Mortgage Aggregation and Credit Supply*

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Abstract

One third of U.S. mortgages are originated by small correspondent lenders and securitized by large aggregators, e.g. Wells Fargo. I show matching frictions impact credit supply using a novel dataset on aggregator-correspondent lender relationships. One standard deviation increase in correspondent lenders' decreases correspondent lenders' credit supply by 12.5% and to low income borrowers by 4.5% more. Origination reductions attenuate when correspondent lenders have lower concentration in selling relationships and more aggregators near their headquarters. My results quantify the role of mortgage aggregation in easing securitization frictions and highlight the specialization of correspondent lenders in ensuring credit access for low-income borrowers.

JEL Codes: G2, L5

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1 Introduction

Mortgage aggregation refers to the activity of purchasing mortgages, typically conducted by aggregators such as Wells Fargo, from non-affiliated institutions (i.e., correspondent lenders) to securitize these mortgages in pools. In the U.S. mortgage market, 70% of lenders rely on mortgage aggregation to securitize their mortgages, and 30% to 50% of securitized mortgages pass through the aggregation market before being securitized by Fannie Mae, Freddie Mac, or Ginnie Mae[1], see Figure 1. Despite its considerable size and importance in channeling funding to the housing market, we have limited knowledge about this market and its impact on credit supply.

It is not evident that disruptions in the aggregation market would affect credit supply. Mortgage lenders have various outlets for originated mortgages, such as keeping mortgages on their balance sheets or selling them to unaffected aggregators. However, if correspondent lenders face matching frictions in the aggregation market and cannot easily substitute aggregation with other types of mortgage funding, they may reduce credit supply. The prediction is also unclear when it comes to the effect on credit access of borrowers. The mortgage origination market is generally considered national and competitive, particularly after the entry of fintech companies after 2010. Correspondent lenders could be easily replaced by other types of lenders. However, if these lenders specialize in specific market segments, their exit could have a significant impact on lending outcomes.

In this paper, I show that mortgage aggregation is not merely a pass-through. It bypasses the hurdle of establishing relationships with government agencies, allowing lenders to increase their mortgage origination capacity by freeing up their balance sheets. Using a surprisingly punitive mortgage servicing right treatment under the Basel III capital requirements in the U.S., I find that a one standard deviation increase in a correspondent

[1] Fannie Mae and Freddie Mac guarantee and securitize conventional mortgages that are not explicitly backed by government programs. Ginnie Mae provides guarantees for mortgages from the federal housing programs through the Federal Housing Administration (FHA), Veterans Affairs (VA), the Department of Agriculture, and HUD's Public and Indian Housing.

lender's exposure to mortgage aggregation deductions leads to a 12.5% reduction in lending. Due to matching frictions and the specialization of correspondent lenders, low-income borrowers experience a 4.5% greater decline in credit supply. These results suggest that bank capital requirements can create unequal credit access through a less-studied segment of the U.S. mortgage market—mortgage aggregation.

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 agency securitization market. To address this 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). This new dataset reveals mortgage aggregation relationships in the agency mortgage market, a previously unexplored area. Using this dataset, I demonstrate how aggregators' strategic behavior can influence the lending activities of correspondent lenders.

The second challenge is identification. The equilibrium amount of mortgage aggregation depends on both aggregators' demand for mortgages and lenders' supply of mortgages for sale. I use a difference-in-differences approach based on the implementation of the Basel III capital requirement on mortgage servicing rights (MSRs)[2] in 2013. Although the implementation of the Basel III Accord was expected, the rule unexpectedly increased the risk weight of MSRs from 100% to 250% and reduced the threshold of the value of MSRs over a bank's common equity from 50% to 10%(Irani, Iyer, Meisenzahl, and Peydró, 2021).

The unanticipated change in standards reduced the appeal of mortgage aggregation to banks, as one key method for obtaining mortgage servicing rights is through aggregation. When aggregators aggregate mortgages from correspondent lenders, they typically acquire

[2]A mortgage servicing right is an asset that is created when a primary lender originates a mortgage that is sold on the secondary market and retains the right to service the loan. The servicer (i.e., financial institutions that hold MSR) collects monthly payments from borrowers and distributes them to the relevant investors. In exchange, the servicer is compensated with a fee equal to a fixed share—typically 25–50 basis points—of the outstanding mortgage balance. Mortgage servicing is a scale business and the value of servicing rights increases with the volume of mortgages serviced under the servicing right. Aggregators purchase mortgages as a way to obtain servicing rights.

the associated MSRs, meaning that correspondent lenders usually do not retain these rights. This feature, combined with the 10% threshold for MSRs relative to a bank's common equity, motivates me to explore variations in treatment exposure across correspondent lenders. I construct my measure based their ex-ante fraction of mortgages sold to aggregators with an MSR/Tier 1 capital ratio above the threshold.

My difference-in-differences approach compares credit supply before and after the policy change across correspondent lenders with varying levels of exposure. I find that correspondent lenders with greater ex-ante exposure to aggregators affected by the regulatory change experience larger decline in mortgage aggregation volume. Furthermore, this decline in aggregation leads to a reduction in the mortgage origination 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.

A potential concern with this approach is that the matching between correspondent lenders and aggregators is not random. Correspondent lenders with varying exposures may have experienced different trends in origination. To alleviate this concern, I show that their loan origination trends did not diverge until after the policy implementation. Another concern is that the decline in origination could be due to the broader regulatory impact of the Basel III Accord. I address this in two ways. First, I show that the MSR exposure of correspondent lenders is not positively correlated with their capital shortfall. Second, I show that my main results are robust when using a subset of shadow bank correspondent lenders, which are not subject to the Basel III Accord. I further show that their primary funding from credit lines was also not affected by the Basel III Accord.

To provide further support for the effect of mortgage aggregation on lending, I explore the heterogeneity across lender types and borrower types. First, I compare the effects across lender types based on their funding models and market overlap with their aggregators. I find a stronger decline in credit supply for shadow banks. As non-depository financial institutions, shadow banks have limited balance sheet capacity and may face greater information asymmetry in the aggregation market. Both factors make it more challenging for shadow banks to substitute aggregation with other funding sources. Additionally, I find a larger decline in credit supply for correspondent lenders with greater market overlap with their aggregators. By doing so, aggregators can maintain portfolio diversification and reduce origination market competition to increase origination profits when facing higher capital costs of holding mortgage servicing rights. This implies that aggregators can leverage aggregation to shape lending outcomes of their correspondent lenders.

Next, I compare the effects across borrower types. Aggregators may opt to reduce the aggregation of mortgages from these groups more significantly because these loans carry a higher likelihood of default and substantially higher servicing costs. Additionally, correspondent lenders incur higher marginal costs when lending to these borrowers due to the challenges of income verification. As a result, when aggregation is disrupted, these lenders tend to decrease the credit supply for low-income mortgages first. My result is consistent with this hypothesis.

In the final part of my paper, I explore the channels driving the decrease in credit access: matching frictions in the aggregation market and correspondent lender specialization. I provide evidence of 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 network. Additionally, correspondent lenders cannot fully offset reduced aggregation volumes from one aggregator by selling to others. Lenders with fewer aggregators, higher concentration in selling relationships, and 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. However, correspondent lenders face frictions in switching to these alternative options.

Next, 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 less likely to reject their applications compared to 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 aggreation and credit supply. Section 6 discussed the forces that drive the reduced credit access. Section 7 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 studied[3], the over-the-counter market for mortgages,

[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

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, this paper is among the first papers to construct mortgage correspondent lender-aggregator relationships after the financial crisis and analyze the matching frictions faced by lenders in this market.

My paper is also related to the extensive literature on shock transmission through financial intermediation[4]. Financial or regulatory shocks propagate through 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 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, they 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 behavior of market participants

(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)

[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); Hakura and Cosimano (2011); Bichsel, Lambertini, Mukherjee, and Wunderli (2022); Auer, Matyunina, and Ongena (2022)

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]. 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 credit supply[9].

[7] See, e.g. Buchak, Matvos, Piskorski, and Seru (2018); Buchak, Matvos, Piskovski, and Seru (2020); 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); Brian Blank, Highfield, and Yerkes (2022); Benson, Kim, and Pence (2023); D'Acunto and Rossi (2022); DeFusco, Johnson, and Mondragon (2020)

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

[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 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, which highlights mortgage aggregation behavior 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 choose to sell mortgages to aggregators to secure funding for originating new loans. Aggregators, in turn, sell most of these mortgages to securitizers. Figure A.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 currrent year and sold in the next year, it is recorded as unsold in HMDA. It is possible that the unsold mortgages will be sold in the next year.

The correspondent system developed in the 1980s, rooted in the separation of mortgage servicing from mortgage origination. 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.

In addition to the volume-driven pricing of mortgage servicing rights, 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 lasting 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 accompanied counterparty risks and reputation risks.

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

[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.

like Wells Fargo, Bank of America, and JPMorgan Chase accumulated significant servicing 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 and Measurement

This section describes the data sources and variable construction. 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. For the analysis, I construct several datasets to examine correspondent lender-aggregator relationships, aggregation activities, origination and application activities by lenders, and detailed loan-level mortgage contract details and performance. The data and matching procedures are described in more detail below.

Home Mortgage Disclosure Act (HMDA): I observe the mortgage origination and purchase activity of lenders using HMDA dataset. HMDA is the most comprehensive information source of 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, 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 is 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 if the financial institution did not make a credit decision on the loan.

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 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, and housing characteristics including 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 sheet and income statement for banks and savings banks. I obtain 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 (2019).

3.3 Sample Construction

In this section, I describe the process of constructing the datasets for my analysis. I first create two novel datasets and then build several panel datasets. The details are provided below.

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

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 A.1 shows the data samples that I conduct my match on. I select mortgages labeled 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 purchased 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 purchased covered loans. I find 1190 aggregators and 4510 correspondent lenders. Table 1 shows the summary statistics for the characteristics of aggregators and correspondent lenders. Comparing the average aggregation and origination amounts, the aggregation market is quite 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. To examine the effects on interest rates, I incorporate data from Fannie Mae and Freddie Mac's Single Family Loan dataset and the Attom Real Estate dataset. I first merge the Attom dataset with HMDA using 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 previous paper Bartlett, Morse, Stanton, and Wallace (2022) that conducts similar match. The resulting dataset includes origination date, census tract, loan characteristics, borrower characteristics, and lender identity.

I further merge the dataset with Fannie Mae and Freddie Mac's 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 aforementioned levels. 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-county level dataset. An average merged correspondent lender provide $165,670 mortgage credit per county per year, indicating that they are small mortgage lenders. This can also been seen from their average asset size.

