FOIA requests to Massachusetts and Washington following Jiang (2023).

3.3 Sample Construction

In this section, I describe the process of constructing the datasets. I construct several datasets on application and origination activities. More importantly, I construct a novel dataset on aggregation activities, shedding light on the correspondent lender-aggregator relationships. I further enrich the data with detailed loan-level mortgage contract details and performance. I provide the details below.

3.3.1 Correspondent Lender-Aggregator Relationships

I merge originated mortgages (action taken code 1) and purchased mortgages (action taken code 6) in HMDA to create a dataset that examines seller-aggregator relationships in correspondent lending. This dataset allows me to observe and analyze the business relationships between financial institutions within the mortgage aggregation market.

Figure 3 shows the data samples that I conduct my match on. I select mortgages labelled as sold to aggregators other than Fannie Mae, Freddie Mac, Ginnie Mae, and private securitization as the originated mortgage sample. Then, I take mortgages aggregated by aggregators in the same year. Both originated and aggregated mortgages contain loan and borrower characteristics. However, originated mortgages lack aggregator identity, while aggregated mortgages lack originator identity. To link originated mortgages with aggregated mortgages, I merge them based on census tract and loan amount. I also incorporate additional dimensions of mortgage characteristics into the merge, such as loan type, property type, borrower income, race, ethnicity, etc. Details of the merge algorithm and summary statistics on merge performance are included in the Appendix A.

My match algorithm gives around 60% match rate between originated covered loans and aggregated covered loans. I find 1190 aggregators and 4510 correspondent lenders. Table 1 shows the summary statistics for the characteristics of aggregators and correspondent lenders. The aggregation market is relatively concentrated, while the origination market is dispersed. Correspondent lenders tend to be smaller than aggregators and originate one-third of the mortgages originated by aggregators. Correspondent lenders have a lower liquidity ratio, a higher capital ratio, and a higher return on assets.

3.3.2 Merged Mortgage Data with Interest Rate and Loan Performance

Although HMDA is the most comprehensive dataset for the mortgage market, it lacks key mortgage contract terms such as interest rates. I incorporate data from Fannie Mae and Freddie Mac Single Family Loan dataset and the Attom Real Estate dataset to examine the effects on interest rates. I first merge the Attom dataset with HMDA using the property census tract and lender name. Following the cleaning procedure detailed in Appendix A, I have 16,300,646 housing transactions with mortgage in Attom and 21,080,734 home purchase mortgages from HMDA during the sample period 2010 - 2017. The match rate is around 80%, comparable to the previous paper Bartlett, Morse, Stanton, and Wallace (2022) that conducts a similar match. The resulting dataset includes origination date, census tract, loan characteristics, borrower characteristics, and lender identity.

I further merge the dataset with the Fannie Mae and Freddie Mac Single Family Loan dataset using loan amount, origination date, and lender. To ensure consistency with the coverage of Fannie Mae and Freddie Mac data, I restrict my sample to conventional, home purchase, fixed-rate mortgages. The match rate is 48%, which is similar to the match rate reported in Buchak, Chau, and Jørring (2023) for HMDA and Fannie Mae and Freddie Mac data after 2017. Details of the matching algorithm and matching performance are provided in Appendix A. I refer to this dataset as the HMDA-Attom-FF dataset.

3.3.3 Panel Datasets

I construct several panel datasets for my analysis. To obtain my main results on the effect of aggregation on credit supply in Section 5, I construct lender level and Lender×County level datasets from the Home Mortgage Disclosure Act. I first construct treatment measures as described in Section 4. Next, I aggregate originated and aggregated home purchase mortgages in the HMDA dataset at the levels above. Then, I merge the collapsed datasets with my treatment measures and lender characteristics from call reports data.

To investigate the effect of aggregation on interest rates and loan performance, I use the loan-level HMDA-Attom-FF data. I select mortgages that are not directly sold to Fannie Mae, Freddie Mac, Ginnie Mae, or private securitizers and then merge this loan-level data with the treatment measure using lender ID from HMDA.

To examine the heterogeneous impact on low-income borrowers, I aggregate the mortgages provided to low-income and high-income borrowers at the Lender×County level. I merge this dataset with the treatment measure using lender ID and add lender characteristics. Low-income borrowers are defined as those with incomes less than 80% of the FFIEC MSA-level median family income.

To show the specialization of correspondent lenders in the origination market, I use the application-level HMDA data to examine rejection rates and reasons for rejection. Additionally, I analyze the interest rates and loan performance of loans originated by correspondent lenders compared to those from other lenders, using the loan-level HMDA-Attom-FF data.

3.4 Summary Statistics

Table 1 reports the summary statistics for the correspondent Lender$\times$County level dataset. An average merged correspondent lender provides $165,670 mortgage credit per county per year, indicating that they are small mortgage lenders, which is also indicated by their average asset size.

On average, a correspondent lender connects with eight aggregators. However, the average HHI is 0.3, and the median is 0.25, indicating highly concentrated selling relationships. In addition, each correspondent lender has eight nearby aggregators. The standard deviation is large, indicating uneven access to aggregation market relationships.

4 Identification Strategy

After the Great Financial Crisis, the Basel Committee proposed a series of reforms aimed at creating a more resilient banking sector. As part of these post-crisis regulations, U.S. regulators announced a reduction in the cap on Mortgage Servicing Rights (MSRs) contributions to Tier 1 capital from 50% to 10% and an increase in their risk weight from 100% to 250%. This heightened regulatory burden was driven by concerns about MSRs. First, their market value fluctuations could weaken banks' regulatory capital and threaten their stability. Second, the uncertainty in valuing MSRs, exposure to contingent recourse liabilities, and the illiquid servicing transfer market made it difficult to realize their book value. For example, the FDIC found that 31 out of 36 failed banks held MSRs, but the fixed transaction costs associated with a sale exceeded the value of these MSRs.

Though MSRs were generally seen as risky, the strict regulatory treatment they received was largely unexpected by market participants (Irani, Iyer, Meisenzahl, and Peydró, 2021). First, U.S. regulatory agencies adopted the MSRs treatment under Basel III framework without considering the uniqueness of MSRs in the U.S. mortgage market. In Europe, a large proportion of mortgages are retained on the balance sheet by the originating banks and funded with covered bonds. No MSRs are created under this system because the servicing cash flow is not separated from the underlying mortgage loans. This fundamentally differs from the U.S. mortgage market, where most mortgages are securitized, and MSRs are separated from the underlying mortgages. The treatment of MSRs disproportionately affected U.S. institutions in relation to non-U.S. institutions while U.S. financial institutions expected regulatory agencies to provide "a more level playing field".[14] Second, the treatment of MSRs is extremely punitive. The risk weights of MSRs are much higher than other balance sheet items, which have equal or greater risk characteristics. For example, the Mortgage Bankers Association noted that the 250% risk weight assigned to MSRs was nearly double that of High Volatility Acquisition Development and Construction (HVADC) loans, which carried a 130% risk weight, despite being considered the riskiest assets on the list. Third, the caps and risk weights were viewed as "arbitrary". For example, a 2013 *Forbes* article commented on the new regulation that "[t]he new mortgage servicing regulations appear quite arbitrary. The amount of capital banks are required to hold against servicing rights was increased dramatically."[15]

The increased capital requirements on banks' MSR holdings, combined with the *ex-ante* variation in banks' sensitivity to the additional capital charges under Basel III, make the mortgage business less attractive for banks. Specifically, it reduces banks' interest in

[14] https://www.fdic.gov/system/files/2024-07/2012-ad-95-96-97_c_857.pdf

[15] See, https://www.forbes.com/sites/richardfinger/2013/05/30/banks-are-not-lending-like-they-should-and-with-good-reason/

mortgage aggregation. One channel for banks to obtain mortgage servicing rights is to aggregate mortgages from other financial institutions.[16] Figure 5 shows the strong positive correlation between aggregation and mortgage servicing rights, suggesting that a higher cost of holding servicing rights on balance sheets could reduce the attractiveness of the aggregation business.

To examine how the plausibly exogenous change in mortgage aggregation affects correspondent lenders' credit supply, I construct the treatment exposure at the correspondent lender level. I first define the regulatory exposure of a bank b as the share of MSRs in Tier 1 capital of traditional bank b in Q4 2011.

$$\text{MSRT1}_b \equiv \frac{MSR_{b_{2011}}}{Tier1Capital_{b_{2011}}} \tag{1}$$

Next, I define the correspondent lender level treatment variable as

$$\text{MSR}_s \equiv \sum_{b \in s} \left(\mathbb{1}_{\text{MSRT1}_b \geq 0.1} \times \frac{Aggregation_{bs_{2011}}}{\sum_{b \in s} Aggregation_{bs_{2011}}} \right) \tag{2}$$

$\mathbb{1}_{\text{MSRT1}_b \geq 0.1}$ is 1 if the share of MSRs over Tier 1 capital exceeds 10% and otherwise 0, where 10% is the cap on MSRs' contribution towards tier 1 capital set up by new Basel III Accord. I aggregate bank-level exposure to the correspondent lender level by using bank b's aggregation share for a given correspondent lender s, $\frac{Aggregation_{bs_{2011}}}{\sum_{b \in s} Aggregation_{bs_{2011}}}$. The measure thus captures the share of mortgages sold to aggregators with *ex-ante* MSR/Tier 1 capital over 10%.

One concern about the treatment is that the increased capital requirements on mortgage servicing rights can directly affect correspondent lenders and change their origination behaviour. However, when correspondent lenders sell mortgages, they usually

[16] This is mentioned by Ocwen Financial Corp, a leading mortgage company in their 10-K file in 2024: "We originate and purchase residential mortgage loans that we promptly sell or securitize on a servicing retained basis, thereby generating mortgage servicing rights." Also mentioned by Reuters: "Banks typically use correspondent lending to generate more mortgages to, in turn, sell to investors and service them."

sell mortgages with servicing released and gain a servicing premium in return. I count the correspondent lenders with *ex-ante* MSR exposure in 2011 Q4 over 10% and none of the correspondent lenders are subject to the cap requirement in 2013.

5 Mortgage Aggregation and Credit Supply

In this section, I present evidence showing that the reduction in aggregation leads to decreased mortgage lending by correspondent lenders, following unexpectedly punitive capital treatment on Mortgage Servicing Rights (MSRs). I conduct several robustness tests, including analyses of dynamic effects and potential confounding events. Finally, I estimate the impact on total credit supply by analyzing data at the county level. These results suggest the role of mortgage aggregation in easing securitization frictions and expanding credit access.

5.1 Main Results

It is difficult to estimate the causal impact of aggregation on credit supply. The equilibrium aggregation volume is driven by both aggregators' demand for mortgages and correspondent lenders' supply of mortgages, thus directly testing the relationship between aggregation and origination suffers from the issue of reverse causality. To address this issue, I use the surprisingly punitive MSR treatment from the Basel III Accord as a source of exogenous variation in mortgage aggregation.

I first test if the punitive MSR treatment leads to decreased aggregation volume. I estimate a difference-in-differences model described in the following form:

$$y_{s,c,t} = \beta_1 \mathrm{MSR}_s \times \mathrm{Post}_t + \xi' X_{s,t-1} + FE + \epsilon_{s,c,t} \tag{3}$$

The dependent variable is either the logarithm of aggregation volume, the logarithm of origination volume, or the approval rate. MSR_s is the correspondent lender level treatment exposure as defined in Equation (2). Post_t is a dummy variable that is 1 if the year is on or after 2013 and otherwise 0. I add a vector of lagged time-varying lender-level controls $X_{s,t-1}$ from various balance sheet data, including logarithm of assets, return on assets, capital ratio and liquidity ratio.

I include correspondent lender, County×Year, and correspondent Lender×County fixed effects in the model. The year fixed effects control for national trends in aggregation, while the County×Year fixed effects account for local loan demand. I also add Lender×County fixed effects to control for the selection of correspondent lenders entering different counties. I cluster standard errors at the correspondent lender level. The coefficient of interest is β_1, which captures the differential effect of exposure to Basel III capital requirements on aggregation amounts and origination amounts.

Table 2 reports the results for aggregation volume, origination volume and approval rates. Columns (1)-(3) show the estimates for aggregation volume. Column (1) adds correspondent Lender×County fixed effects, column (2) adds year fixed effects, and column (3) adds County×Year fixed effects. The coefficient on the interaction term between the MSR exposure and post dummy is negative and statistically significant across all specifications. This indicates that the quantity of mortgages being aggregated is more negatively affected if the correspondent lenders have larger exposure to aggregators subject to the Basel III capital requirements on MSRs. The estimation result suggests that following the Basel III capital requirements, the mortgage aggregation amount decreases significantly. A one standard deviation increase in the *ex-ante* share of mortgages sold to affected aggregators (0.25) leads to a 20.5% decrease in aggregation volume.

After examining the effect on aggregation volume, I next check if the decrease in aggregation volume is followed by a decline in origination volume. Because aggregation acts as a funding source by allowing correspondent lenders to reinvest their assets into more lending, a decrease in aggregation volume could reduce credit supply. However, the decline in origination volume is not apparent *ex-ante* given that correspondent lenders have various funding sources for mortgage origination. If correspondent lenders could substitute alternative funding sources frictionlessly, I would not be able to observe a decrease in origination volume.

To examine the effect of a decrease in aggregation on origination, I re-estimate the regression model in Equation (3) using log mortgage origination amount and mortgage approval rate as the dependent variables. I use approval rate to partially address the concern that the results are driven by the decrease in correspondent lender-specific demand. Columns (4)-(6) and columns (7)-(9) display regression estimates for log origination amount and approval rate as the dependent variable, respectively. I apply the same set of fixed effects to these columns. The coefficient on the interaction term remains negative, significant at 5% level, and similar in magnitude across all specifications. These results indicate that credit supplied by correspondent lenders with higher *ex-ante* exposure to MSRs through aggregation is more negatively affected by the regulatory change than those with lower exposure. The estimated coefficients imply that, for a one standard deviation increase in the correspondent lender level exposure, mortgages supply decreases by 12.5%.

The results at the lender-county level could be subject to various endogenous issues, such as non-random matching between aggregators and correspondent lenders, pre-trends in origination amount, direct impact of Basel III capital requirement on depository correspondent lenders. I discuss these factors in Section 8 and conduct several robustness tests. In addition, I discuss confounding events such as guarantee fee change, litigation risks and put-back risks in Section A.2.1.

5.2 Aggregate Credit Supply Effects

After showing that the mortgage aggregation market disruption affects credit supply at the correspondent lender level, I turn to a county-level analysis to estimate the aggregate effects of mortgage aggregation on credit access.

The effect on credit access is *ex-ante* unclear. The mortgage origination market is generally viewed as national and competitive, which allows for easy substitution of lenders. Though correspondent lenders cut lending in response to the decrease in aggregation volume, borrowers can switch to other lenders to obtain credit. If borrowers could frictionlessly transition to other lenders and still achieve favourable application outcomes, the overall credit availability would remain unaffected despite declines in credit supply from correspondent lenders.

To estimate the impact on overall credit access, I conduct my analysis at the county level. I construct the county level treatment variable as the following:

$$\text{MSR\%}_{Agg,c} \equiv \sum_{b \in s} \left(\mathbb{1}_{\frac{MSR_{b_{2011}}}{Tier1Capital_{b_{2011}}} \geq 0.1} \times \frac{Aggregation_{bc_{2011}}}{\sum_{b \in c} Aggregation_{bc_{2011}}} \right) \tag{4}$$

where $\frac{MSR_{b_{2011}}}{Tier1Capitals_{b_{2011}}}$ is the share of MSRs in Tier 1 capital of traditional bank b in Q4 2011. It measures the exposure of bank b to the regulatory change in the capital treatment of MSRs. If the share of MSRs exceeds 10% of tier 1 capital, then the bank b receives a value of 1, where 10% is the cap on MSRs' contribution towards tier 1 capital under the new Basel III capital requirements. I aggregate bank-level exposure to Basel III at the county level by using bank b's aggregation share in a given county c, $\frac{Aggregation_{bc_{2011}}}{\sum_{b \in c} Aggregation_{bc_{2011}}}$. The measure at the county level thus captures the share of mortgages sold to aggregators with *ex-ante* MSR/Tier 1 capital over 10% in county c.

