

The Economic Consequences of Mergers Between Real Estate Agencies and Mortgage Lenders

Rebecca A. Jorgensen*

November 4, 2024

Abstract

This paper studies the consequences of joint ownership between real estate agencies and mortgage lenders for consumers, lenders, and mortgage market structure. I construct a novel data set which matches home buyers' real estate agencies, lenders, and loan characteristics while tracking ownership of lenders and agencies over time. Using hand-collected data for over 100 mergers involving real estate agencies or lenders, I implement a staggered differences-in-differences strategy that compares lender-agency pairs which are jointly owned due to horizontal mergers between real estate agencies to lender-agency pairs that are never jointly owned. After merging, lenders double their loan shares within jointly owned real estate agencies with little impact on a lender's CBSA market share. Buyers who use a lender jointly owned with their real estate agency pay interest rates 9 basis points higher, amounting to \$225 in additional interest per year on the average loan. However, I find no evidence that home buyers' credit characteristics, delinquency rates, or transaction speed change following these mergers. Finally, I develop a structural model of the mortgage market to recover marginal cost estimates and study the welfare implications of mergers under counterfactual policies. I find evidence of cost efficiencies from mergers and that regulation would improve consumer welfare.

*I would like to thank my committee, Ben Keys, Maisy Wong, and Fernando Ferreira for their advice on this project. I would also like to thank Sasha Indarte, Lu Liu, Jessie Handbury, James Vickery, Bryan Stuart, Ryan Goodstein, You Suk Kim, Charles Taragin, David Benson, and seminar participants at the Wharton Urban Lunch, the Federal Reserve Bank of Philadelphia, the FDIC, the Board of Governors of the Federal Reserve System, the CFPB, University of Zurich, Miami University, Baylor University, the Department of Justice, the Office of Financial Research, and the Office of the Comptroller of the Currency for their insights.

Disclaimer: The opinions and analyses contained herein are solely of the users/authors of any data analyses or papers, and the FHFA cannot and does not attest to nor vouch for the quality, accuracy, or timeliness of the data, or analyses derived from these data after the data has been retrieved from FHFA.gov. This material is based upon work supported by the National Science Foundation Graduate Research Fellowship Program under Grant No. DGE-1845298. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the National Science Foundation. The author received a travel grant from the IAAE to present this paper in June 2023.

1 Introduction

The years following the financial crisis saw a wave of technology-rich non-banks, referred to as “FinTech” gaining significant market share in mortgage lending (Buchak, Matvos, Piskorski and Seru (2018), Fuster, Plosser, Schnabl and Vickery (2019)).¹ Non-bank lenders have merged with real estate agencies, who can refer prospective borrowers to specific lenders to overcome the fact that they do not have the pre-existing customer base of checking and savings account customers that traditional banks have.

How mergers between real estate agencies and mortgage lenders affect lender market shares, mortgage interest rates, time to close, the credit characteristics of borrowers, and mortgage marginal costs is especially important to understand given the size and scope of the mortgage market. For most buyers, a mortgage represents the largest debt and debt financing obligation they will face. Merger theory is clear that mergers between lenders and real estate agencies will increase lender market share, but remains ambiguous on how interest rates, borrower characteristics, and time to close will be affected. Ultimately, this depends on the balance between efficiency gains and increased market power.

In terms of efficiency gains, the prior literature says that within the financial sector, mergers can lead to more efficient firms.² Cost-based efficiencies would reduce the marginal cost of originating a loan, which could be passed on to borrowers in the form of lower rates. Efficiencies coming from better communication between a lender and real estate agent could show up in faster time to close on a home or in a change in the credit profile of borrowers. Real estate agents “vouching” for more

¹See Jiang (2023) for a model of the vertical relationships between non-bank and traditional bank lenders, Jiang, Matvos, Piskorski and Seru (2020) and Irani, Iyer, Meisenzahl and Peydró (2020) for discussions of the capital structures of banks and non-banks, (n.d.) on bank vs. non-bank debt forbearance, and Agarwal, Hu, Roman and Zheng (2023) for a discussion of how non-banks affect the transmission of monetary policy.

²See Berger, Demsetz and Strahan (1999) for a discussion on the potential efficiency gains from mergers in the financial sector.

marginal borrowers may help increase credit access. If real estate agents instead communicate concerns about the riskiness of particular borrowers to lenders after a merger, this would decrease credit access.

However, the increased market power from a merger between a real estate agency and mortgage lender may have negative consequences for buyers as well. Prior literature has documented that real estate agents influence the decisions of buyers.³ Mergers between real estate agencies and mortgage lenders may allow lenders to use the influence real estate agencies have over buyers to charge higher interest rates to borrowers coming from the newly merged real estate agency.⁴ The potential coexistence of positive and negative consequences, in particular for borrowers, from mergers between real estate agencies and mortgage lenders make it difficult to determine the net welfare consequences without understanding both the consequences of these mergers and how counterfactual regulatory policy would reshape the mortgages consumers select.