A correspondent lender on average connects with 8 aggregators, however, the average HHI is 0.3 and the median is 0.25, indicating highly concentrated selling relationships. In addition, each correspondent lender on average has 8 nearby aggregators. The standard deviation is large, indicating that 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 treatment of MSRs was more stringent than international standards and was largely unanticipated by market participants (Berrospide and Edge, 2016; Irani, Iyer, Meisenzahl, and Peydró, 2021). 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, made the mortgage business less attractive for banks.

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

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

$\mathbb{1}_{\frac{MSR_{b_{2011}}}{Tier1Capital_{b_{2011}}} \geq 0.1}$ is 1 if the share of MSRs in 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%.

The treatment is relevant for mortgage aggregation because one channel for banks to obtain mortgage servicing rights is to aggregate mortgages from other financial institutions[14]. Figure 3 shows the strong positive correlation between aggregation and mortgage servicing rights, providing support that a higher cost of holding servicing rights on balancesheets could reduce the attractiveness of aggregation business.

One concern about the treatment is that correspondent lenders can be directly affected by the increased capital requirement on mortgage servicing rights and change their origination behavior. However, when correspondent lenders sell mortgages, they usually 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 have their own *ex-ante* MSR exposure over 10% in my sample.

5 Mortgage Aggregation and Credit Supply

In this section, I present evidence showing that the reduction in aggregation led 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 factors. Additionally, I explore heterogeneity across lender types, loan types, and borrower characteristics. These results suggest that the strategic behavior of aggregators influences lending outcomes and indicate the distributional impacts of MSR regulation on mortgage supply.

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

[14] This is mentioned by Ocwen Fianncial 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."

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 exogeneous variation in mortgage aggregation.

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

$$y_{s,c,t} = \beta_1 MSR_s \times Post_t + \xi' X_{s,t-1} + FE + \epsilon_{s,c,t} \tag{3}$$

The dependent variable is log aggregation amount and log origination amount of correspondent lenders. 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. 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 amount of mortgages being aggregated is more negatively affected if the correspondent lenders have larger exposure to aggregators subject to the Basel III capital requirement on MSR. The estimation result suggests that following the Basel III capital requirement, the mortgage aggregation amount decrease significantly. A one standard deviation increase in the *ex-ante* share of mortgages sold to affected aggregators (0.25) leads to 20.5% decrease in aggregation volume.

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 business relationship. It may be that correspondent lenders who have less mortgages for sale sell to aggregators that experience negative regulatory shocks. To address the selection problem, I also conduct my analysis at the correspondent lender-aggregator level using an within-firm estimator(Khwaja and Mian, 2008). Specifically, I estimate the equation:

$$y_{s,b,t} = \beta_1 MSR_b \times \text{Post}_t + FE + \epsilon_{s,b,t} \tag{4}$$

Here MSR_b is a bank level exposure to 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 correlates with the aggregation volume. Moreover, I add correspondent lender-aggregator fixed effects $FE_{s,b}$ to address the endogeneous 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 are coming from the aggregator side. Correspondent lenders indeed face reduction in the purchase volume when their aggregators are subject to the regulatory change.

As aggregation acts as a funding source by allowing correspondent lenders to reinvest their asset into more lending, decrease in aggregation volume could lead to decrease in credit supply. However, the decrease in origination volume is not obvious given that correspondent lenders have various funding sources for mortgage origination. If correspondent lenders can substitute alternative funding sources with aggregator purchase frictionlessly, I would not be able to observe a decrease in origination volume. After examining the effect on aggregation volume, I next check if the decrease in aggregation volume is followed by decrease in origination volume. I re-estimate the regression model in Equation (3) using log mortgage origination amount and mortgage approval rate as the dependent variable. I use approval rate to partially address the concern that the results are driven by decrease in correspondent lender-specific demand.

Table 3 presents the results. Columns 1–3 and 4–6 display regression estimates for log origination amount and approval rate as the dependent variable, respectively. Column 1 and column 4 add correspondent lender-county fixed effects, column 2 and column 5 add year fixed effects and column 3 and column 6 add county-year fixed effects to control for local loan demand. 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 are more negatively affected by the regulatory change compared to correspondent lenders with lower MSR exposure. The estimated coefficients imply that, for a given one standard deviation increase in the correspondent lender level exposure, mortgages supply decrease by 12.5%.

5.2 Robustness Tests

5.2.1 Pre-trends and Dynamic Effects

A possible concern with the identification strategy could be that there are pre-existing trends that 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:

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

The dependent variables are log aggregation amount, log origination amount of correspondent lenders and log 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 4 shows the 95% confidence interval plots for the estimated coefficients from Equation 5. It is evident from the figure that there is no pre-trends in either the aggregation amount or origination amount of correspondent lenders prior the announcement of Basel III implementation in 2012.

The figures also show interesting dynamic effects. After the Basel III implementation, the aggregation volume declines first but the magnitude of effects starts to fade after 2016. This suggests that the correspondent lenders could slowly adjust their aggregation relationships across time. I will discuss aggregation market matching friction in detail in Section 6.1. Despite the faded impact in aggregation, the affected correspondent lenders never revert their origination volume to the pre-shock level.

It is also possible that low quality correspondent lenders are more likely to be matched with aggregators that hold a high ex-ante level of mortgage servicing rights, the decrease in purchase volume would be correlated with the decrease in aggregation and origination volume. To address the concern, I conduct balanced t-stats tests for the characteristics of the treated and control groups, where the treated and control group are defined as having exposure higher and below the median exposure. Table A.3 shows that there is no significant difference along observable characteristics including capital ratio, liquidity ratio, return on assets and size.

5.2.2 Effects of Basel III Capital Requirement

Identification using Basel III capital requirement is tricky because the banking sector regulation could affect multiple players through various channels. I try to address concerns arising from Basel III capital requirement below.

First, bank correspondent lenders may reduce lending if they have capital shortfall. If their capital shortfall is positively correlated with their exposure to MSR through aggregation, then I cannot conclude that the decrease in purchase volume leads to the decrease in the origination volume. I test if the positive correlation exists in the data. Table **??** shows the correlation between Basel III capital shortfall and correspondent lenders' MSR exposure through aggregation[15]. There is no positive correlation between the exposure to aggregator treatment and their own Basel III capital shortfall across all subsamples.

Second, shadow bank correspondent lenders may reduce lending if large aggregators decrease their warehouse funding to shadow banks due to regulatory exposure from Basel III capital requirement. Since 60%-70% of shadow bank funding comes from bank credit lines, the reduction in shadow bank funding could have non-trivial impact on their lending decisions.

Using the credit line data from shadow bank call reports data, 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

$$y_{s,b,t} = \beta_1 \text{Exposure}_b \times \text{Post}_t + FE + \epsilon_{s,b,t} \tag{6}$$

Similar to Equation 4, I add correspondent lender-year fixed effects $FE_{s,t}$ which absorb any confounding factors at the shadow bank-year level that may correlates with the funding amount utilization rate. Moreover, I add correspondent lender-aggregator fixed effects $FE_{s,b}$ to address the endogeneous matching between shadow banks and their

[15]Thanks to Berrospide and Edge (2016) for providing the capital shortfall measure.

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 across all specifications, the coefficient β is not significant. The MSR exposure does not has a significant impact on the funding of shadow banks.

Having confirmed that the quantity and utilization rate of the credit line experienced by shadow bank do not change, I check the main results using shadow correspondent lender subsample. Since shadow banks are not regulated by the Basel III capital requirement, these results are not subject to the concern that lending reduction are driven by Basel III capital requirement. Table A.5 shows that shadow bank correspondent lenders also experience significant decline in the origination volume, given that their credit lines are not affected by Basel III Accord.

5.3 Heterogeneity Tests

In this section, I conduct several heterogeneity tests to provide further evidence on the role of aggregation on credit supply. I consider heterogeneity of lenders and borrowers that shape the lending outcomes.

5.3.1 Lender

I consider two characteristics of correspondent lenders that might affect their lending, funding model and competition with aggregators in the origination market.

First, the lending decisions of correspondent lenders can be shaped by their funding model and the aggregators they connect with. Correspondent lenders can be classified into non-depository institutions, i.e. shadow banks and depository institutions, e.g. community banks, savings banks, commercial banks, credit union. Compared to depository institutions, non-depository correspondent lenders may experience a larger decline in origination for at least two reasons. First, they have limited balance sheet capacity. Without aggregators actively buying mortgages off their balance sheet, the cost of originating mortgages would be higher compared to those correspondent lenders who can hold mortgages on their balance sheet. Second, they may face more difficulty in finding new aggregators to connect to because they face higher level of information asymmetry in the aggregation market due to limited financial information and risky business model. Thus I hypothesize that facing the same regulatory exposure, correspondent lenders who are shadow banks experience a larger decline in lending.

To test this hypothesis, I estimate the following regression model

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

where Shadow_s is an indicator variable that takes value of 1 if the financial institution is classified as an independent mortgage company in the Avery file. All other variables are as previously defined in Equation (3). The coefficient of interest is β_1, which captures how a financial institutions funding model affects the impact of aggregation on credit supply. A negative β_1 indicates that shadow banks experience larger origination volume decline compared to depository institutions. Column 1 in Table 4 contains estimates for Equation (7) using log amount as the dependent variable. The coefficient on the tripple interaction term is negative and statistically significant. This implies that the aggregation effect on credit supply is stronger for shadow banks.

One caveat in the aggregation market is that most aggregators are also mortgage lenders. Basel III capital requirement on MSR directly affects the origination decisions of aggregators because aggregators can also generate mortgage servicing rights through their own loan production(Buchak, Matvos, Piskorski, and Seru, 2018). A natural question to ask is that how aggregators change their origination and aggregation volume in response to the regulation. By examining the relationship formation between correspondent lenders and aggregators, I find that majority of the relationships are established when correspondent lenders and aggregators have a low market overlap, see Figure A.6. This indicates that aggregators strategically form aggregation business relationships with correspondent lenders. They can diversify their mortgage portfolio and avoid competition in the mortgage lending market by forming relationship with mortgage lenders with low market overlap.

When facing a negative shock to aggregation, aggregators can reduce the aggregation to correspondent lenders more through either diversification motive or the competition reduction motive in the spirit similar to the funding channel in Jiang (2019). Facing increasing capital costs on mortgage servicing rights, aggregators may reduce aggregation volume more for correspondent lenders with high market overlap with them. By reducing origination market competition, aggregators can potentially increase their origination profits without sacrificing portfolio diversification.