I estimate the following model at the county level:

$$y_{c,t} = \beta_1 MSR\%_{Agg,c} \times \text{Post}_t + \xi' X_{c,t-1} + FE_c + FE_t + \epsilon_{c,t} \tag{5}$$

The dependent variables are the number of correspondent lenders and log amount of originated mortgages. The coefficient of interest, β_1, represents the differential effect of exposure to mortgage aggregation reduction on mortgage lending. Following Buchak, Matvos, Piskorski, and Seru (2018), I control for population, population density, racial and ethnic characteristics, education, income and poverty, and home ownership statistics in the county level regressions. I also control for lagged unemployment rate to adjust for differences in local economic conditions that might drive local loan demand. I further include year and county fixed effects to account for persistent county characteristics and macroeconomic trends. I cluster standard errors by county.

Table 3 reports the results. In columns (1) and (2), the coefficients on the interaction term are negative and statistically significant. The point estimates suggest that moving from a county with 0 p.p exposure to a county with 100 p.p exposure to the aggregation market shock is associated with the number of correspondent lenders decreasing by two and total credit supply decreasing by 10 p.p. The results suggest that aggregation market disruption has a non-trivial impact on credit access.

The effect on overall credit access can also mask heterogeneities along borrower characteristics, e.g. borrower income level. Given that correspondent lenders are more likely to operate in low-income areas (see Figure 8), they may specialize in providing credit to low-income borrowers. The funding impact on correspondent lenders can disproportionately affect this disadvantaged borrower group. I estimate the following regression to examine the heterogeneous effects across borrower income levels:

$$y_{c,t,i} = \beta_1 MSR\%_{Agg,c} \times \text{Post}_t \times \text{LowInc}_i + \xi' X_{c,t-1} + FE_c + FE_t + \epsilon_{c,t} \quad (6)$$

The dependent variable is the log amount of mortgages originating in county c in year t for borrower type i. LowInc_i is a dummy variable that takes a value of 1 if the borrower type is low-income. Column (3) in table 3 reports the result. The triple interaction term has a negative and significant coefficient, while the interaction between county-level aggregation market treatment and the post-dummy is negative but not significant. The result suggests that low-income borrowers experience a significantly larger credit supply decline following the aggregation market shock, and the overall reduction in credit supply is mainly driven by the decrease in credit supply to low-income borrowers.

The declining credit supply to low-income borrowers could result from (1) a decrease in applications from low-income borrowers, either due to fewer available lenders or rising housing prices which increase the difficulty for these borrowers to meet downpayment requirements; and (2) higher rejection rates from correspondent lenders constrained by the aggregation volume reduction. The former suggests a demand-side effect, while the latter implies a supply-side effect. To examine these factors, I re-estimate equation (6), using the share of mortgage applications from low-income borrowers as the dependent variable. I report the estimation result in column (4). While the coefficient is negative, it is not statistically significant. The result suggests a supply-side effect: low-income borrowers do not apply less than high-income borrowers. Instead, they experience lower credit supply than high-income borrowers because lenders reject low-income borrowers more often due to aggregation market constraints.

6 Funding Frictions

After confirming the effect of aggregation on credit supply, I show that funding frictions drive the lending reduction. Correspondent lenders have multiple margins of adjustment when facing a decline in aggregation. First, correspondent lenders can sell their mortgages to other aggregators. Second, correspondent lenders can consider channels other than aggregation to sell their mortgages. On the one hand, they can establish new relationships with government agencies and sell a fraction of mortgages directly to agencies without relying on aggregators. On the other hand, they can use their balance sheet funding to support new mortgage lending if they are depository institutions. The effect of the aggregation volume reduction would be limited if correspondent lenders could switch to any of the channels mentioned above. However, if correspondent lenders face search frictions in the aggregation market or cannot frictionlessly switch to other funding sources, they may reduce their credit supply as shown in Section 5.

To show the matching frictions in the aggregation market, I first check if correspondent lenders have sticky relationships with their aggregators. Correspondent lenders and aggregators usually set up their contracts as advance commitments on a mortgage for sale. Though sellers can sell mortgages via auctions through an online platform like Optimal Blue, these auctions are invited auctions sent out by the sellers to their connected aggregators. Thus, the relationship between sellers and aggregators could be sticky regardless of the method of sale. To test the sticky relationship between correspondent lenders, I construct a dataset using all possible pairs of correspondent lenders and aggregators in their choice sets for aggregation relationships. I next test if a previous relationship between a correspondent lender and an aggregator can predict their relationship in the next period. Table A.10 shows the regression result. While the probability of finding a random match between a correspondent lender and an aggregator is close to 0, the aggregator that served as the prior aggregator of a correspondent lender has a 45% greater likelihood of servicing as the new aggregator, even after controlling for an aggregator's average market share.

Having verified the sticky relationships between correspondent lenders and aggregators, I consider the switching frictions within aggregator-correspondent lender relationships and correspondent lenders' outside options of aggregators. First, correspondent lenders that connect with multiple aggregators may be able to sell their mortgages to unaffected ones if one aggregator is affected. These correspondent lenders may be less affected by the decline in aggregation volume if they can optimally reallocate their sell volume based on the treatment exposure of aggregators. Second, correspondent lenders with low diversification in selling mortgages to their aggregators may experience difficulties switching to other aggregators. Third, correspondent lenders that are located near many other aggregators may find it easier to establish new relationships. Thus, these correspondent lenders could be less affected by aggregation shocks.

Motivated by the above observations, I construct two measures for frictions in aggregation relationships: the Herfindahl-Hirschman index (HHI) of selling concentration and the number of nearby aggregations. I define nearby aggregators as those with headquarters within a 100 km radius of a correspondent lender. I assign each variable one if the value is above the median and otherwise 0. I estimate the following equation:

$$y_{s,c,t} = \beta_1 \text{MSR}_s \times \text{Post}_t \times \text{FundingFriction}_s + FE + \epsilon_{s,c,t} \tag{7}$$

FundingFriction_s is a correspondent lender-level measure based on my correspondent lender-aggregator relationships data.

Table 4 shows that correspondent lenders can partially attenuate the effect of a lending cut from aggregators by switching away. Specifically, correspondent lenders physically near other aggregators or whose current connections are less concentrated suffer smaller declines in lending post the Basel III shock.

I next explore other options that correspondent lenders can use to attenuate the adverse effects arising from aggregation shocks. Correspondent lenders can choose to establish new relationships with Fannie Mae, Freddie Mac and Ginnie Mae and sell more mortgages to these purchasers directly. They can also extend their aggregator network. I formally check how correspondent lenders use these options by estimating the following equation:

$$y_{s,t} = \beta_1 \text{MSR}_t \times \text{Post}_t + FE + \epsilon_{s,t} \tag{8}$$

The dependent variables are a dummy variable indicating if a correspondent lender directly sells to Fannie Mae, Freddie Mac and Ginnie Mae, the share of mortgages directly sold to agencies, the share of mortgages sold to aggregators and the number of connected aggregators. MSR_t is the correspondent lender level treatment exposure as defined in

Equation (2). Post_t is a dummy variable with a value of 1 if the year is on or after 2013 and otherwise 0. I add a vector of lagged time-varying lender-level controls $X_{s,t-1}$ from various balance sheet data, including logarithm of assets, return on assets, capital ratio and liquidity ratio.

Table 5 shows that after the shock, correspondent lenders with more *ex-ante* exposure are more likely to form relationships with agencies, and they sell more mortgages directly to agencies. They also reduce the fraction of mortgages sold to aggregators but connect to a larger number of aggregators.

Since deposit funding is another primary source of funding for banks to originate mortgages, I check if correspondent lenders increase the amount of deposits to boost mortgage origination. Results in Table 6 show that more exposed correspondent lenders are not likely to increase their deposit funding. One possible explanation is that the cost of increasing deposit funding may be high for correspondent lenders. With other options to securitize mortgages, the deposit funding channel is less attractive.

Overall, the above results show that correspondent lenders can attenuate the effect of mortgage aggregation on origination by selling to other aggregators. However, correspondent lenders cannot entirely avoid the impact on origination by switching aggregators, selling to agencies directly, or using their own balance sheets.

The funding frictions should be exacerbated if correspondent lenders are more likely to face adverse selection in the funding market, which includes cases when correspondent lenders ex-ante have lower capital and liquidity and are smaller. To test these cases, I further estimate the following regression model:

$$y_{s,c,t} = \beta_1 \text{MSR}_s \times \text{Post}_t \times \text{LenderType}_s + FE + \epsilon_{s,c,t} \tag{9}$$

LenderType_s is a correspondent lender-level measure to proxy for the level of adverse selection that correspondent lenders face in the funding market. Table 7 reports the results.

Consistent with my hypothesis, correspondent lenders that face a higher level of adverse selection in the funding market experience a larger decline in lending.

In summary, I show that correspondent lenders experience funding frictions that constrain lending. The impact of an aggregation market disruption intensifies as adverse selection in the funding market increases.

7 Drivers of Distributional Effects

The funding frictions do not explain the heterogeneous impacts on low-income borrowers. In this section, I show that aggregators' portfolio reallocation and correspondent lender specialization lead to the disproportionately larger impact on low-income borrowers in the mortgage market.

7.1 Portfolio Choice of Aggregators

Aggregators face a complex profit maximization problem. Their aggregation decisions are based on marginal aggregation revenue and cost. Their revenues come from the spread between resale/securitization and aggregation prices, plus servicing fees set by mortgage-backed securities issuers. Their costs include servicing expenses and the balance sheet cost of holding mortgage servicing rights. While increasing the number of serviced mortgages increases revenue, given that they have paid the fixed costs to set up a servicing system, it also increases the likelihood of servicing low-quality loans that are more likely to be delinquent. The servicing cost of a delinquent mortgage is over 10 times higher than that of a performing loan.[17] As balance sheet costs rise, low-income borrowers' mortgages are more likely to be on the margin and first excluded from the aggregation portfolio. This is similar to the practice that large servicers sell low-quality servicing assets first when facing

[17] https://www.urban.org/sites/default/files/publication/77626/2000607-Servicing-Costs-and-the-Rise-of-the-Squeaky-Clean-Loan.pdf

increasing balance sheet cost of holding mortgage servicing rights (Hamdi, Jiang, Lewis, Padi, and Pal, 2023).

I first check if aggregators decrease their aggregation volume more for low-income, high-risk mortgages. I estimate the following regression at the correspondent lender-aggregator level using a within-firm estimator (Khwaja and Mian, 2008). Specifically, I estimate the equation:

$$y_{s,b,i,t} = \beta_1 MSR_b \times \text{Post}_t \times \text{LoanType}_i + FE + \epsilon_{s,b,i,t} \tag{10}$$

Here, MSR_b is a bank-level exposure to the MSR policy change. I further interact LoanType_i with $\text{MSR}_b \times \text{Post}_t$. The LoanType_i is a dummy variable to proxy for the risk level of mortgages. I use three measures for loan risk: borrower income, property location, and loan-to-income ratio. I first classify mortgages by borrower income, property location, and loan-to-income ratio, assigning 1 to mortgages of low-income borrowers, from low-income areas, of low-income borrowers from low-income areas and high loan-to-income ratio and summarize the loan level data at the correspondent lender, aggregator, loan type level. In the specification, I add correspondent lender-year fixed effects $FE_{s,t}$, which absorb any confounding factors at the correspondent lender-year level that may correlate with the aggregation volume. Moreover, I add correspondent lender-aggregator fixed effects $FE_{s,b}$ to address the endogenous matching between correspondent lenders and aggregators.

Table 8 reports the results. Aggregators with larger exposure to the Basel III capital requirements on MSRs reduce their aggregation for *ex-ante* riskier mortgages.

Motivated by the anecdotal evidence and observed aggregation choices, I test the heterogeneous effects on low-income borrowers at the correspondent lender level. Given that aggregation is a main source of funding for correspondent lenders, the changes in aggregation composition can be passed down to the origination decisions of correspondent lenders. To test this hypothesis, I estimate the following regression model:

$$y_{s,c,t,i} = \beta_1 \text{MSR}_t \times \text{Post}_t \times \text{LoanType}_i + FE + \epsilon_{s,c,t} \tag{11}$$

where i indicates borrower type group. I adopt two measures for disadvantaged borrower groups, low-income borrowers and borrowers from low-income areas. All other variables are as previously defined in Equation (3), and I cluster standard errors at the lender level. The coefficient of interest is β_1, which captures how borrowers could be differentially affected by the regulatory shock through the aggregation market. A negative β_1 indicates that low-income borrowers or borrowers from low-income areas experience a larger origination volume decline compared to other borrowers.

Table 9 shows the results. The coefficient on the triple interaction term is negative and statistically significant. This implies that the aggregation effect on credit supply is stronger for both low-income borrowers and borrowers from low-income areas. The magnitude indicates that given one standard deviation increase in correspondent lender exposure, low-income borrowers experience a 4.5% larger decline in credit supply. The results suggest that the behaviour of aggregators transmits to origination decisions of correspondent lenders through aggregation market connections. Aggregators play an important role in shaping the composition of the lending portfolio of correspondent lenders.

7.2 Specialization of Correspondent Lenders

In this section, I show how the specialization of correspondent lenders in serving low-income borrowers can contribute to credit decline. If correspondent lenders specialize in using soft information to screen or serve low-income borrowers, their exit or reduced credit supply can worsen credit access for these borrowers. Low-income borrowers may struggle to find equivalent credit from other lenders, further limiting their access.

I first examine if low-income borrowers, compared to high-income borrowers, are more likely to seek mortgage credit from correspondent lenders in the same location and period. The regression specification is

$$Correspondent_{j,k,t} = \beta \times LowInc_{i,j,k,t} + \gamma X_{i,j,k,t} + FE_k + FE_t + \epsilon_{i,j,k,t} \tag{12}$$

for borrower i, lender j, property's census tract k, and year t. $Correspondent_{j,k,t}$ is an indicator variable equal to 1 if the lender j is a correspondent lender in census tract k and year t and otherwise 0. $LowInc_{i,j,k,t}$ is an indicator variable equal to 1 if the borrower of mortgage i originated by lender j in census tract k and year t is a low-income borrower and otherwise 0. $X_{i,j,k,t}$ are borrower and loan characteristics. Borrower characteristics include gender and co-borrower presence dummies. Loan characteristics include loan-amount percentile and loan-type fixed effects. Census tract-year fixed effects are also included to account for local application trends. The coefficient of interest is β, which represents the propensity of a low-income borrower applying for credit from correspondent lenders.

I estimate the specification (12) for 2010-2015. The results are reported in column (1) of Table 10. After controlling for observable borrower and loan characteristics, I find that low-income borrowers are 0.7% more likely to apply for mortgages from a correspondent lender.

Second, I test if correspondent lenders, compared to other types of lenders, are more likely to provide credit to low-income borrowers given the same demographic characteristics of borrowers and the same set of loan characteristics. It is *ex-ante* ambiguous whether low-income borrowers are more or less likely to be rejected by correspondent lenders. On the one hand, correspondent lenders may be better at screening low-income borrowers and have higher rejection rates than other types of lenders, given the observable characteristics of low-income borrowers. If this is true, the mortgages they originated should have better performance. On the other hand, correspondent lenders may specialize in providing credit to low-income borrowers. If they provide detailed instructions and are willing to file additional reports for low-income borrowers, they may be less likely to reject low-income borrowers. This may be observed from their rejection reasons - their rejection reasons should be less likely to be incomplete or unverifiable information. In addition, the loans they originated should not necessarily have worse performance, but they may charge higher interest rates or origination fees for additional services.