I hypothesize that aggregators decrease the aggregation volume more for correspondent lenders who have a high market overlap with them, which leads to larger decline in the origination volume of these correspondent lenders. To test this hypothesis, I estimate the following regression model

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

Following Jiang (2019), I construct the overlap measure as the following

$$\text{Overlap}_{s,b,t} = \frac{\Sigma_c I\left(\sigma_{s,k,t} > 0, \sigma_{b,c,t>0}\right)}{\Sigma_c I\left(\sigma_{s,c,t} > 0\right) + \Sigma_c I\left(\sigma_{b,c,t} > 0\right)} \tag{9}$$

where $\sigma_{s,c,t} = \frac{\text{LoanVolume}_{s,c,t}}{\Sigma_c \text{ LoanVolume }_{s,c,t}}$ is the share of institution s's total loan origination in county c in year t. A larger Overlap indicates more geographic mortgage overlap. I further aggregate the overlap measure at the correspondent lender level in 2011 using the share of mortgages sold from correspondent lender s to aggregator b.

$$\text{Overlap}_s = \sum_{b \in s} \frac{Aggregation_{bs_{2011}}}{\sum_{b \in s} Aggregation_{bs_{2011}}} \times \text{Overlap}_{s,b,t} \tag{10}$$

All other variables are as previously defined in Equation (3). The coefficient of interest is β_1, which captures how a financial institutions funding model affects the impact of aggregation on credit supply. A negative β_1 indicates that shadow banks experience larger origination volume decline compared to depository institutions. Column 1 in Table 4 contains estimates for Equation (8) using log amount as the dependent variable. The coefficient on the tripple interaction term is negative and statistically significant. This implies that the aggregation effect on credit supply is stronger for correspondent lenders with a larger market overlap with their aggregators. Thus, my findings again support the hypothesis that aggregation affects credit supply.

5.3.2 Borrower

Given that correspondent institutions are extended lending arms of aggregators, they may pay a special role in serving market segments where aggregators face high entry costs and high screening costs. Correspondent lenders tend to operate in low income areas and have a larger share of low-income borrowers in their customer base. I hypothesize that correspondent lenders may also affect the credit supply to disadvantaged groups, e.g. low income and minority groups. When the aggregation volume decline, aggregators may choose to decrease the aggregation for risky loans first and correspondent lender may choose to decrease their credit supply to low-income borrowers more due to the high marginal cost of lending to low-income borrowers. It suggests that in case of aggregation decline, correspondent lenders would respond by reducing the credit supply to low income borrowers and borrowers from low income areas more. I adopt three measures for disadvantaged borrower groups, low income borrowers, borrowers from low income areas and minority.

To test this hypothesis, I estimate the following regression model

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

where i indicates borrower type group. 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 larger origination volume decline compared to other borrowers.

Table 5 shows the results. The coefficient on the tripple 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 4.5% larger decline in credit supply.

6 Channels

After confirming the effect of aggregation on credit supply, I show that two forces are driving the lending reduction, first, funding frictions, and second, correspondent lender specialization in the mortgage market.

6.1 Funding Frictions

Correspondent lenders have multiple margins of adjustment when facing 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. One the one hand, they can try to 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 can switch to any of the channels mentioned above. However, if correspondent lenders face searching 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 searching 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 contract as an advance commitment 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 previous relationship between a correspondent lender and an aggregator can predict their relationship in the next period. Table A.8 shows the regression result. While the probability of finding a random match between a correspondent lender and a 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 shocked. These correspondent lenders may be less affected by the aggregation volume decline if they can optimally reallocate their sell volume based on treatment exposure of aggregators. Second, correspondent lenders that have low diversification in selling mortgages to their aggregators may experience difficulty in switching to other aggregators. Third, correspondent lenders that are located near 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 three measures for frictions in aggregation relationships: number of aggregators, herfindahl-hirschman index (HHI) of selling concentration, number of nearby aggregations. I define nearby aggregators as those with headquarters within 100 km radius of a correspondent lender. For each variable, I assign 1 if the value is above median and otherwise 0. I estimate the following equation:

$$y_{s,c,t} = \beta_1 MSR_s \times \text{Post}_t \times \text{FundingFriction}_s + FE + \epsilon_{s,c,t} \tag{12}$$

FundingFriction_s is a correspondent lender-level measure based on my correspondent lender-aggregator relationships data. Table 6 reports the results.

I next explore other options that correspondent lenders can use to attenuate the negative 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 try to extend their aggregator network. I formally check how correspondent lenders use these options by estimating the following equation:

$$y_{s,t} = \beta_1 MSR_s \times \text{Post}_t + FE + \epsilon_{s,t} \tag{13}$$

The dependent variable are a dummy variable indicating if a correspondent lender directly sell to Fannie Mae, Freddie Mac and Ginnie Mae, the share of mortgages directly sell to agencies, the share of mortgages sell to aggregators and the number of connected aggregators. 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 find that after the shock, correspondent lenders with larger *ex-ante* exposure are more likely to form relationships with agencies, sell more mortgages directly to agencies. They also connect to more aggregators while actively reduce the fraction of mortgages sold to aggregators.

Overall, the above results show that correspondent lenders can attenuate the effect of mortgage purchase on origination by selling to other aggregators. However, it does not appear like correspondent lenders can fully avoid the effect on origination, either by switching aggregators, selling to agencies directly, or using their own balance sheets.

6.2 Specialization of Correspondent Lenders

It is not immediately clear whether the reduced credit supply from correspondent lenders would lead to worse credit access for low income borrowers. If low income borrowers can easily get credit from other types of lenders, the decrease of credit supply from correspondent lenders would not lead to any change in the low-income credit in equilibrium. However, if correspondent lenders specialize in screening low-income borrowers using soft information or providing services to low-income borrowers, then the decrease of credit supply from mortgage aggregation could have real impact on the overall credit access of low-income borrowers.

In this section, I conduct several tests to show the role of correspondent lenders in supplying low-income credit. First, I 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

$$Correspondent_{j,k,t} = \beta \times LowInc_{i,j,k,t} + \gamma X_{i,j,k,t} + FE_k + FE_t + \epsilon_{i,j,k,t} \tag{14}$$

for borrower i, lender j, property's census tract k, and year t. $Correspondent_{j,k,t}$ is a dummy variable for correspondent lender and $LowInc_{i,j,k,t}$ is a dummy variable indicating if the borrower is a low-income borrower. $X_{i,j,k,t}$ 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 trend. 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 (14) for 2010-2015. The results are reported in column (1) of Table 8. Controlling for observable borrower and loan characteristics, 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 thus have higher rejection rates compared to other types of lender given observable characteristics of low-income borrowers. If this is true, the mortgages originated by them 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, then 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 originated by them should not necessarily have worse performance, but they may charge higher interest rate or origination fees for additional service.

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 vs other lenders using the following specification:

$$y_{i,j,k,t} = \beta \times Correspondent_{i,k,t} + \gamma X_{i,j,k,t} + FE_k + FE_t + \epsilon_{i,j,k,t} \tag{15}$$

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 y variables and 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. 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 pattern and rejection reasons and use Attom-HMDA-FF data to examine loan interest rate and performance. Since Attom-HDMA-FF data allows me to observe more mortgage contract terms and borrower characteristics, e.g. LTV, DTI, FICO, first time home buyer indicator, I use these variables as controls as well. Census tract-year fixed effects are also included to account for local application trend. The coefficient of interest is β, which shows how correspondent lenders' differ from other lenders in originating mortgages.

Columns (2)-(4) of Table 8 report the results for rejection and rejection pattern. Correspondent lenders are 4.28% less likely to reject applications from low income borrowers compared to other. Given the average rejection rate for low income borrowers is 15%, this indicate that the rejection rate of correspondent lenders for low income borrowers are 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 service to help borrowers satisfy application requirements.

Columns (5)-(6) of Table 8 report the results for interest rates and delinquency. Correspondent lenders seem to charge higher interest rate compared to other lenders, but the economic magnitude is small - their interest rate is only 0.007% higher compared to other lenders. It is possible that they charge service through points and origination costs[16], however, such variables are not observable during this sample period. The results here also partially address the concern that high quality low-income borrowers are more likely to apply for mortgages from correspondent lenders.

Having provided evidence for the potential benefits of low income borrowers to get credit from correspondent lenders, I provide suggestive explanation for the special role played by correspondent lenders in providing low-income credit. One possible explanation is geographical proximity. Correspondent lenders are more likely to locate in low income area, which makes it easier for low income borrowers to access credit from them. The geographical proximity does not only provide convenience, but may also allow correspondent lenders to obtain soft information about local borrowers. Though the mortgages are more likely to be examined by Automated Underwriting System (AUS), lenders can also use discretion to overwrite the decision from the system. Correspondent lenders can specialize in providing such service and facilitate the credit access of low income borrowers. 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 5.

[16] 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.

7 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 decline in mortgage aggregation, driven by Basel III capital requirements on mortgage servicing rights, impacts credit supply, particularly for low-income borrowers. Using a unique dataset, I find that disruptions in the aggregation market reduce credit availability to low-income borrowers due to matching frictions and the specialization of correspondent lenders.

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 that 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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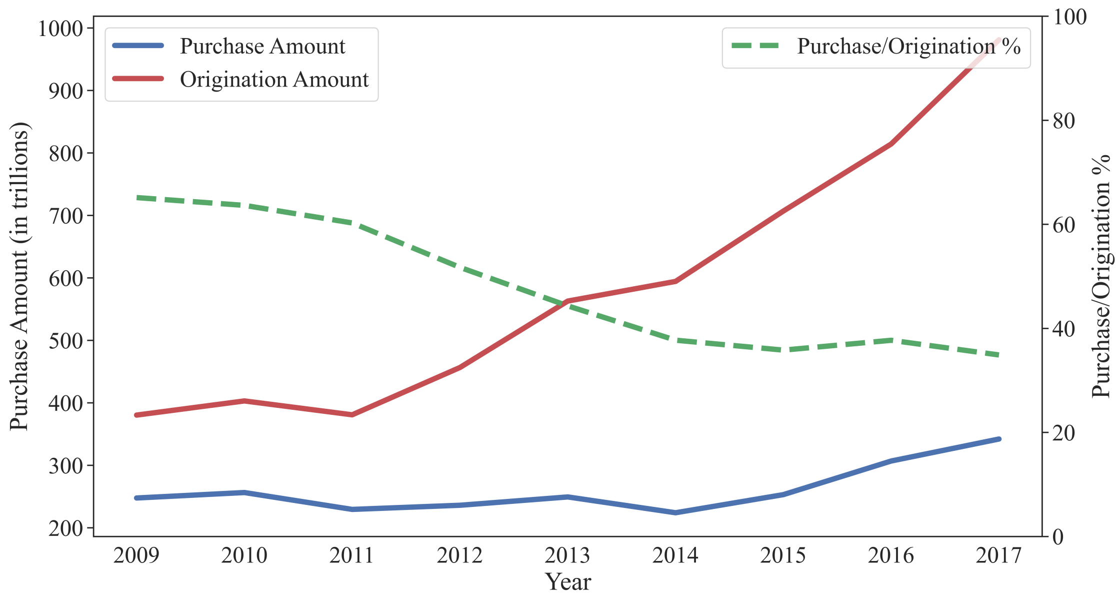
Figure 1: Size of the Mortgage Aggregation Market

This figure shows the size of the mortgage aggregation market. time series of amount of mortgages originated. The first figure shows the amount of originated, purchased mortgages and the purchase/origination share in Home Mortgage Disclosure Act data. The second figure shows the correspondent lending share of mortgages in Fannie Mae and Freddie Mac Single Family Loan-Level dataset. [17]



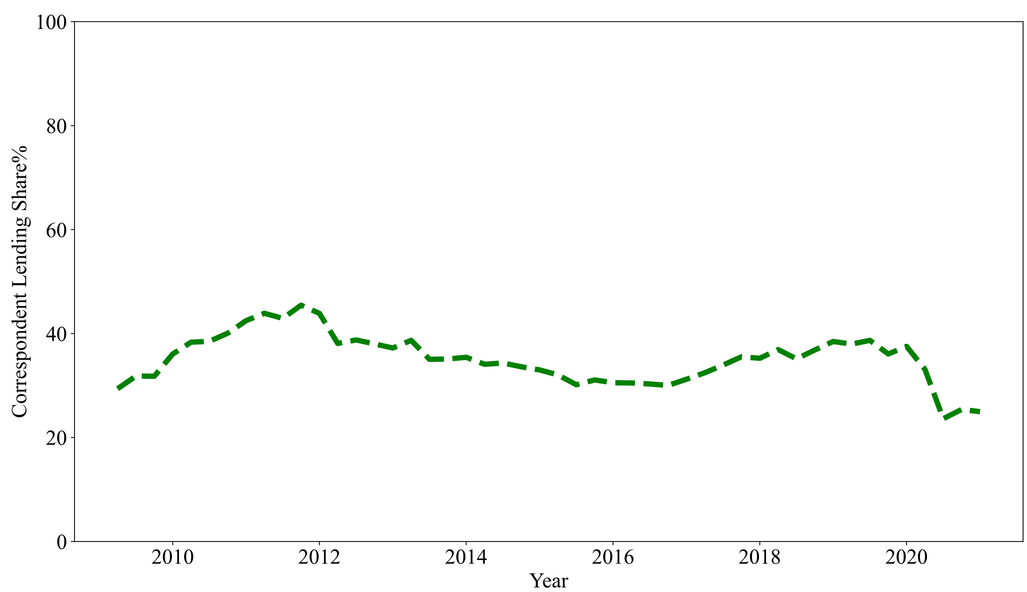


Figure 2: Market Structure

This figure shows the mortgage market structure studied in this paper. The arrows show the flow of funds in the market. Securitizers, e.g. Fannie Mae, Freddie Mac, Ginnie Mae and other private securitizers purchase mortgages from lenders that they have relationships with, and give funding in exchange for mortgages. For downstream lenders without direct access to securitizers, they sell mortgages to upstream aggregators which have access to securitizers.

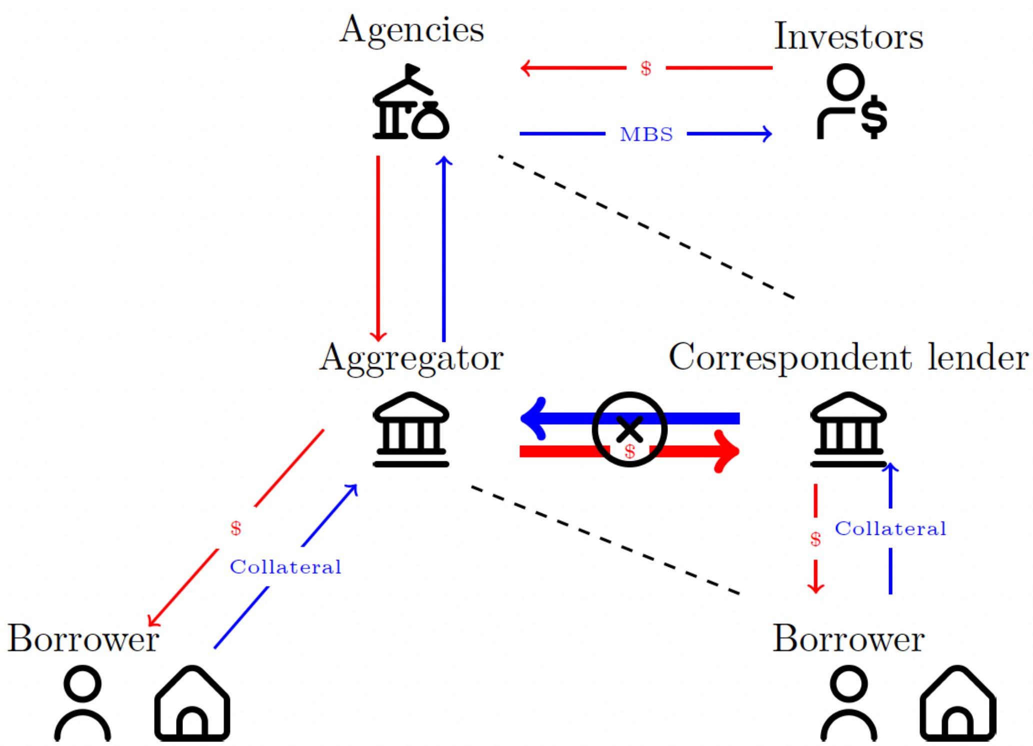


Figure 3: Relationship between mortgage servicing right holding and aggregation market share

This figure is a binned scatter plot that shows the relationship between the share of mortgage servicing right and the aggregation market share.

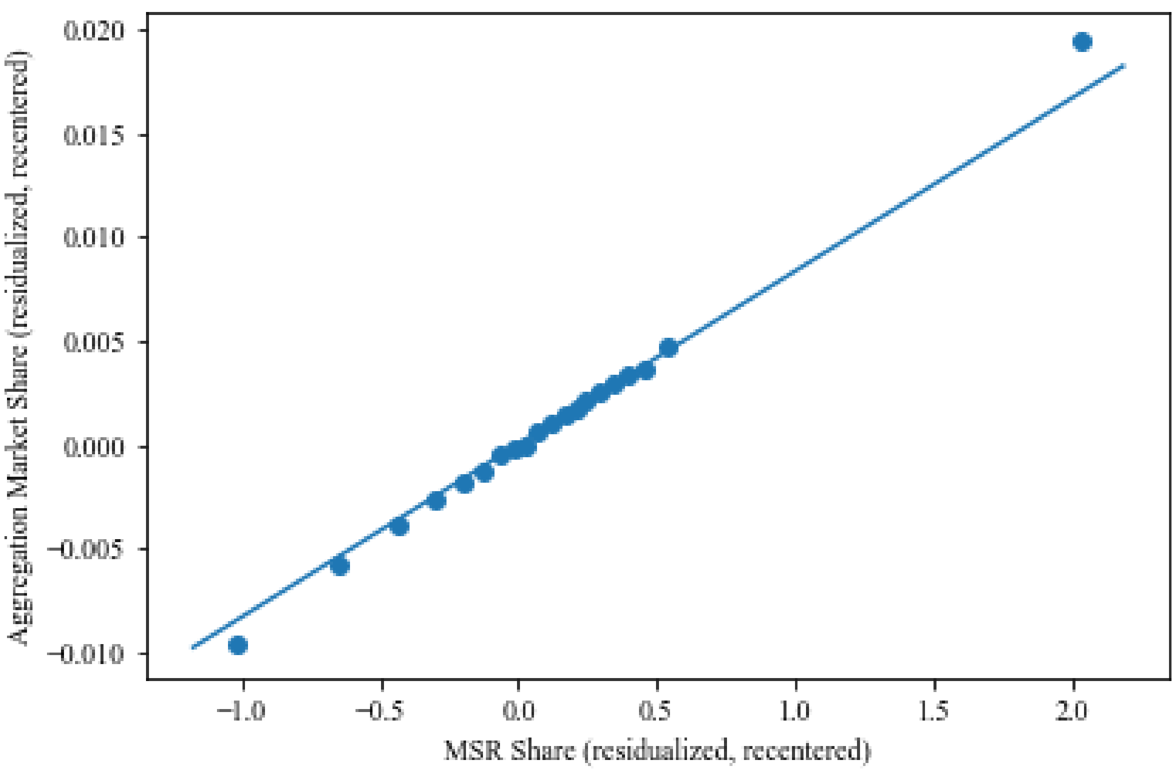
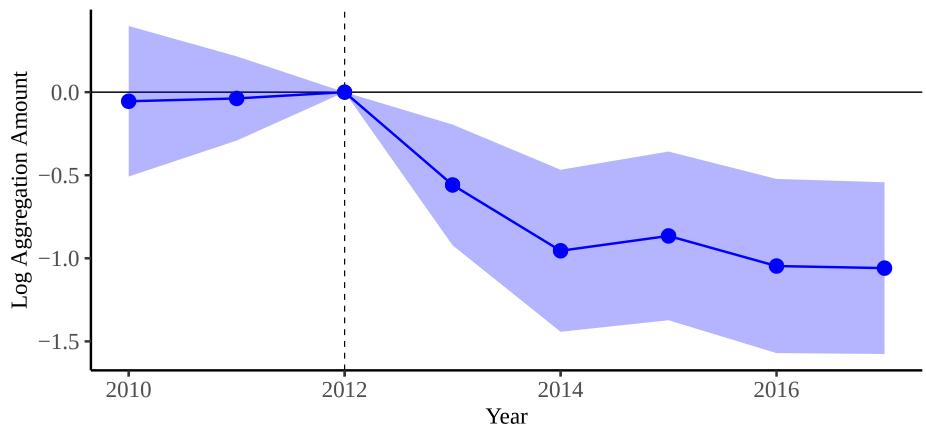


Figure 4: Seller county level - Coefficient estimates by year

This figure shows the coefficients estimated using $Y_{s,c,t} = \sum_{\tau=-2}^{5} (\beta_\tau \text{MSR}_s \times \text{Post}_{t+\tau}) + \gamma X_{s,t-1} + FE + \epsilon_{s,c,t}$. 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 y variable is the log aggregation amount and in the lower panel, the y variable is the origination amount of correspondent lenders. The ribbon shows the 95% confidence interval.