To test the above hypotheses, I check rejection action, rejection reasons, interest rate and loan performance of low-income borrowers who submit their applications to correspondent lenders versus other lenders using the following specification:

$$y_{i,j,k,t} = \beta \times Correspondent_{i,k,t} + \gamma X_{i,j,k,t} + FE_k + FE_t + \epsilon_{i,j,k,t} \tag{13}$$

where $y_{i,j,k,t}$ is the lending outcome of an application or an originated mortgage of borrower i, lender j, property's census tract k, and year t. I use the rejection dummy, rejection reason dummy and delinquent dummy as dependent variables, where the delinquent dummy is 1 if the loan is more than 90 days delinquent within 2 years after origination. $X_{i,j,k,t}$ are borrower and loan characteristics and otherwise 0. Borrower characteristics include gender, minority indicator, and co-borrower presence dummies. Loan characteristics include loan-amount percentile fixed effects. I use HMDA data to check rejection patterns and reasons for rejection, and I use Attom-HMDA-FF data to examine loan interest rates and performance. Since Attom-HDMA-FF data allows me to observe more mortgage contract terms and borrower characteristics, e.g. LTV, DTI, FICO, and first-time home buyer indicator, I also use these variables as controls. Census tract-year fixed effects are included to account for local application trends. The coefficient of interest is β, which shows how correspondent lenders differ from other lenders in originating mortgages.

Columns (2)-(4) of Table 10 report the results for rejection and rejection pattern. Correspondent lenders are 4.28% less likely to reject applications from low-income borrowers than other lenders. Given that the average rejection rate for low-income borrowers is 15%, this indicates that the rejection rate of correspondent lenders for low-income borrowers is 28% lower. In addition, they are 1.34% less likely to reject applications due to unverifiable information and 6.09% less likely to reject applications due to incomplete information, suggesting that correspondent lenders may provide additional services to help borrowers satisfy application requirements.

Columns (5)-(6) of Table 10 report the results for interest rates and delinquency. Correspondent lenders charge higher interest rates than other lenders, but the economic magnitude is small - their interest rates are only 0.007% higher than other lenders. They may charge service through points and origination costs.[18] However, such variables are not observable during this sample period. The results also partially address the concern that high-quality, low-income borrowers are more likely to apply for mortgages from correspondent lenders.

Having shown the potential benefits correspondent lenders provide for low-income borrowers, I next provide a suggestive explanation for these lenders' unique role in providing low-income credit. One possible explanation is geographical proximity. Correspondent lenders are more likely to locate in low-income areas, making it easier for low-income borrowers to access their credit. The geographical proximity provides convenience and may also allow correspondent lenders to obtain soft information about local borrowers. Though mortgages are more likely to be examined by the Automated Underwriting System (AUS), lenders can also use discretion to overwrite decisions in the system. Correspondent lenders can specialize in providing such services and facilitate low-income borrowers' credit access. For the proximity channel, I show that the share of mortgages sold to aggregators has a significant and negative correlation with the census tract median family income, see Figure 8.

[18] Buchak and Jørring (2021) and Liu (2019) both indicate that origination cost is an important pricing dimension. Lenders can raise origination when they face less competition or higher funding costs.

8 Robustness Tests

8.1 Endogenous Matching

One possible concern with estimating the regression model, Equation (3), at the correspondent lender level is that non-random matching between correspondent lenders and aggregators may interfere with interpretation of the results. Either correspondent lenders or aggregators can choose the financial institution with which they establish a business relationship. Correspondent lenders with low loan demand could sell to aggregators that experience negative regulatory shocks, thus I cannot conclude that the results are driven by the MSR regulation. To address the selection problem, I conduct my analysis at the correspondent lender-aggregator level using an within-firm estimator (Khwaja and Mian, 2008). Specifically, I estimate the equation:

$$y_{s,b,t} = \beta_1 MSR_b \times \text{Post}_t + FE + \epsilon_{s,b,t} \tag{14}$$

Here MSR_b is a bank-level exposure to the MSR policy change. In the specification, I add correspondent lender-year fixed effects $FE_{s,t}$, which absorb any confounding factors at the correspondent lender-year level that may correlate with the aggregation volume. Moreover, I add correspondent lender-aggregator fixed effects $FE_{s,b}$ to address the endogenous matching between correspondent lenders and aggregators.

Table A.2 shows the estimation results. The point estimates are stable across columns. Notably, after adding correspondent lender-year fixed effects to control for the correspondent lender side supply of mortgages, the effect is still negative and significant, suggesting that the effects come from the aggregator side. Correspondent lenders indeed face a reduction in the purchase volume when their aggregators are subject to the regulatory change.

8.2 Pre-trends and Dynamic Effects

A possible concern with the identification strategy could be that pre-existing trends are driving the difference in lending of differentially exposed correspondent lenders after the regulatory shock. To address this concern, I check the existence of trends in the aggregation and origination volume. I estimate the following model:

$$Y_{s,c,t} = \sum_{\tau=-2}^{5} (\beta_\tau \text{MSR}_s \times \text{Post}_{t+\tau}) + \gamma X_{s,t-1} + FE + \epsilon_{s,c,t}. \tag{15}$$

The dependent variables are the logarithm of aggregation amount, the logarithm of origination amount of correspondent lenders and the logarithm of origination amount of correspondent lenders. The main coefficients of interest are β_τ, which show the difference in aggregation and origination in treated and control groups in each period in the sample. This specification also allows us to see the dynamic effects of the shock on origination. Figure 6 shows the 95% confidence interval plots for the estimated coefficients from Equation 15. It is evident from the figure that there are no pre-trends in either the aggregation amount or origination amount of correspondent lenders prior to the announcement of Basel III implementation in 2012. The figures also show interesting dynamic effects. After the Basel III implementation, the aggregation volume declines, and correspondent lenders never revert their origination volume to the pre-shock level, representing a permanent market structure shift.

The lack of pre-trends does not necessarily rule out the possibility that low-quality correspondent lenders are more likely to be matched with aggregators with a high *ex-ante* level of mortgage servicing rights. I further conduct balanced t-stats tests for the characteristics of the treated and control groups, where the treated and control groups are defined as having exposure higher and below the median level. Table A.3 shows that there is no significant difference along observable characteristics, including capital ratio, liquidity ratio, return on assets and size.

8.3 Effects of Basel III Capital Requirements

Identification using Basel III capital requirements on mortgage servicing rights is complicated because the banking sector regulations could affect multiple players through various channels. I try to address these concerns.

First, I check the main results using a subsample of shadow bank correspondent lenders. Since shadow banks are not regulated by the Basel III capital requirements, this subsample analysis is not subject to the concern that the lending reduction is directly driven by the Basel III capital requirements. Table A.5 shows that the fall in origination and approvals for shadow bank correspondent lenders is quantitatively similar to the full sample in Table 3. Therefore, it is likely that the indirect effect of Basel III, through the cost of MSRs for aggregators, is the driving force behind the declines.

A follow-up concern is that the results on shadow banks can also arise from the direct effect of Basel III through shadow bank funding. 60%-70% of shadow bank funding comes from bank credit lines (Jiang, 2023). Shadow bank correspondent lenders may reduce lending if large aggregators decrease their warehouse funding to shadow banks due to regulatory exposure from the Basel III capital requirements. Using the credit line data from shadow bank call reports, I test if the log credit line amount, utilization ratio of shadow banks' credit line and estimated interest change according to the regulatory exposure of their warehouse lenders. I estimate the following model

$$y_{s,b,t} = \beta_1 \text{Exposure}_b \times \text{Post}_t + FE + \epsilon_{s,b,t} \tag{16}$$

Similar to Equation 14, I add correspondent lender-year fixed effects $FE_{s,t}$ which absorb any confounding factors at the shadow bank-year level that may correlate with the funding amount utilization rate. Moreover, I add correspondent lender-aggregator fixed effects $FE_{s,b}$ to address the endogenous matching between shadow banks and their warehouse lenders. The main variable of interest the coefficient β of the interaction term

$Exposure_b \times \text{Post}_t$, where the measure Exposure_b is defined as in Equation 1. The main coefficient of interest captures the difference in the funding supply of warehouse lenders that are affected by the Basel III MSR exposure. Table A.4 shows that the coefficient β is insignificant across all specifications. The MSR exposure does not have a significant impact on the credit line funding of shadow banks, thus suggesting that Basel III impacts shadow bank correspondent lenders through through their business relationships with affected bank aggregators.

Second, bank correspondent lenders may reduce lending because of their capital shortfall. If their capital shortfall is positively correlated with their exposure to MSRs through aggregation, then I cannot conclude that the decrease in purchase volume leads to the decrease in the origination volume. I test if a positive correlation exists in the data. Table A.6 shows that the correlation between Basel III capital shortfall and correspondent lenders' MSR exposure through aggregation is 0.02 and statistically insignificant.[19] Therefore, capital shortfall is unlikely to drive the pattern in the correspondent lenders' decline in lending following Basel III.

The results could be confounded by events happened at the same/similar time with the implementation of Basel III capital requirements such as put-back risk, litigation risk and guarantee fee change. I discuss these events in the section A.2.1.

9 Conclusion

After the Global Financial Crisis, the mortgage market underwent significant transformations, including stricter bank regulations, the rise of shadow banks, and a sharp decline in credit supply to low-income borrowers. This paper examines whether the decrease in mortgage aggregation, driven by Basel III capital requirements on mortgage servicing rights impacts credit supply. Using a unique dataset, I find that disruptions in the aggregation

[19] I thank Berrospide and Edge (2016) for providing the capital shortfall measure.

market reduce aggregate credit supply, especially credit supply to low-income borrowers.

These findings underscore the critical role of mortgage aggregation in mitigating securitization frictions, especially in underserved low-income areas predominantly served by small correspondent lenders. Financial technologies that reduce search frictions between correspondent lenders and aggregators could help address the credit access gap in these regions. This also suggests regulators must account for the close ties between mortgage aggregation and mortgage servicing rights when crafting regulatory weights and caps. Efforts to enhance financial stability may inadvertently limit credit access, particularly in the mortgage market.

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Figure 1: **Size of the mortgage aggregation market**

This figure shows the size of the mortgage aggregation market relative to origination. The upper figure uses data from the Home Mortgage Disclosure Act data. The red line is the time series of the national mortgage origination amount (in billions). The blue line is the time series of the national mortgage aggregation amount (in billions). The green dashed line is the time series of aggregation amount over origination amount (in percentage). The lower figure uses Fannie Mae and Freddie Mac Single Family Loan Level data. The green dashed line shows the time series of the share of fixed-rate conventional mortgages from the correspondent channel, i.e. sold to Fannie Mae and Freddie Mac via aggregators.

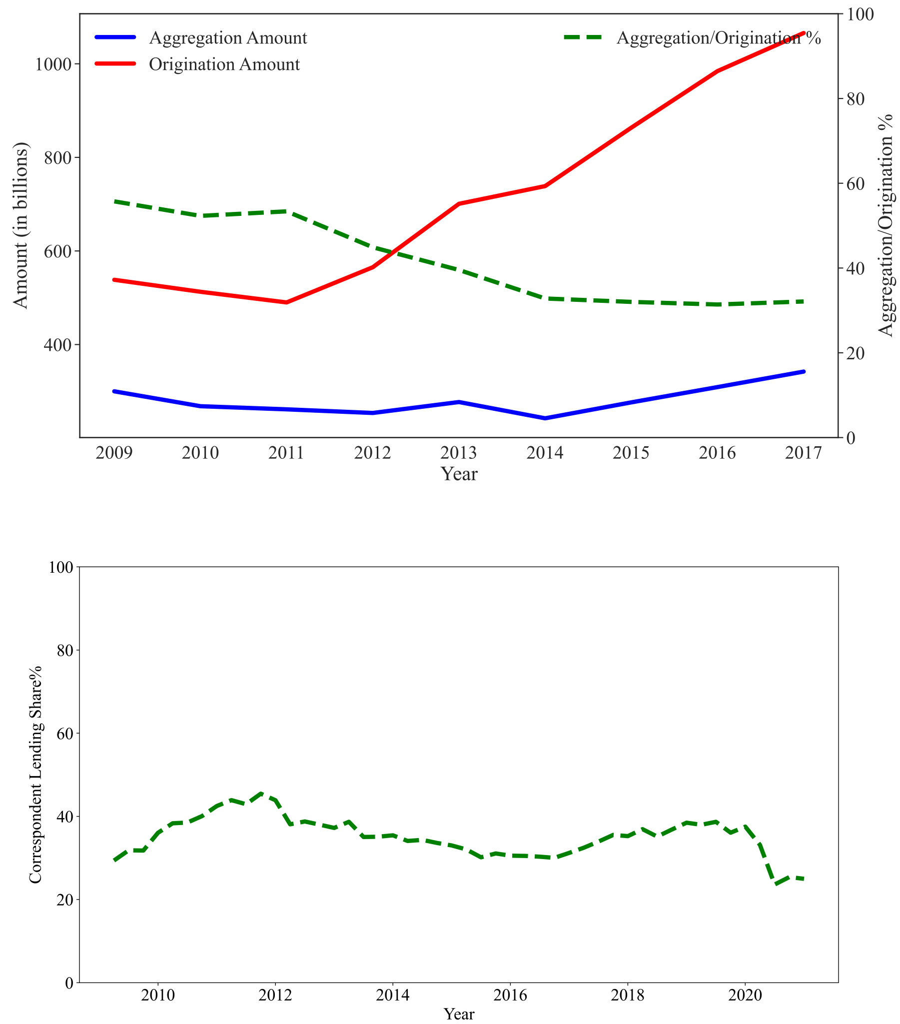


Figure 2: **Market structure**

This figure illustrates the mortgage market structure analyzed in this paper. The red arrows show the flow of mortgage funding. The blue arrows show the flow of mortgages. The black dashed arrows show the flow of mortgage payments. Agencies are main securitizers such as Fannie Mae, Freddie Mac and Ginnie Mae. Aggregators are large financial institutions such as Wells Fargo, Bank of America and JP Morgan Chase. They have three roles in the mortgage market: (i) originating mortgages to borrowers, (ii) purchasing originated mortgages from other financial institutions, and (iii) collecting mortgage payments and transferring payments to investors of mortgage-backed securities (MBS), also called servicing. They have business relationships with agencies. Correspondent lenders do not have direct access to securitizers; they originate mortgages and sell them to non-affiliated financial institutions (aggregators).

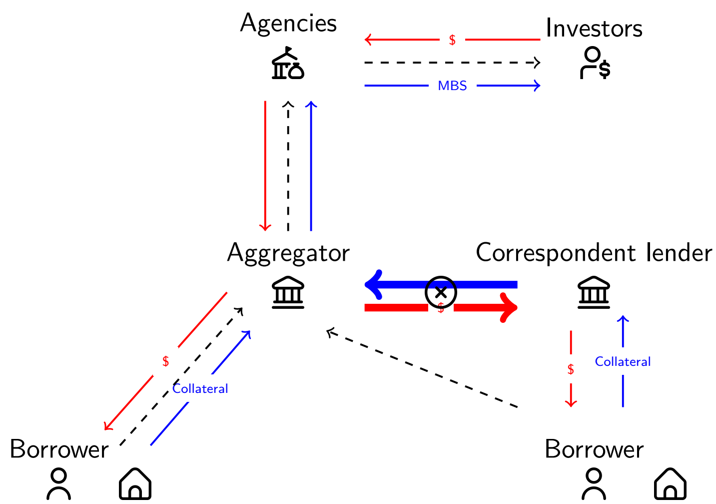


Figure 3: **Sample construction**

This figure shows the data coverage and sample construction using Home Mortgage Disclosure Act (HMDA) data. The green rectangle represents the data covered by HMDA, and the red rectangle represents the data covered in my sample.