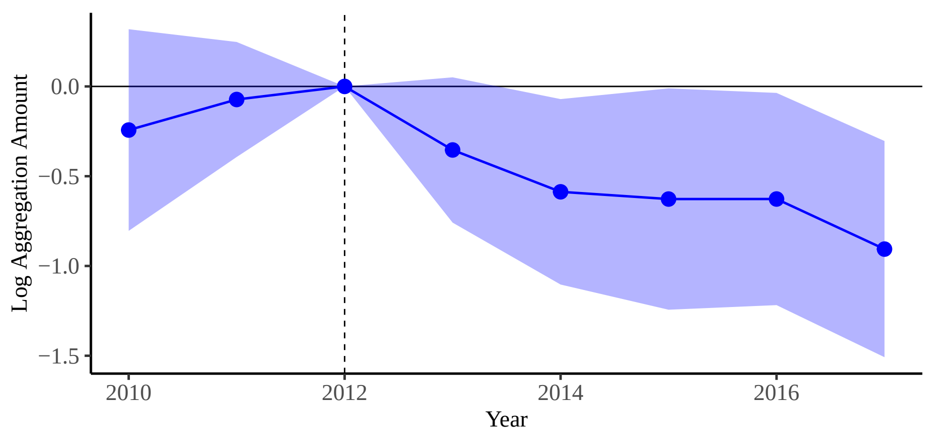


Figure 5: Relationship between census tract income and downstream lender market share

This figure is a binned scatter plot that shows the relationship between census tract income and the fraction of loans sold to third party financial companies, banks, credit unions etc.

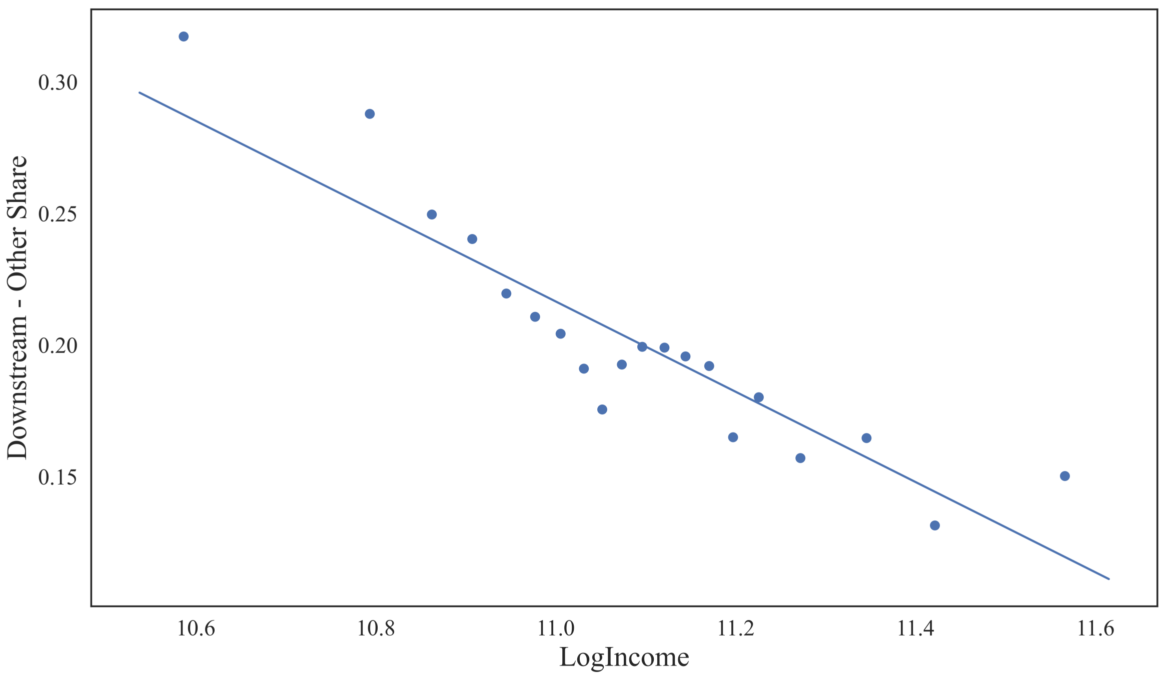


Table 1: Summary statistics of correspondent lender-county level data

This table shows the summary statistics of the panel dataset at the correspondent lender-county level. The logged value is calculated as log (1+amount), where the amount is reported in thousands in HMDA. MSR_s is defined in Equation 2.

	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
ROA (t-1)	437,272	0.00	0.01	0.00	0.00	0.01
LogAsset (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
HHI	693,191	0.30	0.18	0.20	0.25	0.33
Num Aggregators within 100 Km	624,026	8.37	7.94	2.00	5.00	14.00

Table 2: **The Effect of MSR Regulation on Aggregation Amount**

This table reports estimates the effect of MSR regulation on aggregation amount. Panel A reports the estimates from Equation (3) estimated at the seller level over the period 2010 - 2017. The dependent variable is log aggregation 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. Column 1 add correspondent lender-county fixed effects; columns 2 add year fixed effects; and column 3 add county-year fixed effects. Standard errors clustered at the correspondent lender level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. Panel B reports the estimates from Equation

Dependent Variable:	Log Aggregation Amt		
Model:	(1)	(2)	(3)
$\text{MSR}_s \times$ Post	-0.823***	-0.764***	-0.817***
	(0.190)	(0.188)	(0.185)
Post	0.791***		
	(0.080)		
Lender controls	Yes	Yes	Yes
Fixed-effects			
Lender-County	Yes	Yes	Yes
Year		Yes	Yes
County-Year			Yes
Fit statistics			
Observations	429,318	429,318	429,318
R^2	0.745	0.748	0.767

Table 3: **Effect on Origination Amount**

This table reports estimates the effect of MSR regulation on origination amount. Panel A reports the estimates from Equation (3) estimated at the seller level over the period 2010 - 2017. The dependent variable is log 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. Columns 1 and 4 add correspondent lender-county fixed effects; columns 2 and 5 add year fixed effects; and column 3 and 6 add county-year fixed effects. Standard errors clustered at the correspondent lender level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variables:	Log Origination Amount			Approval Rate		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
$\text{MSR}_s \times \text{Post}$	-0.516**	-0.451**	-0.505**	-4.90**	-4.76**	-4.58**
	(0.223)	(0.220)	(0.234)	(2.15)	(2.18)	(2.14)
Post	0.782***			2.14***		
	(0.087)			(0.690)		
Lender controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Lender-County	Yes	Yes	Yes	Yes	Yes	Yes
Year		Yes	Yes		Yes	Yes
County-Year			Yes			Yes
Fit statistics						
Observations	429,318	429,318	429,318	355,200	355,200	355,200
R^2	0.825	0.827	0.841	0.618	0.617	0.656

Table 4: **Effect on Origination Amount: By Lender Types**

This table reports estimates from Equation (7) and Equation (8) estimated at the seller level over the period 2010 - 2017. The dependent variable is log origination amount by correspondent lender s in county c and in year t. The main independent variable is $\text{MSR}_s \times \text{Post}_t \times \text{LenderType}_s$, 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) and lender type LenderType_s. 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 type is either a shadow bank dummy Shadow_s or a correspondent lender level measure of the origination market overlap with their aggregators Overlap_s as defined in Equation (10). ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variable:	Log Origination Amount	
Model:	(1)	(2)
$\text{MSR}_s \times \text{Post} \times \text{Shadow}_s$	-0.138*	
	(0.073)	
$\text{MSR}_s \times \text{Post} \times \text{Overlap}_s$		-0.277*
		(0.154)
$\text{MSR}_s \times \text{Post}$	-0.459***	-0.505***
	(0.044)	(0.055)
$\text{Post} \times \text{Shadow}_s$	-0.140***	
	(0.049)	
$\text{Post} \times \text{Overlap}_s$		0.345***
		(0.098)
Fixed-effects		
Lender-County	Yes	Yes
County-Year	Yes	Yes
Fit statistics		
Observations	437,272	437,272
R^2	0.842	0.842

Table 5: **Effect on Origination Amount: By Borrower Types**

This table reports estimates from Equation (11) estimated at the seller level over the period 2010 - 2017. The dependent variable is log purchase amount in year t. 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. The borrower type is a dummy variable for low income borrowers or borrowers from low income area. Low income borrower is defined as borrowers with income less than 80% of the FFIEC MSA median family income. Low income area is defined as census tracts with median family income lower than 80% of the FFIEC MSA median family income. Correspondent 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. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variable:	Log Origination Amount	
Model:	(1)	(2)
MSR_s × Post × Low Income Borrower	-0.183***	
	(0.040)	
MSR_s × Post × Low Income Area		-0.205***
		(0.041)
MSR_s × Post	-0.358***	-0.279***
	(0.039)	(0.037)
Post ×Low Income Borrower	-0.474***	
	(0.018)	
Post ×Low Income Area		-0.120***
		(0.019)
MSR_s × Low Income Borrower	0.369***	
	(0.034)	
MSR_s × Low Income Area		-0.010
		(0.037)
Lender controls	Yes	Yes
Fixed-effects		
Lender-County	Yes	Yes
County-Year	Yes	Yes
Fit statistics		
Observations	874,544	874,544
R^2	0.704	0.716

Table 6: **Matching Frictions in the Aggregation Market**

This table reports estimates from Equation (12) estimated at the seller level over the period 2010 - 2017. The dependent variable is log purchase 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. Standard errors clustered at the correspondent lender level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variable:	Log Origination Amount		
Model:	(1)	(2)	(3)
$\text{MSR}_s \times$ Post $\times$ ConnectedAggregators	0.086		
	(0.113)		
$\text{MSR}_s \times$ Post $\times$ Concentration		-0.239***	
		(0.075)	
$\text{MSR}_s \times$ Post $\times$ OutsideOption			0.541***
			(0.079)
$\text{MSR}_s \times$ Post	-0.582***	-0.392***	-0.776***
	(0.105)	(0.055)	(0.057)
Post $\times$ ConnectedAggregators	-0.018		
	(0.046)		
Post $\times$ Concentration		-0.017	
		(0.037)	
Post $\times$ OutsideOption			-0.261***
			(0.040)
Lender controls	Yes	Yes	Yes
Fixed-effects			
Lender-County	Yes	Yes	Yes
County-year	Yes	Yes	Yes
Fit statistics			
Observations	437,272	437,272	425,026
R^2	0.842	0.842	0.843