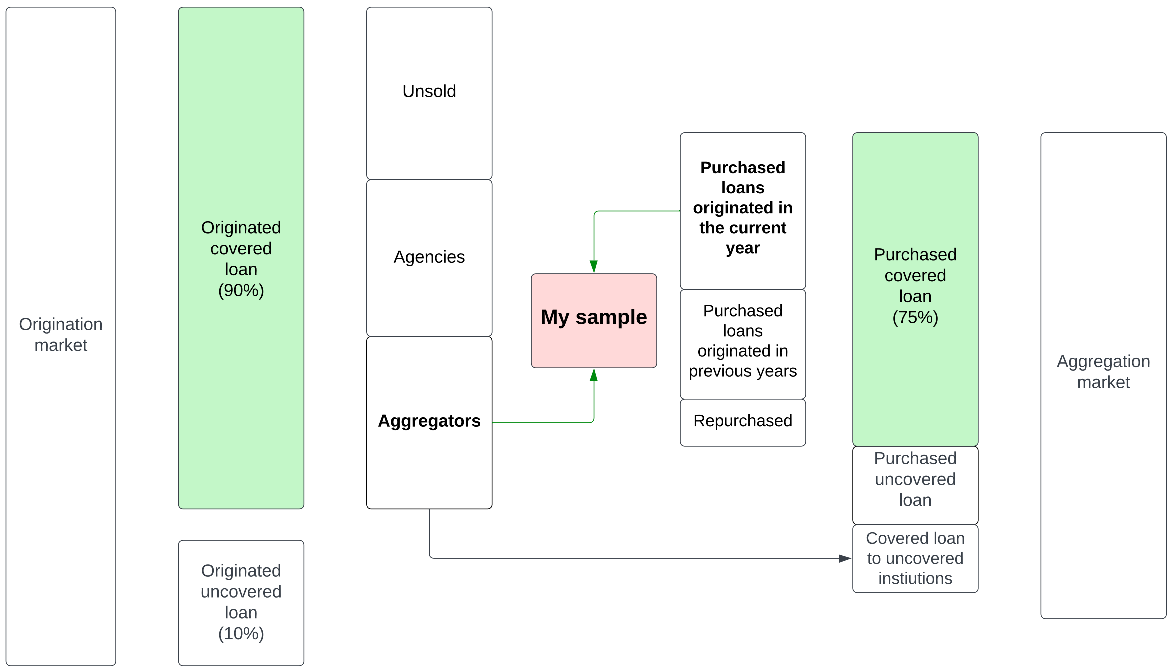
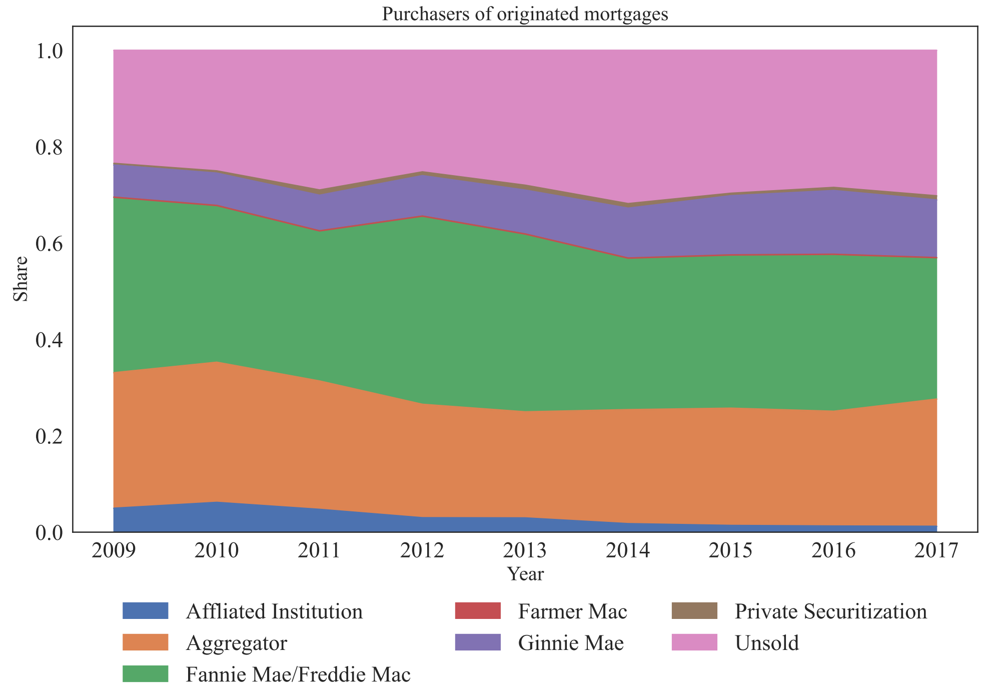


Figure 4: **Purchasers of aggregated mortgages**

This figure shows the fraction of originated and aggregated mortgages sold to different purchasers/securitizers. The sample period is 2009–2017. In the Home Mortgage Disclosure Act (HMDA) data, originated mortgages have an action taken code 1, and aggregated mortgages have an action taken code 6. Aggregators include commercial banks, savings banks or savings institutions, credit unions, mortgage banks, financial companies, life insurance companies, and finance companies.



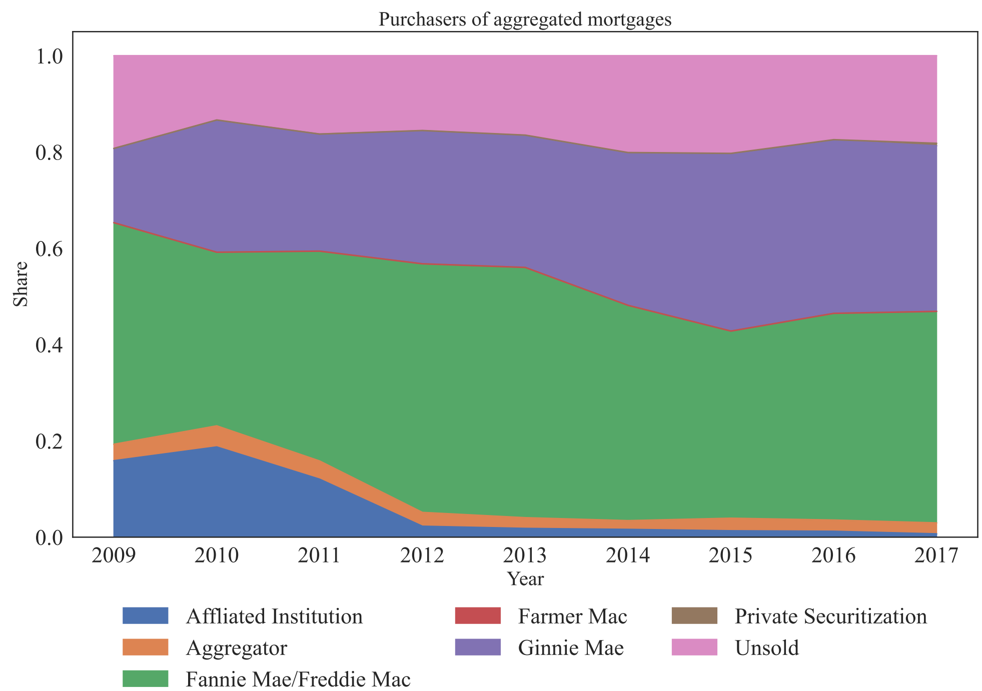


Figure 5: **Mortgage servicing and aggregation**

This figure is a binned scatter plot that shows the relationship between servicing market share and aggregation market share of commercial banks. The servicing market share MSRShare_b of bank b is measured as $\frac{\text{MSR}_b}{\sum_b MSR_b}$, where MSR_b is the amount of mortgage servicing right held by bank b. The aggregation market share AggShare_b of bank b is measured as $\frac{\text{Agg}_b}{\sum_b \text{Agg}_b}$, where Agg_b is the amount of mortgages aggregated by bank b. Both servicing and aggregation market shares are residualized by the logarithm of bank assets. The residualized servicing and aggregation market shares are grouped into 20 equal-sized bins. Each dot shows the average for mortgage aggregation market share for a given level of mortgage servicing market share, holding the asset value constant. The blue line is the best linear fit line for residualized aggregation market share and servicing market share.

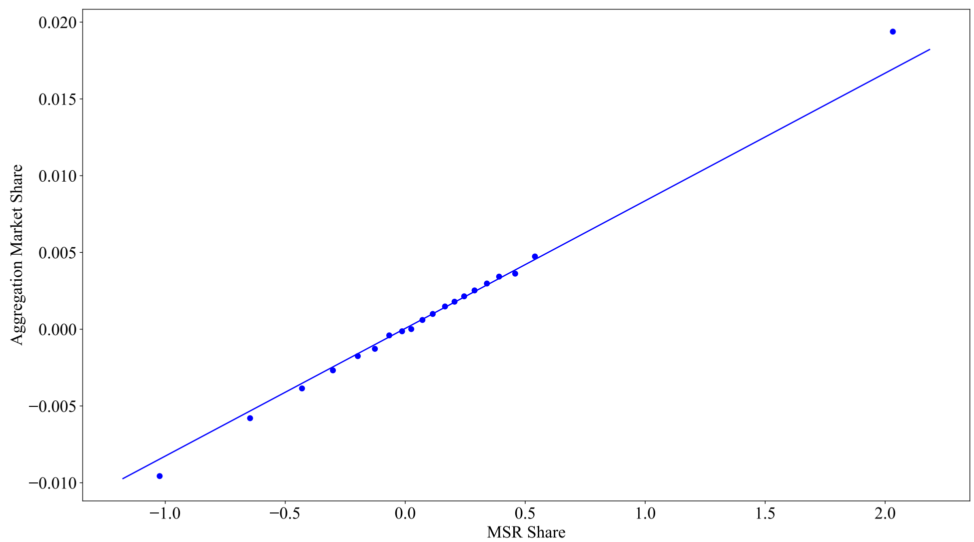
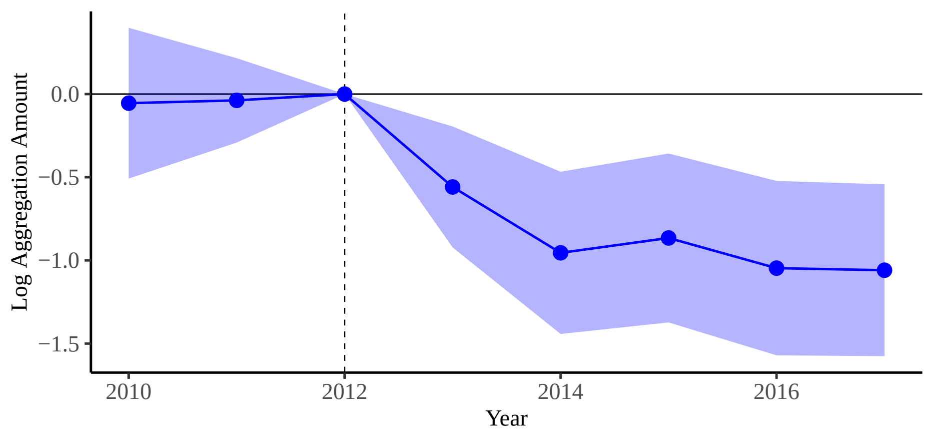


Figure 6: **Seller county level - Coefficient estimates by year**

This figure shows the coefficients estimated using $Y_{s,c,t} = \sum_{\tau=-2}^{5} (\beta_\tau \text{MSR}_s \times \text{Post}_{t+\tau}) + \gamma X_{s,t-1} + FEs + \epsilon_{s,c,t}$. The sample period is 2010–2017. The main independent variable is $\text{MSR}_s \times \text{Post}_t$, the interaction between correspondent lender-level exposure to the Basel III capital requirements on mortgage servicing rights (MSR_s) and the post dummy variable (Post_t). Correspondent lender-level exposure to Basel III is measured as the share of mortgages sold to bank aggregators with *ex-ante* MSR/Tier 1 capital over 10%, as defined in Equation (2). The post dummy variable equals 1 if year t is 2013 or later. The control variables include capital ratio, liquidity ratio, return on assets and log assets. Fixed effects include correspondent lender fixed effects, County×Year fixed effects, and correspondent Lender×County fixed effects. The standard errors are clustered at the correspondent lender level. In the upper panel, the dependent variable is the logarithm of the aggregation amount. In the lower panel, the dependent variable is the logarithm of the origination amount of correspondent lenders. The ribbon shows the 95% confidence interval.



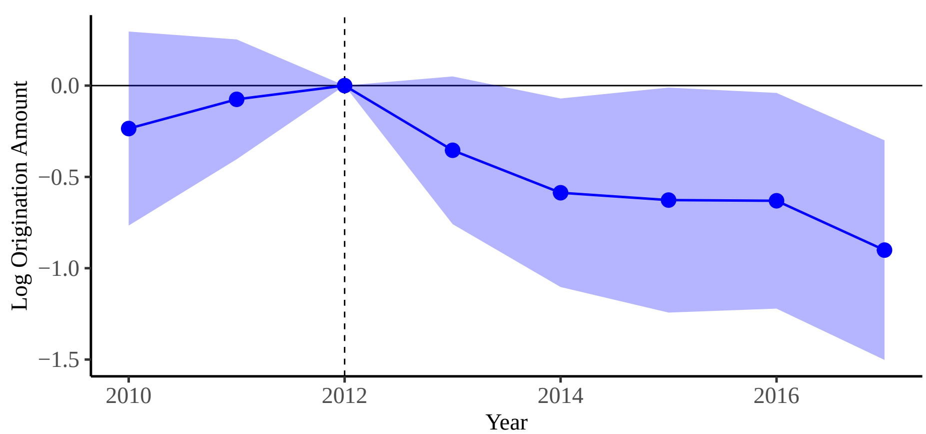


Figure 7: **Persistence of correspondent lender-aggregator relationship**

This figure shows the persistence of the relationships between correspondent lenders and aggregators. The real probability is measured as the faction of sellers selling to the same aggregator in year i conditional on selling to the aggregator in year $i-1$. The baseline is measured as the fraction of sellers selling to the same aggregator in year i when the seller is equally likely to sell to any aggregators in the data set.

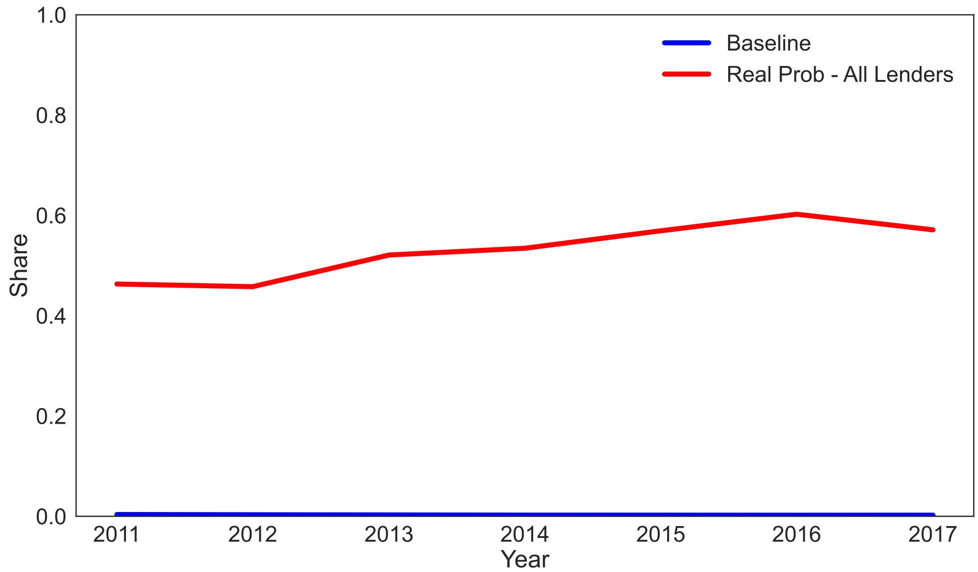


Figure 8: **Census tract income and aggregation market share**

This figure is a binned scatter plot that shows the relationship between the logarithm of census tract income and the fraction of mortgages sold to aggregators. The logarithm of census tract income and the fraction of mortgages sold to aggregators are grouped into 20 equal-sized bins. Each dot shows the average for the fraction of mortgages sold to aggregators for a given census tract income level. The blue line is the best linear fit line for the logarithm of census tract income and the fraction of mortgages sold to aggregators.

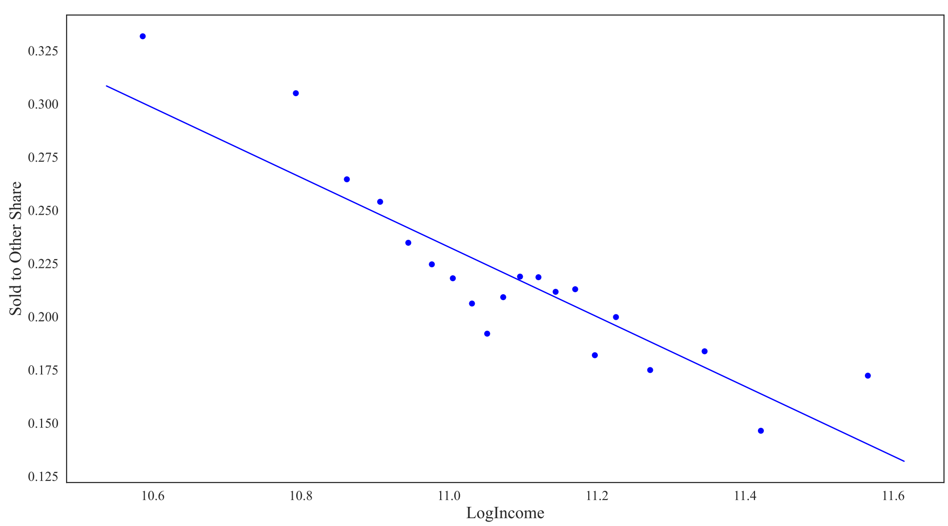


Table 1: **Summary statistics**

This table shows the summary statistics of the panel dataset at the correspondent lender-county level. The sample period is 2010 - 2017. The logarithm of the mortgage amount is calculated as log(1 + amount), and the amount is in thousands. Low-income borrowers are defined as borrowers with income less than 80% of MSA median income. Low-income areas are defined as census tracts with median income less than 80% of MSA median income. MSR_s is the correspondent lender level exposure to the Basel III capital requirements on mortgage servicing rights as defined in Equation 2. This table also reports measures for aggregation market relationships: (i) the number of aggregators that a correspondent lender sells their mortgages to, (ii) the concentration in the selling relationships, measured using the Herfindahl–Hirschman index and (iii) the number of nearby aggregators measured as the number of aggregators with their headquarters within 100 kilometres.

	Count	Mean	Std	25%	50%	75%
Log aggregation amount	693,191	4.37	3.13	0.00	5.29	6.49
Log origination amount	693,191	5.11	3.26	4.01	5.77	7.31
Approval rate (%)	550,344	76.59	26.90	63.94	83.06	100.00
Log low income borrower home purchase amount	693,191	2.82	3.20	0.00	0.00	5.67
Log low income area home purchase amount	693,191	1.77	2.87	0.00	0.00	4.68
MSR_s	693,191	0.33	0.25	0.11	0.33	0.50
Capital ratio (t-1)	437,272	0.13	0.06	0.09	0.11	0.14
Liquidity ratio (t-1)	437,272	0.15	0.12	0.06	0.12	0.21
Return on assets (t-1)	437,272	0.00	0.01	0.00	0.00	0.01
Log assets (t-1)	437,272	16.25	2.93	13.53	15.94	18.96
Shadow bank dummy	693,191	0.59	0.49	0.00	1.00	1.00
Number of aggregators	693,191	8.13	7.84	2.00	6.00	12.00
Aggregation market Herfindahl–Hirschman index	693,191	0.30	0.18	0.20	0.25	0.33
N. aggregators within 100 Km	624,026	8.37	7.94	2.00	5.00	14.00

Table 2: **Effects on aggregation, origination and approval rates**

This table shows the effect of the MSR regulation on aggregation amount. It reports the estimates from Equation (3) at the lender-county level from 2010–2017. The dependent variables are the logarithm of the aggregation amount, the logarithm of the origination amount and approval rates (in percentage) from correspondent lender s in county c and year t. The main independent variable is $\text{MSR}_s \times \text{Post}_t$, the interaction between correspondent lender-level exposure to the Basel III capital requirements on mortgage servicing rights (MSR_s) and the post dummy variable (Post_t). Correspondent lender-level exposure to Basel III is measured as the share of mortgages sold to aggregators with *ex-ante* MSR/Tier 1 capital over 10%, as defined in Equation (2). The post dummy variable equals 1 if year t is 2013 or later. Lender controls include lagged log asset, capital ratio, liquidity ratio and return on assets. All columns add Lender×County fixed effects; columns (2), (5) and (8) add Year fixed effects, and columns (3), (6) and (9) add County×Year fixed effects. Standard errors clustered at the correspondent lender level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	Log Aggregation Amount			Log Origination Amount			Approval Rate		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{MSR}_s \times \text{Post}_t$	-0.823***	-0.764***	-0.817***	-0.516**	-0.451**	-0.505**	-4.90**	-4.76**	-4.58**
	(0.190)	(0.188)	(0.185)	(0.223)	(0.220)	(0.234)	(2.15)	(2.18)	(2.14)
Post_t	0.791***			0.782***			2.14***		
	(0.080)			(0.087)			(0.690)		
Lender controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender×County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes		Yes	Yes		Yes	Yes
County×Year FE			Yes			Yes			Yes
Observations	429,318	429,318	429,318	429,318	429,318	429,318	355,200	355,200	355,200
R^2	0.745	0.748	0.767	0.825	0.827	0.841	0.618	0.617	0.656

Table 3: **Aggregate effects**

This table reports estimates from Equation (6) at the county level from 2010–2017. In columns (1)-(3), the dependent variables are the number of correspondent lenders, the share of applications from low-income borrowers, and the origination amount at the county level; the main independent variables are $\text{MSR}_c \times \text{Post}_t$, the interaction between county-level exposure to the Basel III capital requirements on mortgage servicing rights (MSR_c) and the post dummy variable (Post_t). County-level exposure to Basel III is measured as the share of mortgages sold to aggregators with *ex-ante* MSR/Tier 1 capital over 10%, as defined in Equation (4). The post dummy variable equals 1 if year t is 2013 or later and otherwise 0. In column (4), the dependent variable is the logarithm of the origination amount by county, year and loan type. LowInc_i is 1 for the origination amount of mortgages to low-income borrowers and 0 for the high-income borrowers in county c and year t. Low-income borrowers are defined as borrowers with income less than 80% of the MSA median family income. All columns include county and year fixed effects. Standard errors clustered at the county level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	Num Crspdt Lenders	Log Origination Amount		Low Inc Appl Share
	(1)	(2)	(3)	(4)
$\text{MSR}_{Agg,c} \times \text{Post}_t$	-2.3***	-0.10***	-0.07	-0.009
	(0.48)	(0.04)	(0.04)	(0.008)
$\text{MSR}_{Agg,c} \times \text{Post}_t \times \text{LowInc}_i$			-0.12**	
			(0.05)	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Observations	18,646	18,646	37,292	18,646
R^2	0.967	0.861	0.960	0.992

Table 4: **Matching frictions in the aggregation market**

This table shows the matching frictions in the aggregation market. It reports estimates from Equation (7) estimated at the correspondent lender-county level from 2010–2017. The dependent variable is the logarithm of the origination amount in year t. The main independent variable is $\text{MSR}_s \times \text{Post}_t \times \text{FundingFriction}_s$, the interaction between correspondent lender-level exposure to the Basel III capital requirements on mortgage servicing rights (MSR_s) and the post dummy variable (Post_t). Correspondent lender-level exposure to Basel III is measured as the share of mortgages sold to aggregators with *ex-ante* MSR/Tier 1 capital over 10%, as defined in Equation (2). The Post_t dummy variable equals 1 if year t is 2013 or later and otherwise 0. FundingFriction_s includes two measures. The first is Concentration_s, a Herfindahl–Hirschman index measuring the concentration in mortgages that correspondent s sold to connected aggregators in 2011. The second is OutsideOption_s, which is the number of aggregators whose headquarters are within 100 kilometres of the headquarter of correspondent lender s. Lender controls include lagged log asset, capital ratio, liquidity ratio and return on assets. All columns have Lender×County and County×Year fixed effects. Standard errors clustered at the correspondent lender level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	Log Origination Amount	
	(1)	(2)
$\text{MSR}_s \times \text{Post}_t \times \text{Concentration}_s$	-0.239***	
	(0.075)	
$\text{MSR}_s \times \text{Post}_t \times \text{OutsideOption}_s$		0.541***
		(0.079)
$\text{MSR}_s \times \text{Post}_t$	-0.392***	-0.776***
	(0.055)	(0.057)
$\text{Concentration}_s \times \text{Post}_t$	-0.017	
	(0.037)	
$\text{OutsideOption}_s \times \text{Post}_t$		-0.261***
		(0.040)
Lender controls	Yes	Yes
Lender×County FE	Yes	Yes
County×Year FE	Yes	Yes
Observations	437,272	425,026
R^2	0.842	0.843

Table 5: **Substitution margins**

This table shows the substitution margins of correspondent lenders. It reports estimates from Equation (8) estimated at the correspondent lender level from 2010–2017. The dependent variables are the agency relationship dummy, the share of mortgages sold to agencies, the share of mortgages sold to aggregators, and the number of connected aggregators of correspondent lenders s in year t. The agency relationship dummy is 1 if correspondent lender s sells its mortgages to either Fannie Mae, Freddie Mac or Ginnie Mae and otherwise 0. The main independent variable is $\text{MSR}_s \times \text{Post}_t$, the interaction between correspondent lender-level exposure to the Basel III capital requirements on mortgage servicing rights (MSR_s) and the post dummy variable (Post_t). Correspondent lender-level exposure to Basel III is measured as the share of mortgages sold to aggregators with *ex-ante* MSR/Tier 1 capital over 10%, as defined in Equation (2). The post dummy variable equals 1 if year t is 2013 or later. Lender controls include lagged log asset, capital ratio, liquidity ratio and return on assets. All columns use lender and year fixed effects. Standard errors clustered at the correspondent lender level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	Agency Relationship	Share - Agency	Share - Aggregator	Num Aggregators
$\text{MSR}_s \times \text{Post}_t$	0.113***	0.081***	-0.045**	1.80***
	(0.028)	(0.017)	(0.018)	(0.351)
Lender controls	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	13,686	13,686	13,686	13,686
R^2	0.735	0.817	0.824	0.849

Table 6: **Balance sheet funding**

This table shows the effect of the MSR regulation on the deposit funding of correspondent lenders. It reports estimates from Equation (7) estimated at the Lender×County level from 2010–2017. The dependent variable is the logarithm of the deposit amount of correspondent lender s in county c and year t. The deposit amount comes from the FDIC Summary of Deposits data. The main independent variable is $\text{MSR}_s \times \text{Post}_t$, the interaction between correspondent lender-level exposure to the Basel III capital requirements on mortgage servicing rights (MSR_s) and the post dummy variable (Post_t). Correspondent lender-level exposure to Basel III is measured as the share of mortgages sold to aggregators with *ex-ante* MSR/Tier 1 capital over 10%, as defined in Equation (2). The post dummy variable equals 1 if year t is 2013 or later and otherwise 0. Lender controls include lagged log asset, capital ratio, liquidity ratio and return on assets. All columns use lender and year fixed effects. Standard errors clustered at the correspondent lender level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	Log Deposits			
	(1)	(2)	(3)	(4)
$\text{MSR}_s \times \text{Post}_t$	0.155	0.064	0.067	-0.136
	(0.114)	(0.049)	(0.049)	(0.123)
MSR_s	0.048			
	(0.110)			
Post_t	-0.023	0.046***		
	(0.033)	(0.014)		
Lender controls	Yes	Yes	Yes	Yes
Lender×County FE		Yes	Yes	Yes
Year FE			Yes	
County×Year FE				Yes
Observations	15,933	15,933	15,933	15,933
R^2	0.026	0.944	0.945	0.979

Table 7: **Adverse selection in the funding markets**

This table reports estimates from Equation (9) estimated at the seller county level from 2010–2017. The dependent variable is the logarithm of the origination amount in year t. The main independent variable is $\text{MSR}_s \times \text{Post}_t$, the interaction between correspondent lender-level exposure to the Basel III capital requirements on mortgage servicing rights (MSR_s) and the post dummy variable (Post_t). Correspondent lender-level exposure to Basel III is measured as the share of mortgages sold to aggregators with *ex-ante* MSR/Tier 1 capital over 10%, as defined in Equation (2). The post dummy variable equals 1 if year t is 2013 or later. $\text{Size}_{s,t-1}$, $\text{CapitalRatio}_{s,t-1}$ and $\text{LiquidityRatio}_{s,t-1}$ are the lagged size, capital ratio and liquidity ratio of correspondent lender s. Lender controls include lagged log asset, capital ratio, liquidity ratio and return on assets. Standard errors clustered at the correspondent lender level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	Log Origination Amount		
	(1)	(2)	(3)
$\text{MSR}_s \times \text{Post}_t \times \text{Size}_{s,t-1}$	0.380**		
	(0.149)		
$\text{MSR}_s \times \text{Post}_t \times \text{CapitalRatio}_{s,t-1}$		-1.89	
		(1.26)	
$\text{MSR}_s \times \text{Post}_t \times \text{LiquidityRatio}_{s,t-1}$			0.856***
			(0.322)
$\text{MSR}_s \times \text{Post}_t$	-1.59***	-0.268*	-0.648***
	(0.439)	(0.153)	(0.073)
$\text{Size}_{s,t-1} \times \text{Post}_t$	-0.206***		
	(0.045)		
$\text{CapitalRatio}_{s,t-1} \times \text{Post}_t$		-1.08*	
		(0.599)	
$\text{LiquidityRatio}_{s,t-1} \times \text{Post}_t$			0.014
			(0.144)
Lender controls	Yes	Yes	Yes
Lender×County FE	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes
Observations	437,272	398,294	398,294
R^2	0.842	0.836	0.836