Table 7: **Other Substitution Margins**

This table reports estimates from Equation (13) estimated at the seller level over the period 2010 - 2017. The dependent variable is log purchase 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. All columns use lender and year fixed effects. Standard errors clustered at the correspondent lender level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variables:	Agency Relationship	Share - Agency	Share - Aggregator	Num Aggregators
$MSR_s \times$ Post	0.113***	0.081***	-0.045**	1.80***
	(0.028)	(0.017)	(0.018)	(0.351)
Lender controls	Yes	Yes	Yes	Yes
Fixed-effects				
Lender	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	13,686	13,686	13,686	13,686
R^2	0.735	0.817	0.824	0.849

Table 8: **Specialization of Correspondent Lenders**

This table reports estimates from Equation (14) and (15) over the period 2010 - 2015. Column (1) reports the estimates from Equation (14). 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. The main independent variable is a low income dummy variables $LowInc_{i,j,k,t}$, which is 1 if the borrower i is a borrower with income lower than 80% of FFIEC median family income at the MSA level. Columns (2)-(6) reports the estimates from Equation (15) for low income borrowers. The y variables are rejection dummy, rejection reason dummy for unverifiable information, rejection reason dummy for incomplete application, interest rate and delinquent over 90 days within two years after origination. Column (2)-(4) uses HMDA data and Column (5)-(6) uses HMDA-Attom-FF data. In Column (5)-(6), other borrower and loan characteristics including LTV, 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 column (2)-(6), standard errors are double clustered at the lender and census tract level. Standard errors are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variables: Model:	Correspondent (1)	Rej (2)	Rej - Unverifiable (3)	Rej - Incomplete (4)	Interest Rate (5)	Delinquent (6)
Variables						
LowInc	0.669***					
	(0.025)					
Correspondent		-4.28***	-1.34***	-6.09***	0.007*	0.056
		(0.604)	(0.436)	(1.19)	(0.004)	(0.046)
Fixed-effects						
Income quantile		Yes	Yes	Yes	Yes	Yes
Loan amount quantile	Yes	Yes	Yes	Yes	Yes	Yes
Loan type		Yes	Yes	Yes		
Applicant sex	Yes	Yes	Yes	Yes	Yes	Yes
Co-applicant	Yes	Yes	Yes	Yes	Yes	Yes
Minority	Yes	Yes	Yes	Yes	Yes	Yes
Census tract - Year	Yes	Yes	Yes	Yes	Yes	Yes
Controls						
Other characteristics					Yes	Yes
Fit statistics						
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, Fannie Mae and Freddie Mac single family loan level dataset, Attom dataset and additional datasets in A.1.1.1, A.1.1.2, A.1.1.3 and A.1.1.4. In Appendix A.1.1.5 I describe my matching algorithm. Descriptive figures and tables for these data sets and additional details about the matching performance are provided in Appendix A.2.

A.1.1 Home Mortgage Disclosure Act (HMDA)

I use mortgage data from Home Mortgage Disclosure Act to (i) construct the aggregator-correspondent lender network (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 the resultant 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 itself at the application level. For example, I observe the location, income, race, ethnicity, and gender of borrowers. For lenders, I observe their name and address, as well as a unique lender identifier.

HMDA classifies applications into origination, rejection, purchase(aggregation) and others based on action taken code. HMDA specifies who reports the decision on 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 code.

- **Origination:** A financial institution reports their decision on an application if they or their agents make credit decision prior to closing or account opening. 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 prior to 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[18].

HMDA covers over 90% of all originated mortgages in the United States[19]. 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 HMDA. Fourth, if a loan is first purchased by a financial institution A and then sold by

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

[19] 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.

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 HMDA, first, the originated loans that are labeled as sold to commercial bank, savings bank or savings association, credit union, mortgage bank, finance company, affiliated institutions, and other type of purchaser and second, purchased loans as indicated by action taken code 6. I conduct the merge over the sample period 2010 - 2023[20]. The merged dataset allows me to observe the buy/sell relationships between financial institutions. The details of the matching algorithm are provided in Section A.1.5.

The caveats of HMDA data bring concerns to my matching results. First, if most loans are not sold within the current calendar year, then the observed network may not be representative. The concern is lessened by the following facts observed from the HMDA data: 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. Second, if a financial institution purchase most mortgages originated in the previous year, my matching algorithm that only allows match between an originated loan and a purchased loan within the same calendar would result in biased network. However, majority of loans are sold within 2 months of origination by industry standard. This also ensures that the matching on loan amount is reasonable. Because the loan amount in origination is the original unpaid balance and the amount in purchase is the unpaid balance at the time of purchase the loan amount barely changes within 2 months. Since HMDA documents the loan amount as rounded to nearest 1,000 dollars or as the mid point of 10,000 dollars, the match makes sense. I also tried matching year t's aggregation to year t-1's unsold mortgages, the fraction of loans matched is less than

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

2%. Partially address the concern that the loan is not. Third, though firms do not originate any loans may not be required to file with HMDA thus do not show up in my network, the top aggregators in the mortgage market are mostly mortgage lenders. The aggregation market is high concentrated and the top 10 aggregators in HMDA takes up 40% of market share according to Mortgage Bankers Association survey. So the resulted network in my data still captures majority of the business relationships in the mortgage market. Fourth, if there are extremely long intermediation chain, then the network I capture in my paper is incomplete. I only consider the case when the loan is originated, sold to an aggregator and securitized, without considering the possibility of longer intermediation chain. I show that 80% aggregated loans are sold directly to Fannie Mae, Freddie Mac and Ginnie Mae, without channeling to another financial institution, otherwise they would be recorded as other. In addition, I only keep one-to-one match in my dataset, which represents 87% of the match, which also indicates that the longer intermediation chains in HMDA is kind of rare.

In my dataset, I define the lender that originate 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 channel could differ from definitions from 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 sell 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 Fannie Mae and Freddie Mac Single-Family Loan-Level dataset, such a loan is considered as a correspondent lending loan if a third party correspondent lender is involved in the origination process and a broker is not used in the process. I focus on the case when correspondent lenders can make decisions because it represents their willingness to supply credit.

Table A.1 compares the summary statistics of matched vs unmatched mortgages among the set of purchased mortgages in HMDA. The only noticeable difference is that the matched sample covers more conventional mortgage compared to unmatched sample.

My algroithm 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.2. The match rate in the recent years (2018 - 2020) reaches 78%. The match rate at the county level shows the match rate are generally high across the counties in United States, with high match rate concentrated in the middle states, see Figure A.3.

One concern with the merge is that HMDA reports the total loan amount of originated mortgages while unpaid balance of purchased mortgages, so that merging on loan amount and unpaid balance leads to error. However, most agency securitized mortgages are sold within two months of origination. The difference between total loan amount and unpaid balance should be small and taken care of by the amount difference allowed in my matching algorithm.

Another concern with the merge is that HMDA includes covered loans originated and sold by the financial institutions but repurchased from the financial entity that the loans were sold to. However, mortgage repurchase is generally rare[21]. 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[22]. In addition, I show that the fraction of mortgages purchased by a financial institution from its own origination or origination of subsidiaries is less than 10%. Note that this provides an upper bound for the fraction of repurchased mortgages in my matched

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

[22] By way of comparison, 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.

dataset.

A.1.2 Attom Real Estate Data

Attom Real Estate Data includes covers more than 155 million properties, 500 million real estate and loan transactions in over 2690 counties. Similar to other popular real estate datasets such as Corelogic and Zillow, the Attom dataset is divided into a transaction dataset and an assessment dataset. The former dataset contains information on transfers, mortgages and other real estate transactions. The latter dataset contains information on property charactersitics.

To clean the Attom data, I follow published papers such as Reher and Valkanov (2021), , and adapt the cleaning procedure to Attom. The details are listed below:

- Exclude Arm's length transactions, based on the indicator variable used by Attom to flag such transactions
- Exclude observations with QuitClaimFlag as 1
- Exclude observations with DocumentTypeCode as DTIT (Intrafamily Transfer) and DTGF (gift deed).
- Exclude observations that are not classified as "Transfer" or "Subdivision Related Transfer" in TransferInfoPurchaseTypeCode
- Exclude foreclosures, based on the indicator variable used by Attom to flag such transactions.
- Keep only transactions where buyers are not company
- Keep only properties that are single family or condo
- Exclude transactions with transfer amount smaller than 10000

- Exclude transactions mortgage amount larger than 99th percentile of HMDA application amount in 2022 ($1,800,000)
- Exclude transactions with LTV ratio is larger than 125%, corresponding to the largest standardized loan product
- Exclude transactions without valid buyer and seller names
- Exclude properties missing census tracts

These filters limit the transactions to valid residential home purchase transactions with reasonable mortgage amount and loan to value ratio. These filters 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 commerical properties in the Attom dataset when I merge Attom with HMDA, I would obtain a downwardly biased estimate. The remaining filters further rule out extreme cases or observations highly subject to measurement error.

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

I merge the Attom dataset with HMDA dataset. The merge allows me to obtain 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 provides single family loan level dataset provides a subset of their 30-year and less, fully amortizing, full documentation, single-family, conventional fixed-rate mortgages. The dataset does not only includes the loan characteristics but also the monthly performance of each loan. The loan characteristics includes the loan origination channel (retail, correspondent and broker), Loan to value ratio, debt to income ratio, loan amount, interest rate, seller identity, servicer identity etc, and also includes 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 dataset do not have the lender identity or the exact location of loans. The location of loans is at the three digit zipcode 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 rate 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 balance sheet and income statements of banks and thrift financial institutions[23]

- Shadow bank call reports data: I submit FOIA request to Massachusetts and Washington to obtain company level information of shadow banks that operate in these two states. Though I only source data from two states, the resulting dataset covers shadow banks that originate over 80% of the origination of all shadow banks

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

in the U.S. over 2012 - 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 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 annual income lower than $35,000, fraction of residents with a bachelor's degree, fraction of residents over 65 years old, etc from the U.S. Census API.