Table 8: **Choices of aggregators**

This table shows the choices of aggregators. It reports estimates from Equation (10) estimated at the correspondent lender-aggregator level from 2010–2017. The dependent variable is the logarithm of the aggregation amount sold by correspondent lender s to aggregator b in year t by loan type$i$. The main independent variable is $\text{MSR}_b \times \text{Post}_t \times \text{LoanType}_i$, the interaction between aggregator-level exposure to the Basel III capital requirements on mortgage servicing rights (MSR_b) and the post dummy variable (Post_t) and loan type LoanType_i. Aggregator-level exposure to Basel III is 1 if *ex-ante* MSR/Tier 1 capital over 10%, as defined in Equation (1) and otherwise 0. The post dummy variable equals 1 if year t is 2013 or later and otherwise 0. Loan types LoanType_i include a low-income borrower dummy LowInc_i, a low-income area dummy LowIncArea_i, a dummy variable for low-income borrowers from low-income area $\text{LowIncLowIncArea}_i$ and a dummy for high loan-to-income (LTI) mortgages. A low-income borrower is a borrower with income less than 80% of the FFIEC MSA median family income. A low-income area is a census tract with a median family income lower than 80% of the FFIEC MSA median family income. A high LTI mortgage has a loan-to-value ratio above the median level of loan-to-value ratio in mortgage applications. Lender×Year, Aggregator, Year, and Lender×Aggregator fixed effects are added to all columns. Standard errors are clustered at the correspondent lender-year level. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	Log Aggregation Amount			
	(1)	(2)	(3)	(4)
$\text{MSR}_b \times \text{Post}_t \times \text{LowInc}_i$	-0.125***			
	(0.029)			
$\text{MSR}_b \times \text{Post}_t \times \text{LowIncArea}_i$		-0.110***		
		(0.032)		
$\text{MSR}_b \times \text{Post}_t \times \text{LowIncLowIncArea}_i$			-0.103***	
			(0.035)	
$\text{MSR}_b \times \text{Post}_t \times \text{HighLTI}_i$				-0.066***
				(0.025)
$\text{MSR}_b \times \text{Post}_t$	-0.072*	-0.060	-0.076*	-0.058
	(0.041)	(0.042)	(0.044)	(0.040)
$\text{LowInc}_i \times \text{Post}_t$	-0.102***			
	(0.018)			
$\text{LowIncArea}_i \times \text{Post}_t$		0.273***		
		(0.019)		
$\text{LowIncLowIncArea}_i \times \text{Post}_t$			-0.152***	
			(0.021)	
$\text{HighLTI}_i \times \text{Post}_t$				-0.020
				(0.016)
$\text{MSR}_b \times \text{LowInc}_i$	-0.147***			
	(0.021)			
$\text{MSR}_b \times \text{LowIncArea}_i$		-0.412***		
		(0.026)		
$\text{MSR}_b \times \text{LowIncLowIncArea}_i$			0.013	
			(0.028)	
$\text{MSR}_b \times \text{HighLTI}_i$				0.032*
				(0.019)
LowInc_i	-0.818***			
	(0.014)			
LowIncArea_i		-1.65***		
		(0.016)		
$\text{LowIncLowIncArea}_i$			-0.179***	
			(0.017)	
HighLTI_i				0.241***
				(0.012)
Lender×Year FE	Yes	Yes	Yes	Yes
Aggregator FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Lender×Aggregator FE	Yes	Yes	Yes	Yes
Observations	152,685	145,039	79,527	155,966
R^2	0.772	0.773	0.760	0.778

Table 9: **Effects on origination amount by borrower types**

This table reports estimates from Equation (11) estimated at the correspondent lender level from 2010–2017. The dependent variable is the logarithm of the origination amount of correspondent lender s in year t by borrower type i. The main independent variable is $\text{MSR}_s \times \text{Post}_t \times \text{Borrower}_i$, the interaction between correspondent lender-level exposure to the Basel III capital requirements on mortgage servicing rights (MSR_s) and the post dummy variable (Post_t) and borrower type Borrower_i. Correspondent lender-level exposure to Basel III is measured as the share of mortgages sold to aggregators with *ex-ante* MSR/Tier 1 capital over 10%, as defined in Equation (2). The post dummy variable equals 1 if year t is 2013 or later and otherwise 0. The borrower type includes a dummy variable for low-income borrowers, Low Income Borrower_i and a dummy variable for borrowers from low-income areas, Low Income Area_i. A low-income borrower is a borrower with income less than 80% of the FFIEC MSA median family income. A low-income area is defined as a census tract with a median family income lower than 80% of the FFIEC MSA median family income. Lender controls include lagged log asset, capital ratio, liquidity ratio and return on assets. Lender×County fixed effects, and County×Year fixed effects are added. Column (1) reports the results for low-income borrowers, and column (2) reports the results for borrowers from low-income areas. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	Log Origination Amount	
	(1)	(2)
$\text{MSR}_s \times \text{Post}_t \times$ Low Income Borrower_i	-0.183***	
	(0.040)	
$\text{MSR}_s \times \text{Post}_t \times$ Low Income Area_i		-0.205***
		(0.041)
$\text{MSR}_s \times \text{Post}_t$	-0.358***	-0.279***
	(0.039)	(0.037)
Low Income $\text{Borrower}_i \times \text{Post}_t$	-0.474***	
	(0.018)	
Low Income $\text{Area}_i \times \text{Post}_t$		-0.120***
		(0.019)
$\text{MSR}_s \times$ Low Income Borrower_i	0.369***	
	(0.034)	
$\text{MSR}_s \times$ Low Income Area_i		-0.010
		(0.037)
Lender controls	Yes	Yes
Lender×County FE	Yes	Yes
County×Year FE	Yes	Yes
Observations	874,544	874,544
R^2	0.704	0.716

Table 10: **Specialization of correspondent lenders**

This table reports estimates from Equation (12) and (13) from 2010–2015. Column (1) reports the estimates from Equation (12). The dependent variable is a correspondent lender dummy for an application submitted by borrower i to lender j in census tract k and year t. It takes 1 if the lender j is a correspondent lender as defined in 3 and otherwise 0. The main independent variable is a low-income dummy variable $\text{LowInc}_{i,j,k,t}$, which is 1 if the borrower i is a borrower with income lower than 80% of FFIEC median family income at the MSA level and otherwise 0. Columns (2)-(6) reports the estimates from Equation (13) for low income borrowers. The independent variables are a rejection dummy, a rejection reason dummy for unverifiable information, a rejection reason dummy for incomplete application, an interest rate and a delinquent dummy. The delinquent dummy is 1 if the mortgage is delinquent over 90 days within two years after origination and otherwise 0. Columns (2)-(4) uses HMDA data and columns (5)-(6) uses HMDA-Attom-FF data. In columns (5)-(6), other borrower and loan characteristics, including loan-to-value ratio(LTV), debt-to-income ratio (DTI), FICO, loan term, first-time home buyer indicator and number of units, are added as controls. In column (1), standard errors are clustered at the census tract level. In columns (2)-(6), standard errors are double clustered at the lender and census tract level. Standard errors are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	Correspondent	Rej	Rej - Unverifiable	Rej - Incomplete	Interest Rate	Delinquent
$\text{LowInc}_{i,j,k,t}$	0.669***					
	(0.025)					
$\text{Correspondent}_{i,j,k,t}$		-4.28***	-1.34***	-6.09***	0.007*	0.056
		(0.604)	(0.436)	(1.19)	(0.004)	(0.046)
Income quantile FE		Yes	Yes	Yes	Yes	Yes
Loan amount quantile FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan type FE		Yes	Yes	Yes		
Applicant sex FE	Yes	Yes	Yes	Yes	Yes	Yes
Co-applicant FE	Yes	Yes	Yes	Yes	Yes	Yes
Minority FE	Yes	Yes	Yes	Yes	Yes	Yes
Census tract×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Other characteristics					Yes	Yes
Observations	19,912,317	6,472,836	757,621	757,621	349,318	349,318
R^2	0.11	0.11	0.35	0.38	0.72	0.44

A Appendix

This document contains additional material referenced in the text.

A.1 Data Appendix

I elaborate on the data description in Section 3 by providing additional details about the Home Mortgage Disclosure Act, Attom dataset, Fannie Mae and Freddie Mac Single Family Loan Level Data, and additional datasets in Appendix A.1.1, A.1.2, A.1.3 and A.1.4. I describe my matching algorithm in Appendix A.1.5. I provide descriptive figures and tables for these data sets and additional details about the matching performance in Appendix A.3.

A.1.1 Home Mortgage Disclosure Act (HMDA)

I use mortgage data from the Home Mortgage Disclosure Act to (i) construct the aggregator-correspondent lender network and (ii) obtain mortgage origination amount/count/rejection rate by lender and county.

Home Mortgage Disclosure Act (HMDA) requires financial institutions satisfying minimum asset and loan origination thresholds to disclose information about the mortgage loan applications they receive, making this dataset the most comprehensive source of information on the U.S. residential mortgage market. It contains a rich set of characteristics about the lender, borrower, and mortgage at the application level. For example, I observe the location, income, race, ethnicity, and gender of borrowers. I also observe the name, address, and a unique lender identifier for lenders.

HMDA classifies applications into origination, rejection, purchase(aggregation) and others based on the variable "action-taken code". HMDA specifies who reports the decision on an application and which decision should be reported for an application. Since I use mortgages classified as origination and purchase(aggregation) to construct the aggregator-correspondent network, I provide details of the reporting requirements related to these two action-taken codes.

- **Origination:** A financial institution reports its decision on an application if it or its agents make a credit decision prior to closing or opening an account. The determination as to whether one financial institution is an agent of the other is determined by state law. If more than one institution approved an application before closing or account opening and one of those institutions purchased the loan after closing, the institution that purchased the loan after closing reports the loan as an origination.

- **Purchase:** A financial institution reports a loan purchase if they purchase or repurchase a loan from another financial institution. They do not include purchase or repurchase that is part of an interim funding agreement.[20]

HMDA covers over 90% of all originated mortgages in the United States.[21] Though it is the most comprehensive source of information on the U.S. residential mortgage market, it has several caveats. There are several caveats of HMDA data. First, HMDA only reports the purchaser type in the current year. A mortgage originated in November 2022 and sold in January 2023 would have a purchaser type as "unsold". Second, a financial institution records a purchased loan regardless of whether the purchase/repurchase occurs within the same calendar year that the covered loan was originated or in a different calendar year. Third, firms do not originate any loans but only purchase may not be required to file with

[20] They are sometimes employed as functional equivalents of warehouse lines of credit and often referred to as "repurchase agreements"

[21] Kevin Johnson and Richard M. Todd, "The Value of HMDA Coverage of Home Lending in Rural Areas and Indian Country," Center for Indian Country Development at the Federal Reserve Bank of Minneapolis Working Paper 2019-04, 2019, available at www.minneapolisfed.org/research/cicd-working-paper-series/201904-the-value-of-hmda-coverage-of-home-lending-in-rural-areas-and-indian-country. Consumer Financial Protection Bureau, "Data Point: 2017 Mortgage Market Activity and Trends: A First Look at the 2017 HMDA Data", Washington, D.C.: Consumer Financial Protection Bureau, 2018, available at s3.amazonaws.com/files.consumerfinance.gov/f/documents/bcfp_hmda_2017-mortgage-market-activity-trends_report.pdf.

HMDA. Fourth, if a loan is first purchased by a financial institution, A and then sold by A to another financial institution, B, both financial institutions, A and B, would record the loan as purchase.

With these caveats in mind, I construct the aggregator-correspondent lender network by matching the origination and purchase/aggregation part of HMDA. I merge two parts of the HMDA data: first, the originated loans that are labelled as sold to commercial banks, savings banks or savings associations, credit unions, mortgage banks, finance companies, affiliated institutions, and another type of purchasers, and second, purchased loans as indicated by action taken code 6. I conduct the merge over the sample period 2010–2023.[22] The merged dataset allows me to observe the buy/sell relationships between financial institutions. The details of the matching algorithm are provided in Appendix A.1.5.

The caveats of HMDA data bring concerns to my matching results. First, HMDA only records the actions on loans in the current year. If a loan is originated in year t and sold in year $t+1$, the loan is recorded in year t HMDA data as unsold. If a financial institution purchases most mortgages originated in the previous year, my matching algorithm that only allows a match between an originated loan and a purchased loan within the same calendar would result in a biased network. The concern is lessened by the following facts observed from the HMDA data: (i) Most loans are sold within 2 months of origination by industry standard. Only 20% of loans are not sold in the current year. These loans are likely originated closer to the year-end of a calendar year; (ii) By matching year t's aggregation to year t-1's unsold mortgages, the fraction of loans matched is less than 2%, which indicates only a tiny fraction of aggregated mortgages are not originated in the current year.

[22]Note that after 2018, HMDA assigns a unique loan identifier to all applications. If a loan is originated by financial institution A and subsequently purchased by another financial institution B, both institutions should report the loan under the same identifier. However, such a loan identifier is not available to the public.

Second, HMDA includes covered loans originated and sold by the financial institutions but repurchased from the financial entity to which the loans were sold. There is no indicator for the loans aggregated and repurchased. This leads to errors in matching because I am only interested in the loans aggregated. However, mortgage repurchases are generally rare.[23] For example, Fannie Mae reported that, as of the end of 2013, it requested repurchases for less than 0.25% of the mortgages it acquired between 2009 and 2012 and the repurchase volume may further decline.[24] In addition, I compute that the fraction of mortgages purchased by a financial institution from its origination or origination of subsidiaries is less than 10%. This provides an upper bound for the fraction of repurchased mortgages in my matched dataset.

Third, HMDA reports the total loan amount of originated mortgages while the unpaid balance of purchased mortgages, so merging the loan amount and unpaid balance leads to error. However, most agency-securitized mortgages are sold within two months of origination. At the time of aggregation, the loan amount barely changes within 2 months. If these two numbers are different, the difference between the total loan amount and unpaid balance should be small and taken care of by the difference in the amount allowed in my matching algorithm.

Fourth, HMDA only requires financial institutions that meet specific asset and mortgage origination count thresholds to report their mortgage activities. Firms that do not originate any loans may not be required to file with HMDA and thus do not show up in my network. However, the aggregation market is highly concentrated, and the top 10 aggregators in HMDA take up 40% of the market share, according to the Mortgage Bankers Association survey. So the resulted network in my data still captures majority of the business relationships in the mortgage market.

[23] See Federal Housing Finance Agency report. https://www.fhfaoig.gov/Content/Files/EVL-2014-010_0.pdf

[24] The repurchase rate for mortgages it acquired between 2005 and 2008 was 3.7%. See Fannie Mae, Form 10-K for the Fiscal Year Ended December 31, 2013, at 143.

Fifth, a mortgage can be sold multiple times. The long intermediation chain leads to inaccuracy in the network captured by my matching algorithm as I only consider the case when the loan is originated, sold to an aggregator and securitized. I show that 80% aggregated loans are sold directly to Fannie Mae, Freddie Mac and Ginnie Mae, without selling to another financial institution subsequently. Otherwise, they would be recorded as other. In addition, I only keep one-to-one matches in my dataset, which represents 87% of the match, indicating that the longer intermediation chains in HMDA are not common after the global financial crisis.

In my dataset, I define the lender that originates a mortgage and sell the mortgage to an unaffiliated financial institution as a correspondent lender and the mortgage originated by a correspondent lender and sold to an unaffiliated financial institution as a correspondent loan. HMDA does not have a variable for loan origination channels. My definition of correspondent loans or correspondent lending channels could differ from the definitions of the Fannie Mae and Freddie Mac Single-Family Loan-Level dataset. For example, a financial institution can have a business relationship with a correspondent lender without delegating underwriting. In HMDA, the financial institution that has underwriting records the loan as origination. If the financial institution sells the loan to Fannie Mae, Fannie Mac or Ginnie Mae directly but not to another financial institution, my dataset would not consider the loan as correspondent lending. However, in the Fannie Mae and Freddie Mac Single-Family Loan-Level dataset, such a loan is regarded as a correspondent lending loan if a third-party correspondent lender is involved in the origination process and a broker is not used. I focus on when correspondent lenders can make decisions because it represents their willingness to supply credit.

A.1.2 Attom real estate data

Attom Real Estate Data covers over 155 million properties and 500 million real estate and loan transactions in over 2690 counties. Like other popular real estate datasets, such as CoreLogic and Zillow, the Attom dataset is divided into transaction and assessment datasets. The former dataset contains information on transfers, mortgages, and other real estate transactions, while the latter contains information on property characteristics.

To clean the Attom data, I follow Reher and Valkanov (2021), and adapt the cleaning procedure to Attom. I use the following steps: (i) I obtain a set of non-arms length home purchase transactions. This includes excluding arm's length transactions and foreclosures flagged by Attom, observations with QuitClaimFlag as 1, observations with DocumentTypeCode as DTIT (Intrafamily Transfer) and DTGF (gift deed), observations that are not classified as "Transfer" or "Subdivision Related Transfer" in TransferInfoPurchaseTypeCode; (ii) I keep the individual transactions for home purchasing. This involves keeping only transactions where buyers are not company and properties that are single family or condo; (iii) I keep transactions with valid price, mortgage, location and transactor information. I exclude transactions with transfer amounts smaller than 10000, mortgage amounts larger than the 99th percentile of HMDA application amount in 2022 ($1,800,000), LTV ratios larger than 125% and transactions without valid buyer, seller names and census tracts.

These filters limit the transactions to valid residential home purchase transactions with reasonable mortgage amounts and loan-to-value ratios. They allow me to better match the transaction to Home Mortgage Disclosure Act data and reduce underestimation in calculating match rates. For example, if I include commercial properties in the Attom dataset when I merge Attom with HMDA, I would obtain a downwardly biased estimate. The remaining filters rule out extreme cases or observations highly subject to measurement error.

The resulting dataset is referred to as the "Filtered Attom Dataset." I focus on the sample period 2010–2017. In terms of coverage, the filtered dataset covers 80% of U.S. counties on a population-weighted basis or 70% on an unweighted basis.

I merge the Attom dataset with the HMDA dataset. The merge allows me to obtain the origination month for each mortgage application and observe a subset of mortgage rates. I detail the matching algorithm in Appendix A.1.5.

A.1.3 Fannie Mae and Freddie Mac Single Family Loan Level Dataset

Fannie Mae and Freddie Mac provide a single-family loan-level dataset with a subset of their 30-year and less, fully amortizing, full documentation, single-family, conventional fixed-rate mortgages. The dataset does not only include the loan characteristics but also the monthly performance of each Loan. The loan characteristics include the loan origination channel (retail, correspondent and broker), loan-to-value ratio, debt-to-income ratio, loan amount, interest rate, seller identity, servicer identity, and the monthly performance of loans.

Seller and servicer identity is revealed if a seller or servicer sells or services more than 1% of UPB of the loans acquired in the current year quarter. For loans that are not originated through the retail channel, the identity of the original lender is unknown. In addition, these two datasets do not have the lender identity or the exact location of loans. The location of loans is at the three-digit zip code level.

To overcome these two data shortcomings, I use the resulting dataset from merging HMDA and Attom, which allows me to have the exact location and Loan origination year month. I next merge the dataset with Fannie Mae and Freddie Mac based on loan origination year, month, and loan amount. I can obtain interest rates and loan performance for the matched loans.

A.1.4 Other Datasets

Call Reports Data I collect bank call reports data, shadow bank mortgage call reports data, thrift call reports data and credit union call reports data. I obtain these data from the following sources:

- Bank call reports data: I source the data from Wharton Research Data Services (WRDS) Bank Regulation. The data includes bank and thrift financial institutions' balance sheets and income statements.[25]

- Shadow bank call reports data: I submit FOIA requests to Massachusetts and Washington to obtain company-level information on shadow banks that operate in these two states. Though I only sourced data from two states, the resulting dataset covers shadow banks that originate over 80% of the origination of shadow banks in the U.S. from 2012 to 2017. The dataset is available after 2011, and the coverage is only 50% in 2011.

- Thrift call reports data: I obtain the balance sheet variables for thrift financial institutions before 2012 from The Federal Deposit Insurance Corporation (FDIC) RIS API.

- Credit union call reports data: I download the credit union call reports data from the National Credit Union Administration.

These datasets allow me to control 68% financial characteristics of the correspondent lenders in the mortgage market during my sample period and 79% financial characteristics of the correspondent lenders after 2012.

U.S. Census Data I get the county-level median household income, population, fraction of households with an annual income lower than $35,000, fraction of residents with a bachelor's degree, fraction of residents over 65 years old from the U.S. Census API.

A.1.5 Matching algorithm

Matching HMDA Originated Mortgages with Aggregated Mortgages: I first merge by census tract, loan type, loan purpose and property type and select observations with loan amount difference in [-1,1] range and income difference in [-1, 1] range. I also match on race, sex, and ethnicity if these variables are available. If there is only one

[25] After 2011, all thrift institutions file FFIEC 031/FFIEC 041/FFIEC 051 reports like banks.

unique match, I keep the match. I require an exact match on the loan amounts if there is more than one match. I further examine if an originated loan is matched to multiple purchase/aggregated loans; if so, exclude the originated loan and only keep one-to-one matches. Table A.1 compares the summary statistics of matched vs unmatched mortgages among the purchased mortgages in HMDA. The only noticeable difference is that the matched sample covers more conventional mortgages than the unmatched sample.

My algorithm has a match rate of 60%, with a dip in match rate during 2007-2009 and a trend to go higher in recent years, see Figure A.1. The match rate in recent years (2018–2020) has reached 78%. The match rate at the county level shows that the match rate is generally high across the counties in the United States, with high match rates concentrated in the middle states, see Figure A.2. My algorithm relies on matching census tract and loan amount, which biases the match towards areas with low population density. While the findings may not extend to areas with high density, due to data representatives, borrower financial literacy, lender competition or aggregator competition, my results are present in areas with low population density, and these areas are more likely to have a high fraction of low-income borrowers.

Matching HMDA Originated Mortgages with Attom: I first clean HMDA data to keep home purchase loans only and clean Attom data to keep residential real estate transactions with mortgages. Next, I conduct an exact merge by census tract, loan amount, and a fuzzy match on lender identity. Note that Attom records the lender as the lender that closes the loan, while HMDA records the lender as the lender that makes the credit decision. In the case of table-funding and correspondent lending, the lender identities are likely to differ. When there is only one match based on census tract and loan amount, I ignore the lender name string match. If there are multiple matches, I check the lender name difference and require the fuzz score to be over 70. I clean the lender names in the HMDA and Attom datasets before conducting a fuzzy match.

Matching HMDA-Attom with Fannie Mae and Freddie Mac dataset: I first match mortgages based on the loan amount, three-digit zip code, loan type, and loan purpose. These variables should be matched exactly. I next match mortgages based on loan origination year month and loan-to-value ratio. The difference between loan origination year month should be in [0, 2] months range, and the difference in loan-to-value ratio should be less than 5%.

A.2 Additional Results

A.2.1 Discussion of confounding events

The U.S. mortgage market underwent significant changes after the global financial crisis. Mortgage lenders face heightened and uncertain put-back and litigation risks in addition to tight banking regulations. I discuss how these risks may confound the main analysis.

Put-back risk: Put-back risk can lead to a lending cut and disproportionately affect low-quality loans. Put-backs occur when the origination documents are faulty or fraudulent, e.g. the creditworthiness of borrowers and appraisal value of the property is misrepresented. The put-back risk was material for loans originated during 2006 and 2008 when the fraction of loans repurchased reached about 1% and 2% for 30-year fixed rate, full-amortized and full documentation loans (Goodman, Parrott, and Zhu, 2015). Though the fractions seem small, lenders could be impacted because the share of put-backs on their books could be large. In addition, lenders were concerned about the lack of clarity in repurchase activities, which led to tighter lending standards despite the low realized repurchase rate.[26] Since low-quality loans are more likely to be repurchased, put-backs mainly affect lending of low-quality loans. The predictions seem to align with the impact of Basel III capital requirements of MSRs on correspondent lending if aggregators with a larger servicing right exposure are also the ones more exposed to put back risks.

However, there are at least two reasons to believe that my results are unlikely to be driven by the put-back risk. First, the magnitude of realized repurchase rate was unlikely high enough to explain significant decline in lending. The put-back risk was lower in and after 2013. The realized repurchase rate is only 0.2% for loans originated in 2013, comparable to the repurchase rate before housing boom. Second, the FHFA, Fannie Mae and Freddie Mac each announced a new "rep and warrant relief" framework which relived sell-

[26] See https://www.federalreserve.gov/newsevents/speech/bernanke20121115a.htm

ers from repurchasing obligations for loans that met specific pay history requirements on or after January 1, 2013, after recognizing the negative impact of put-back uncertainty on lending. The announcement of the new framework led to the ease of lending standards among lenders and would bias my estimates towards 0 for the negative impacts I found among correspondent lenders.

Litigation risk: After the global financial crisis, the U.S. Department of Justice brought lawsuits against main FHA lenders under the False Claims Act for alleged fraudulent origination of FHA mortgages. The liability stemming from these prosecutions caused the exit of large FHA lenders from the origination market (Frame, Gerardi, Mayer, Xu, and Zhao, 2024) and the exit of one large FHA aggregator - JPMorgan Chase from the aggregation market (Benson, Kim, and Pence, 2023). My results may be driven by the litigation risks large aggregators face in their FHA market.

To address the problem, I first show that the aggregation and origination pattern of correspondent lenders did not diverge until 2013, one year after the main wave of lawsuits started, see Figure 6. I next show that the decrease in aggregation amount also presents in the conventional loan market, a segment less likely to be directly impacted by the lawsuits aimed at the FHA market, see Table A.7.

Guarantee fee change: Starting in 2011, the GSEs erased the volume discount on guarantee fees. On average, the top 10 GSE sellers paid nine bps lower guarantee fees compared to sellers outside the top 100 before 2011 (Begley and Srinivasan, 2022). The spread was reduced to 6 bps in 2012 and 0 in 2013. The removal of the volume discount decreased the profits of mortgage aggregation and led to the exit of some aggregators. However, the removal of the volume discount did not target bank aggregators.[27] To show that my results

[27] The top 10 GSE sellers in 2010 Q4 are Wells Fargo, N.A., GMAC Mortgage, LLC, U.S. Bank, Citi Mortgage, JP Morgan Chase Bank, Flagstar Bank, Phh Mortgage Corporation, BB&T, Provident Funding Associates, L.P., Bank of America

are not driven by the guarantee fee change, I check if my results are sensitive to controlling for the negative effect from the top 10 GSE sellers. Table A.8 shows the regression results. Controlling for the effect arising from the top 10 GSE sellers does not affect the coefficient estimate of the effect of Basel III mortgage servicing right on aggregation volume. Removing the guarantee fee volume discount reduced total aggregation volume. However, it did not disproportionately affect the correspondent lenders who were more exposed to aggregators affected by the Basel III capital requirements on MSRs.

A.3 Figures and Tables

Figure A.1: Time series match rate

This figure shows the time series match rate of aggregated mortgages in my sample. The sample period is 2000–2021. The matching algorithm is described in Section 3.3.1.

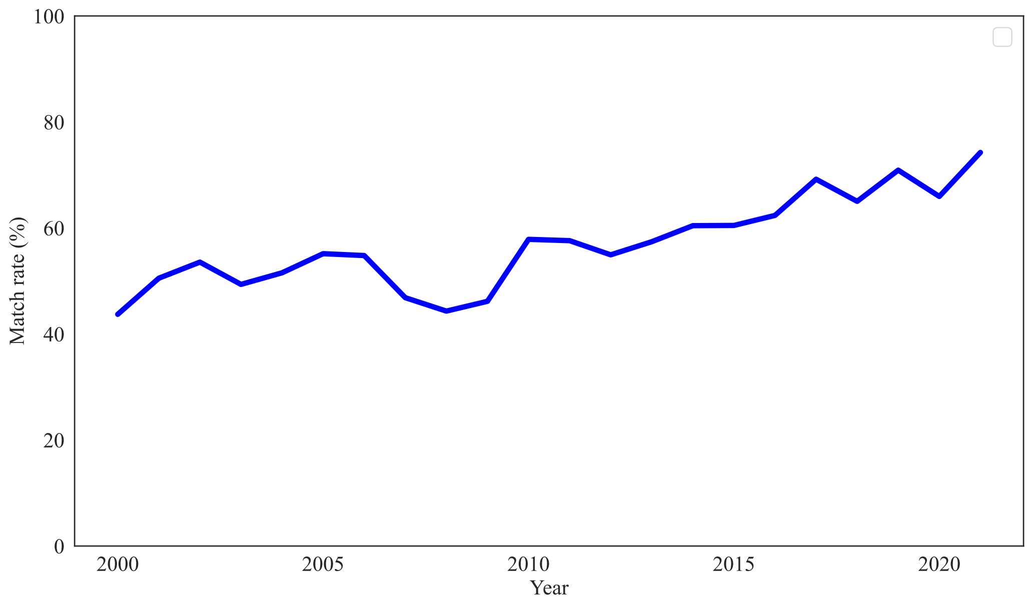


Figure A.2: Cross sectional match rate

This figure shows the cross-sectional match rate of purchased mortgages in my sample. The sample year in the first graph is 2013, and in the second graph is 2021.

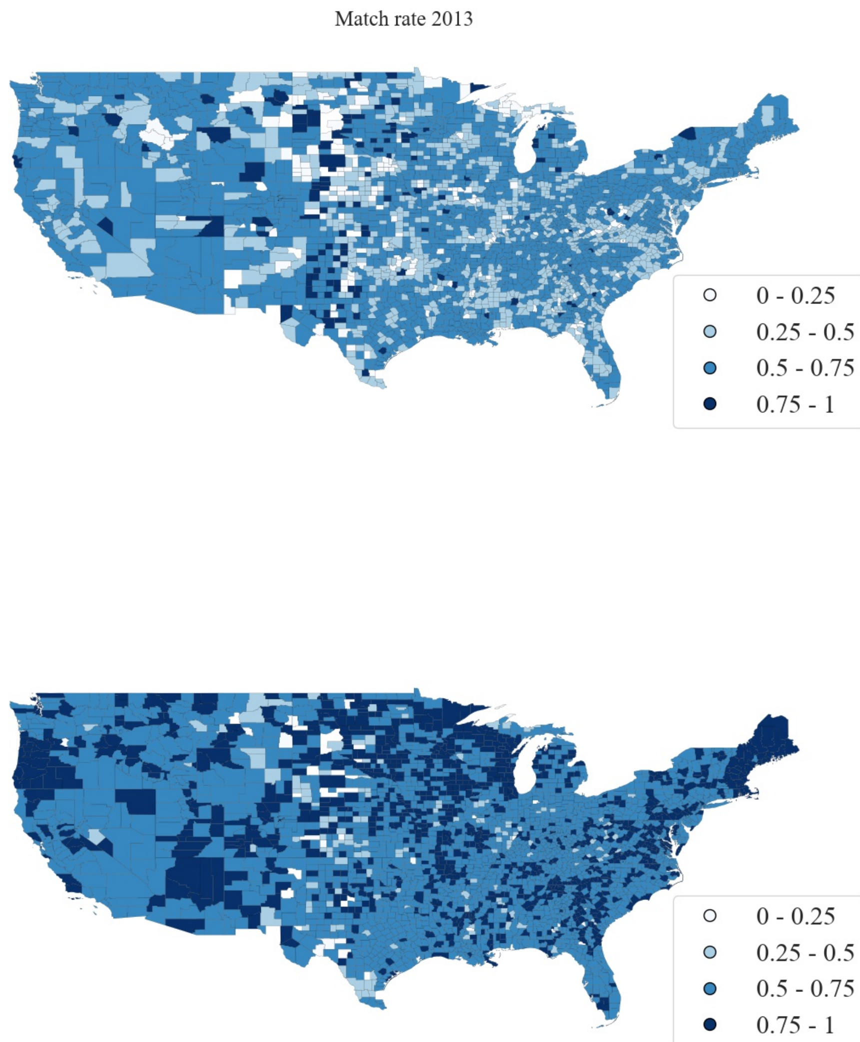


Table A.1: **Summary statistics of matched and unmatched samples**

This table compares loan and borrower characteristics among matched versus unmatched aggregated mortgage samples.