A.1.5 Matching Algorithm

Matching HMDA Originated Mortgages with Aggregated Mortgages: (a) merge by census tract, loan type, loan purpose and property type (b) select observations with loan amount difference in [-1,1] range (c) select observations with income difference in [-1, 1] range (d) match on race, sex, ethinicity if these variables are available (e) If there is only one unique match, keep the match. If there are more than one matches, require exact loan amount match. If there is only one unique match, keep the match and unmatched if not. (f) Examine if an originated loan is matched to multiple purchase/aggregated loans, if so, exclude the originated loan. Only keep one-to-one match.

Matching HMDA Originated Mortgages with Attom: (a) clean HMDA data to keep home purchase loans only and clean Attom data to keep residential real estate transactions with mortgage (b) merge by census tract and loan amount (c) fuzzy match 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 case of table-funding and correspondent lending, the lender identities are likely to be different. 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 name in HMDA and Attom respectively before conducting fuzzy match.

Matching HMDA-Attom with Fannie Mae and Freddie Mac dataset: (a) exact match based on loan amount and 3 digit zip code, loan type and loan purpose (c) matched based on loan origination year month, with the difference in [0, 2] months range. (d) match based on loan to value ratio, require the difference less than 5%.

A.2 Figures and Tables

Figure A.1: Sample construction

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

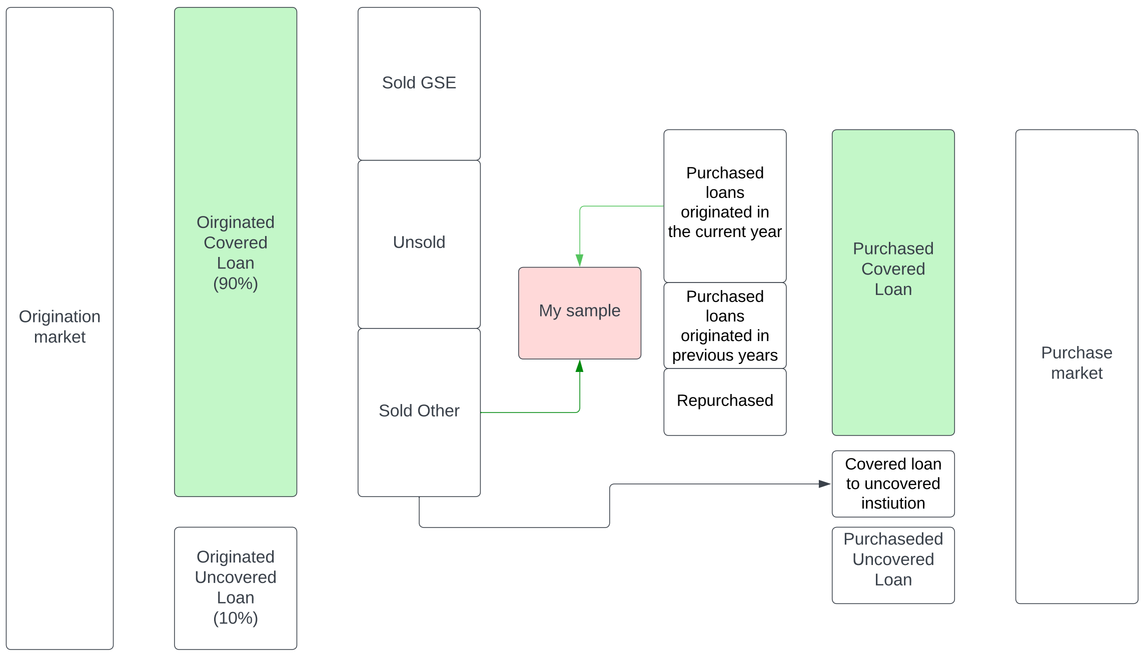


Figure A.2: Time series match rate

This figure shows time series match rate of purchased mortgages in my sample. Sample period is 2000 - 2021.

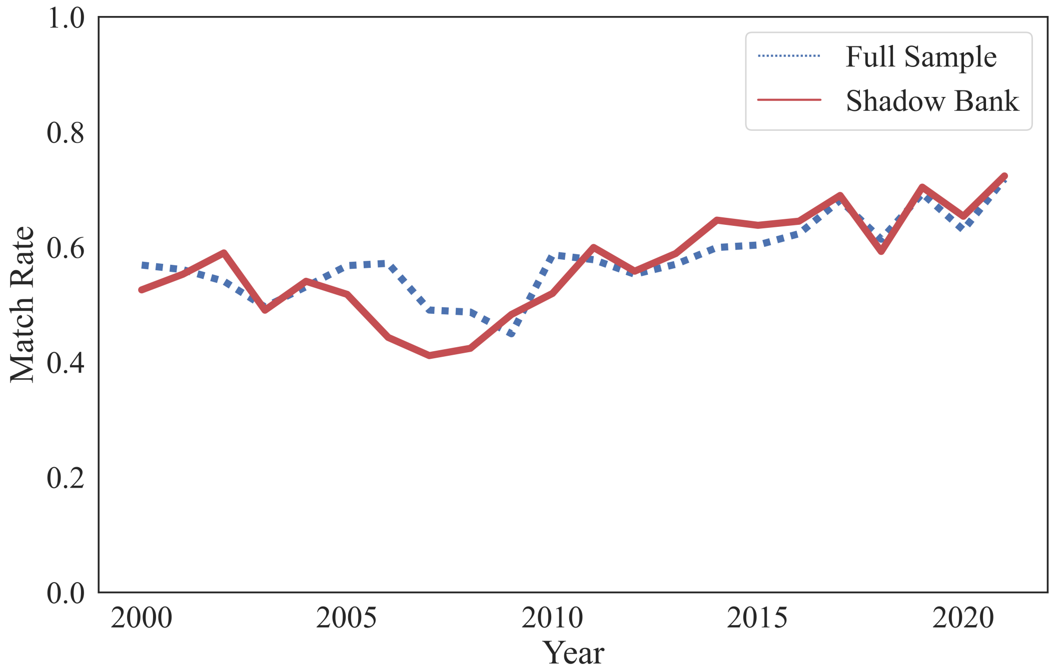
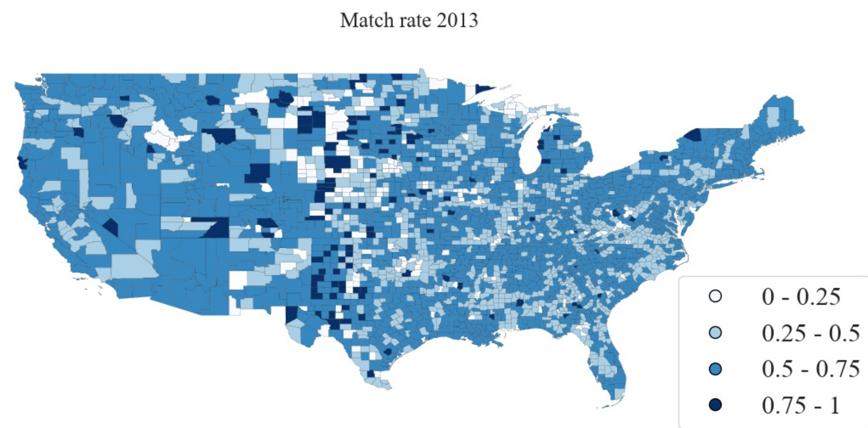


Figure A.3: Cross sectional match rate

This figure shows cross sectional match rate of purchased mortgages in my sample. Sample year in the upper/lower graphs are 2013 and 2021.



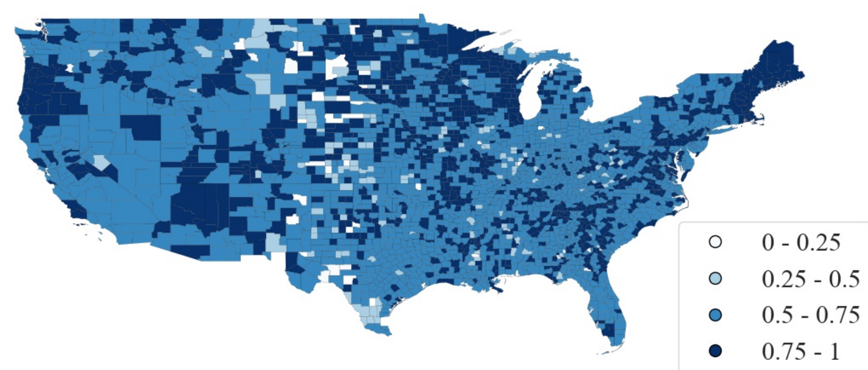


Figure A.4: Purchasers of mortgages purchased by aggregators

This figure shows the fraction of aggregated mortgages sold to different purchasers. Sample period is 2009 - 2017. Data source: Home Mortgage Disclosure Act mortgage data with action taken code 6.

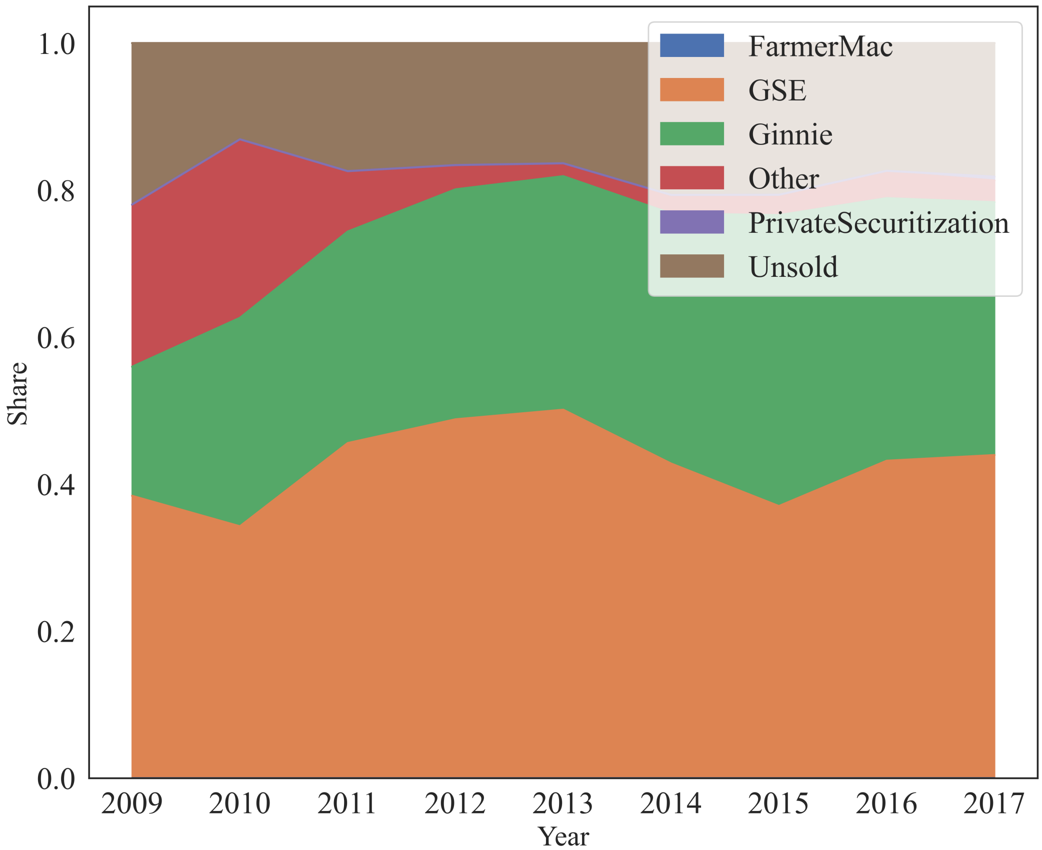


Figure A.5: Persistence of correspondent lender-aggregator relationship

This figure shows the persistence of relationship 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.