Variable	Matched	Unmatched
Loan amount	177.23	170.32
Lender type		
Bank	76.92%	77.43%
Shadow	23.08%	22.57%
Owner-purpose		
Owner-occupied	92.94%	92.73%
NonOwner-occupied	6.18%	6.19%
Loan purpose		
Purchase	63.33%	59.08%
Refinance	44.04%	47.36%
HomeImprov	0.63%	2.17%
Race		
White	35.19%	34.35%
Black	2.35%	3.59%
Asian	2.04%	2.44%
PacificIslander	0.70%	1.26%
AmericanNative	0.19%	0.29%
Missing	3.57%	3.74%
NoCo-applicant	57.89%	37.86%
NotApplicable	45.44%	47.45%

Variable	Matched	Unmatched
Applicant income	76.27	77.00
Loan type		
Cnvt	71.32%	59.31%
FHA	19.73%	29.51%
FSARHS	2.43%	2.58%
VA	6.52%	8.60%
Property type		
1-4 unit	99.43%	98.19%
Manufactured	0.57%	1.43%
multi	0.02%	0.37%
Sex		
Female	12.20%	12.85%
Male	30.63%	32.16%
NotApplicable	54.40%	52.35%
Missing	2.77%	2.64%
Ethnicity		
HispanicLatino	4.16%	5.09%
NotHispanicLatino	41.09%	38.69%
NotApplicable	50.73%	51.57%
Missing	4.03%	4.65%

Table A.2: **Correspondent lender-aggregator level analysis**

This table reports estimates from Equation (14) estimated at the correspondent lender-aggregator level from 2010–2015. The dependent variable is the logarithm aggregation amount in year t. The main independent variable is $\text{MSR}_b \times \text{Post}_t$, the interaction between correspondent lender-level exposure to the Basel III capital requirements on mortgage servicing rights (MSR_b) and the post dummy variable (Post_t). Aggregator-level exposure to Basel III is measured as the banks' ratio of mortgage servicing rights to Tier 1 capital. The post dummy variable equals 1 if year t is 2013 or later and otherwise 0. Column (2) adds year fixed effects; column (3) adds aggregator fixed effects; column (4) adds Lender×Year fixed effects; and column (5) adds Lender×Aggregator fixed effects. Standard errors clustered at the correspondent lender level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	Log Aggregation Amount				
	(1)	(2)	(3)	(4)	(5)
$\text{MSR}_b \times \text{Post}_t$	-1.11***	-0.931***	-0.788***	-1.04***	-1.13***
	(0.147)	(0.146)	(0.139)	(0.134)	(0.115)
MSR_b	6.97***	6.93***			
	(0.107)	(0.107)			
Post_t	0.964***				
	(0.038)				
Year FE		Yes	Yes	Yes	Yes
Aggregator FE			Yes	Yes	Yes
Lender×Year FE				Yes	Yes
Lender×Aggregator FE					Yes
Observations	107,145	107,145	107,145	107,145	107,145
R^2	0.07	0.08	0.22	0.41	0.81

Table A.3: **Balanced t-stats**

This table reports the difference in lender control variables for the treated group and control group in 2012. The treated group includes lenders with above median MSR exposure defined in Equation 2, and the control group includes those lenders with below median exposure defined in Equation 2. Column (1) reports the mean of the treatment group, column (2) reports the mean of the control group, column (3) reports the difference and column (4) reports the t statistics.

Variable:	T	C	Dif	t-stats
Capital ratio	0.103	0.097	0.006	0.63
Liquidity ratio	0.237	0.246	-0.009	-1.24
Return on assets	0.007	0.008	-0.001	-0.91
Log assets	15.00	15.24	-0.24	-1.59

Table A.4: **Shadow bank funding**

This table reports estimates from Equation (16) estimated at the seller level from 2011–2017. The dependent variable is the logarithm of the credit line amount or utilization rate in year t. The main independent variable is $\text{MSR}_b \times \text{Post}_t$, the interaction between funding provider-level exposure to the Basel III capital requirements on mortgage servicing rights (MSR_b) and the post dummy variable (Post_t). The funding provider level The post dummy variable equals 1 if year t is 2013 or later and otherwise 0. Controls include lagged log asset, capital ratio, liquidity ratio and return on assets. Standard errors clustered at the shadow bank-year level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	Log Credit Limit				Used Fraction			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{MSR}_b \times \text{Post}_t$	0.3059	-0.0997	-0.0319	0.2461	0.0159	0.2535	0.2719	0.0940
	(0.4329)	(0.4149)	(0.4156)	(0.5303)	(0.1398)	(0.2533)	(0.2629)	(0.2266)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Shadow bank FE	Yes	Yes	Yes		Yes	Yes	Yes	
Warehouse lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Shadow bank×Year quarter FE				Yes				Yes
Observations	34,828	19,705	16,999	16,999	34,828	19,705	16,999	16,999
R^2	0.85	0.83	0.78	0.83	0.35	0.31	0.28	0.57

Table A.5: **Shadow bank sample**

This table estimates the effect of the MSR regulation on the origination amount using the subsample of shadow banks. Panel A reports the estimates from Equation (3) estimated at the seller level from 2010–2017. The dependent variable is the logarithm of the origination amount by correspondent lender s in county c and in year t and the approval rate (in percentage) of mortgages by correspondent lender s in county c and in year t. The main independent variable is $\text{MSR}_s \times \text{Post}_t$, the interaction between correspondent lender-level exposure to the Basel III capital requirements on mortgage servicing rights (MSR_s) and the post dummy variable (Post_t). Correspondent lender-level exposure to Basel III is measured as the share of mortgages sold to aggregators with *ex-ante* MSR/Tier 1 capital over 10%, as defined in Equation (2). The post dummy variable equals 1 if year t is 2013 or later and otherwise 0. Columns (1) and (4) add correspondent Lender×County fixed effects; columns (2) and (5) add year fixed effects; and columns (3) and (6) add County×Year fixed effects. Standard errors clustered at the correspondent lender level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	Log Origination Amount			Approval Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{MSR}_s \times \text{Post}_t$	-0.573***	-0.659***	-0.615***	-6.36***	-6.30***	-5.21***
	(0.079)	(0.079)	(0.085)	(1.04)	(1.04)	(1.11)
Post_t	0.406***			3.40***		
	(0.041)			(0.528)		
Lender×County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes		Yes	Yes
County×Year FE			Yes			Yes
Observations	175,358	175,358	175,358	149,350	149,350	149,350
R^2	0.869	0.871	0.885	0.678	0.678	0.727

Table A.6: **Basel III capital shortfall and MSR exposure**

This table reports the correlation between the lender-level treatment variable and the Basel III capital shortfall measure from **?**. The sample only includes bank lenders at the bank holding company level. Column (1) uses all lenders, column (2) includes lenders that are subsidiaries of aggregators, and column (3) uses all correspondent lenders. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	MSR		
	All lenders	Subsidiaries	Correspondent lenders
	(1)	(2)	(3)
Shortfall_s	0.29	0.43	0.02
	(0.31)	(0.75)	(0.33)
Constant	0.16***	0.18***	0.16***
	(0.01)	(0.03)	(0.01)
Observations	504	120	384
R^2	0.00175	0.00276	6.14×10^{-6}

Table A.7: **Robustness: Subsample by loan type**

This table reports estimates the effect of the MSR regulation on aggregation activities by loan type. It reports the estimates from Equation (3) estimated at the correspondent lender level from 2010–2017. The dependent variable is the logarithm of the aggregation amount of conventional and FHA mortgages by correspondent lender s in county c and year t. The main independent variable is $\text{MSR}_s \times \text{Post}_t$, the interaction between correspondent lender-level exposure to the Basel III capital requirements on mortgage servicing rights (MSR_s) and the post dummy variable (Post_t). Correspondent lender-level exposure to Basel III is measured as the share of mortgages sold to aggregators with *ex-ante* MSR/Tier 1 capital over 10%, as defined in Equation (2). The post dummy variable equals 1 if year t is 2013 or later. Columns (1) and (4) add correspondent Lender×County fixed effects; columns (2) and (5) add year fixed effects, and columns (3) and (6) add County×Year fixed effects. Standard errors clustered at the correspondent lender level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	Log Aggregation Amount - Cnvt			Log Aggregation Amount - FHA		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{MSR}_s \times \text{Post}_t$	-0.516***	-0.470***	-0.527***	-0.839***	-0.812***	-0.858***
	(0.182)	(0.174)	(0.173)	(0.305)	(0.307)	(0.299)
Post_t	0.567***			0.208**		
	(0.086)			(0.096)		
Lender controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender×County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes		Yes	Yes
County×Year FE			Yes			Yes
Observations	437,272	437,272	437,272	437,272	437,272	437,272
R^2	0.702	0.705	0.726	0.723	0.725	0.747

Table A.8: **Robustness: Guarantee fee**

This table reports estimates from Equation (14) estimated at the seller-aggregator level from 2010–2017. The dependent variable is the logarithm of the aggregated home purchase amount in year t. The main independent variable is $\text{MSR}_b \times \text{Post}_t$, the interaction between aggregator-level exposure to the Basel III capital requirements on mortgage servicing rights (MSR_b) and the post dummy variable (Post_t). Aggregator-level exposure is a dummy variable that is 1 if the bank's ratio of mortgage servicing rights to Tier 1 capital is over 10% and otherwise 0. The post dummy variable equals 1 if the year is 2013 or later and otherwise 0. Top10_s is an indicator that is 1 if aggregator s is among one of the top 10 sellers to Fannie Mae and Freddie Mac sellers and otherwise 0. The Post_{t1} dummy equals 1 if the year is 2011 or later and otherwise 0. Standard errors clustered at the seller-year level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	Log Aggregation Amount	
	(1)	(2)
$\text{MSR}_b \times \text{Post}_t$	-0.192***	-0.192***
	(0.073)	(0.073)
$\text{Top10}_s \times \text{Post}_{t1}$		-0.039
		(0.069)
Lender×Year FE	Yes	Yes
Aggregator FE	Yes	Yes
Year FE	Yes	Yes
Lender×Aggregator FE	Yes	Yes
Observations	131,935	131,935
R^2	0.801	0.801

Table A.9: **Interest rate and loan performance**

This table reports estimates $y_{i,j,b,c,t} = \beta \times \text{MSR}_b \times \text{Post}_t + \gamma X_{i,j,b,c,t} + \eta X_{j,t} + FEs + \epsilon_{i,j,b,c,t}$. The dependent variable is the interest rate or delinquent dummy for a loan i originated by a correspondent lender j, aggregated by aggregator k in county c and year t. The independent variable is the interaction term between MSR_b and Post_t. MSR_b is 1 if the MSR/Tier 1 capital exposure of the aggregator b exceeds 10% and otherwise 0. Post_t is 1 if the year quarter is after Q2 of 2012 and otherwise 0. Borrower controls include loan-to-value (LTV) ratio, debt-to-income (DTI) ratio, FICO, log loan amount, income, and first-time home buyer indicator. Lender controls include lagged log assets, return on assets, capital ratio and liquidity ratio. Columns (1), (3), and (5) add County×YearQuarter and aggregator fixed effects. Columns (2), (4) and (6) further add Lender×Aggregator fixed effects. Standard errors clustered at the correspondent lender-aggregator level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	InterestRate		Delinquent - 60 days		Delinquent - 90 days	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{MSR}_b \times \text{Post}_t$	0.004	0.010*	-8.11×10^{-5}	0.0008	-0.0002	9.97×10^{-5}
	(0.006)	(0.005)	(0.001)	(0.001)	(0.0009)	(0.0010)
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender controls	Yes	Yes	Yes	Yes	Yes	Yes
County×YearQuarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Aggregator FE	Yes		Yes		Yes	
Lender×Aggregator FE		Yes		Yes		Yes
Observations	280,096	280,096	280,096	280,096	280,096	280,096
R^2	0.740	0.756	0.077	0.114	0.069	0.110

Table A.10: **Persistence in relationships**

This table shows the persistence in aggregator-correspondent lender relationships. It estimates $\text{Current}_{i,j,t} = \beta\text{Previous}_{i,j,t-1} + FEs + \epsilon_{i,j,t}$ using all possible pairs of correspondent lenders and aggregators in their choice sets for aggregation relationships. The dependent variable is an indicator that equals 1 if there is an aggregation relationship between correspondent lender i and aggregator j in year t and otherwise 0. The independent variable is an indicator that equals 1 if there is an aggregation relationship between correspondent lender i and aggregator j in year $t-1$ and otherwise 0. Column (2) uses aggregator fixed effects, column (3) uses aggregator×year and correspondent lender headquarter State×Year fixed effects, column (4) uses Aggregator×Year and correspondent lender headquarter State×Year, correspondent lender Size quantile×Year fixed effects, column (5) adds correspondent Lender type×Year fixed effects to fixed effects used in column (4) and column (6) replaces correspondent Lender type×Year fixed effects with correspondent Lender type×Aggregator×Year fixed effects. Standard errors clustered at the correspondent lender level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	Current					
	(1)	(2)	(3)	(4)	(5)	(6)
Previous	0.583***	0.469***	0.464***	0.458***	0.456***	0.453***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.008***					
	(0.0001)					
Aggregator FE		Yes				
Aggregator×Year FE			Yes	Yes	Yes	Yes
State×Year FE			Yes	Yes	Yes	Yes
Size quantile×Year FE				Yes	Yes	Yes
Lender type×Year FE					Yes	
Lender type×Aggregator type×Year FE						Yes
Observations	14,407,066	14,407,066	14,407,066	14,404,750	14,404,750	14,404,750
R^2	0.288	0.340	0.368	0.371	0.372	0.374

Table A.11: **Determinants of relationship formation**

This table shows the matching pattern between correspondent lenders and aggregators. It estimates $\Pr(\text{Agg})_{s,b,t} = \beta \text{LogDistance}_{s,b} + FE_{s,t} + FE_{b,t} + \epsilon_{s,b,t}$ using a sample that includes all possible pairs of correspondent lenders and aggregators in their choice sets for aggregation relationships. The dependent variable $\Pr(\text{Agg})_{s,b,t}$ is an indicator that equals 100 if there is an aggregation relationship between correspondent lender s and an aggregator b in year t and 0 otherwise. The headquarters distance is the distance between the headquarters of the correspondent lender and the aggregator. Column (1) reports the coefficient estimate for the full sample, column (2) reports the coefficient estimate for pairs with headquarters distance less than 500 Km, column (3) reports the coefficient estimate for pairs with headquarters distance less than 1000 Km, column (4) reports the coefficient estimate for large correspondent lenders (top 25%) and column (5) reports the coefficient estimate for small correspondent lenders (bottom 25%). Standard errors double clustered at the correspondent lender and aggregator level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

	Aggregation Relationship				
	All	$\leq$ 500Km	$\leq$ 1000Km	Large	Small
	(1)	(2)	(3)	(4)	(5)
LogDistance	-0.930***	-1.35***	-1.22***	-0.439***	-1.07***
	(0.013)	(0.034)	(0.022)	(0.021)	(0.029)
Lender×Year FE	Yes	Yes	Yes	Yes	Yes
Aggregator×Year FE	Yes	Yes	Yes	Yes	Yes
Observations	7,723,460	976,103	2,428,438	1,219,417	1,219,357
R^2	0.294	0.313	0.317	0.172	0.311