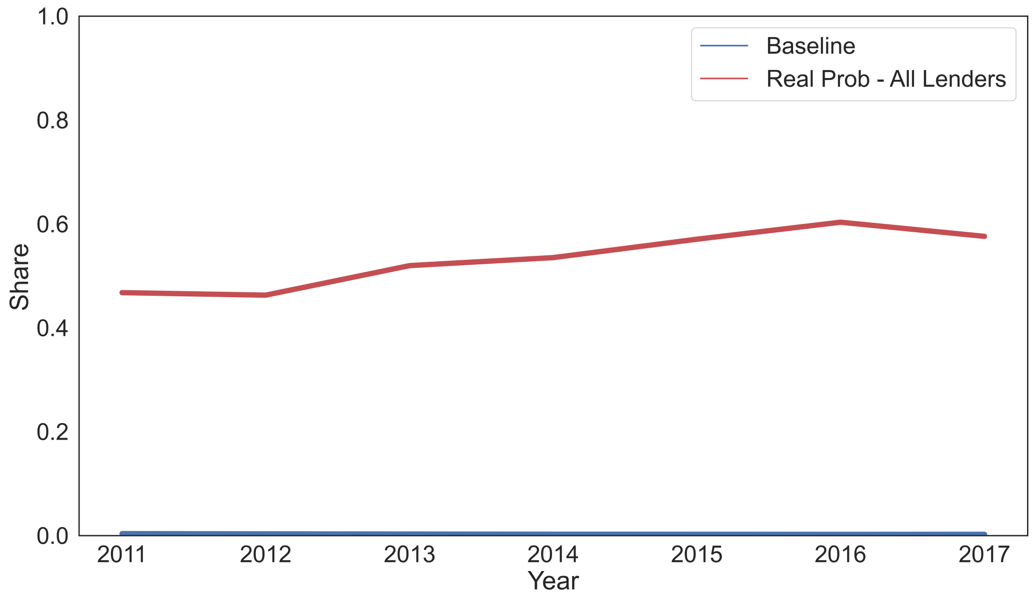


Figure A.6: Frequency of Relationships Based on Market Overlap

This figure shows the distribution of market overlaps between correspondent lenders and aggregators that have established relationships. The market overlap is defined in 9. The x axis divide the market overlap ratio into quintiles, and the y axis shows the fraction of relations that falls into each quintile of market overlap. The blue bar represents the set of formed relationships and the red bar represents the set of unformed relationships.

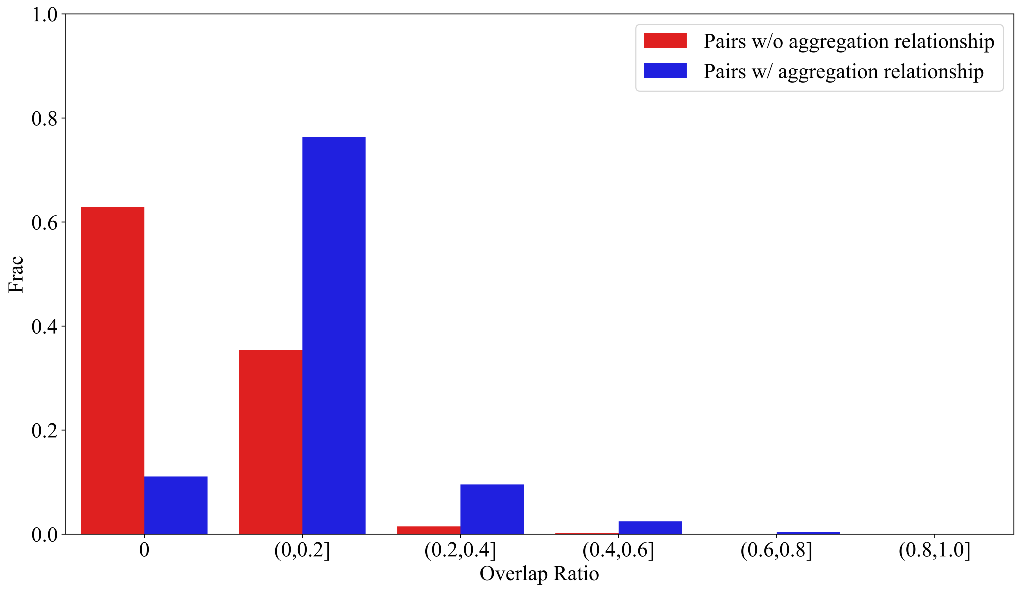


Table A.1: Summary statistics of matched and unmatched samples

This table compares loan and borrower characteristics among matched vs unmatched sample of purchased mortgages.

Var	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%

Var	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 (4) estimated at the correspondent lender-aggregator level over the period 2010 - 2015. The dependent variable is log 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. Columns 2 add year fixed effects; columns 3 add correspondent lender-year fixed effects; and columns 5 add correspondent lender-aggregator fixed effects. Standard errors clustered at the correspondent lender level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variable:	Log Aggregation Amount				
Model:	(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	0.964***				
	(0.038)				
Fixed-effects					
Year		Yes	Yes	Yes	Yes
Aggregator			Yes	Yes	Yes
Correspondent lender-Year				Yes	Yes
Correspondent lender-Aggregator					Yes
Fit statistics					
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 of lender control variables for 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 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 (6) estimated at the seller level over the period 2011 - 2017. The dependent variable is log 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. Standard errors clustered at the shadow bank-year level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variables:	Log Credit Limit				Used Fraction			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{MSR}_b \times \text{Post}$	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)
Fixed-effects								
ShadowBank	Yes	Yes	Yes		Yes	Yes	Yes	
WarehouseLender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearQuarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ShadowBank-YearQuarter				Yes				Yes
Fit statistics								
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 Subsample**

This table reports estimates the effect of MSR regulation on origination amount using the subsample of shadow banks. Panel A reports the estimates from Equation (3) estimated at the seller level over the period 2010 - 2017. The dependent variable is log 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. Columns 1 and 4 add correspondent lender-county fixed effects; columns 2 and 5 add year fixed effects; and column 3 and 6 add county-year fixed effects. Standard errors clustered at the correspondent lender level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variables:	Log Origination Amount			Approval Rate		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
$\text{MSR}_s \times$ Post	-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	0.406***			3.40***		
	(0.041)			(0.528)		
Fixed-effects						
Lender-County	Yes	Yes	Yes	Yes	Yes	Yes
year		Yes	Yes		Yes	Yes
County-Year			Yes			Yes
Fit statistics						
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 lender level treatment variable and Basel III capital shortfall measure from Berrospide and Edge (2016). The sample only includes bank lenders at the bank holding company level. Column (1) uses all lenders in my sample, Column (2) include lenders that are subsidiaries of aggregators, column (3) uses all correspondent lenders, column (4) uses all correspondent lenders with agency access and column 5 uses all correspondent lenders without agency access. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variable:			MSR		
Model:	(1)	(2)	(3)	(4)	(5)
Shortfall	0.29	0.43	0.02	0.39	-0.22
	(0.31)	(0.75)	(0.33)	(0.55)	(0.42)
Constant	0.16***	0.18***	0.16***	0.14***	0.16***
	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)
Fit statistics					
Observations	504	120	384	147	237
R^2	0.00175	0.00276	6.14×10^{-6}	0.00356	0.00121

Table A.7: **Interest Rate and Loan Performance**

This table reports estimates $y_{i,j,k,c,t} = \beta \times \text{MSR}_k \times Post_t + \gamma X_{i,j,k,c,t} + \eta X_{j,t} + FEs + \epsilon_{i,j,k,c,t}$. The dependent variable is 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_k and $Post_t$. MSR_k is 1 if the MSR/Tier 1 capital exposure of the aggregator k exceeds 10% and otherwise 0. Post_t is 1 if the year quarter is after Q2 of 2012. Borrower controls include LTV, DTI, FICO, log loan amount, log income, first time home buyer indicator. Lender controls include log asset, return on assets, capital ratio and liquidity ratio. Standard errors clustered at the correspondent lender-aggregator level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variables:	InterestRate		Delinquent - 60 days		Delinquent - 90 days	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
$\text{MSR}_b \times$ Post	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)
Fixed-effects						
County-YearQuarter	Yes	Yes	Yes	Yes	Yes	Yes
Aggregator	Yes		Yes		Yes	
Correspondent lender-Aggregator		Yes		Yes		Yes
Fit statistics						
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.8: **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 0 other wise. 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 0 other wise. 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*times*year fixed effects. Standard errors clustered at the correspondent lender level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variable:	Current					
Model:	(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)					
Fixed-effects						
Aggregator		Yes				
Aggregator-Year			Yes	Yes	Yes	Yes
State-Year			Yes	Yes	Yes	Yes
Size quantile-Year				Yes	Yes	Yes
Correspondent lender type-Year					Yes	
Correspondent lender type-Aggregator type-Year						Yes
Fit statistics						
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.9: **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 headquarter distance is the distance between the headquarters of correspondent lender and aggregator. Column (1) reports the coefficient estimate for the full sample, column (2) reports the coefficient estimate for pairs with headquarter distance less than 500 Km, column (3) reports the coefficient estimate for pairs with headquarter 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. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variable:	Aggregation Relationship				
Model:	(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)
Fixed-effects					
Seller-Year	Yes	Yes	Yes	Yes	Yes
Purchaser-Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
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