This paper studies the consequences of joint ownership between real estate agencies and mortgage lenders for lender market shares, mortgage interest rates, time to close, and borrower characteristics. First, I construct a novel data set through which I can observe the real estate agency, lender and loan terms and performance for a given house sale as well as track ownership of lenders and real estate agencies over time. Then, I use this data set in a staggered differences in differences design to deal with the potential selection bias of which real estate agencies and mortgage lenders decide to merge and recover estimates for lender market shares, mortgage rates, time to close, and borrower characteristics. Finally, I recover marginal cost estimates and test counterfactual policy counterfactuals with a structural model.

No standard data set contains all the pieces necessary for the analysis in this paper: the real

³See Lopez, McCoy and Sah (2019) for a discussion about agents selling a home directing buyers to particular lenders and potential crowd-out effects, and Barwick, Pathak and Wong (2017) for a discussion about real estate agents steering buyers to homes that pay higher commissions.

⁴Grunewald, Lanning, Low and Salz (2020) find that auto lenders affiliated with dealerships charge higher rates.

estate agency, lender, loan terms and performance, and information about mergers between real estate agencies and mortgage lenders. I therefore construct a novel data set that matches loans to the originating lenders, the underlying home purchase, and the buyers' real estate agencies by merging four CoreLogic data sets. I then hand-match over 100 mergers involving real estate agencies and/or lenders into this data set to obtain the ownership structure over time. For the over one million housing transactions in this data set I observe the buyer's real estate agency, mortgage lender, loan terms and performance, and if the real estate agency and lender are ever merged, including at the time of home purchase.

Simply comparing outcomes before and after a lender and agency are jointly owned is not sufficient, because the firms that decide to merge are likely to be selected. To account for this selection, I exploit the frequent mergers that occur between two real estate agencies, known as horizontal mergers. Horizontal mergers between two real estate agencies will also result in a new joint ownership between a real estate agency and mortgage lender if one of the two real estate agencies horizontally merging is already jointly owned with a lender, what I will call "indirect integration". Furthermore, real estate agency horizontal mergers are occurring to increase the acquiring agency's real estate agency market share, and the lender's books are not the primary concern. Horizontal mergers between real estate agencies which lead to indirect integration are less subject to selection bias as concerns the outcomes in the mortgage market I am concerned with. I identify 87 mergers in the data set I constructed which occur between two real estate agencies but lead to indirect integration. I will use the 87 mergers I identify as the variation for my staggered differences in differences. Observing 87 mergers on a data set of more than one million housing transactions means that I can include fixed effects for real estate agency, mortgage lender, time, and geography to further remove factors which could bias the estimates from the staggered differences in differences.

First, I find that joint ownership with a real estate agency increases a lender's market share. Lenders more than double the share of buyers at a real estate agency they lend to after a lender and real estate agency merge. The lender also gains 0.54 percentage points of market share in a CBSA once they merge with a real estate agency, which is a 16% increase over the average lender's market share due to the fragmented nature of the mortgage market. From the perspective of the lender, merging with a real estate agency allows the lender to grow.

Second, I find that buyers who use a jointly owned real estate agency and mortgage lender pay 9 basis points higher interest rates on their mortgages, even after accounting for credit characteristics and search behavior.⁵ Nine basis points in additional interest amounts to \$225 per year on the average loan.

Prior literature has found effects in the mortgage market of similar magnitudes to the 9 basis points I find from using a jointly owned real estate agent and lender. Bartlett, Morse, Stanton and Wallace (2021) finds that minority borrowers pay 7 basis points more than white borrowers on average, and 9 basis points is 15% of the total dispersion in the mortgage market found by Bhutta et al. (2020).

Third, I find no evidence that buyers using a jointly owned real estate agency and mortgage lender are able to close on their home faster. Buyers who use a jointly owned agency-lender pair close on their home 1.4 days faster, which is statistically significant but not economically significant. There is no significant reduction in the probability of taking more than 45, 60, or 75 days to close on a home, either. There are no efficiency gains from mergers between lenders and agencies with respect to closing speed.

Fourth, I find no evidence of changes in the credit profiles of borrowers taking out loans. Buyers who use a jointly owned real estate agency and mortgage lender look the same on FICO score, loan-

⁵Bhutta, Fuster and Hizmo (2020) find that search behavior is a major determinant of mortgage interest rate.

to-value ratio, loan amount, and delinquency rates before and after the merger. Information passed from agency to lender is neither helping nor hurting borrower credit access.

I set up my structural model to recover marginal cost estimates and run policy counterfactuals. I estimate a logit demand for loans with consumer-specific choice sets and profit maximizing lenders offering differentiated products under Bertrand competition. This is similar to the models in Robles-Garcia (2019) and Benetton (2021).⁶

I estimate that the marginal cost of originating a loan to a consumer from a lender's sibling real estate agency is lower than originating a loan to the general public, and that the difference is statistically significant. Mergers between real estate agencies and mortgage lenders produce cost efficiencies for the lender. Lenders do not pass these savings on to borrowers, however, since the rates consumers using a jointly owned real estate agency and mortgage lender pay 9 basis points more, even after accounting for search behavior and credit risk.

I finish by estimating two policies which could be considered by regulators. In the first, I ban mergers between real estate agencies and mortgage lenders. In the second, I permit the mergers but prevent them from tailoring product offerings based on the real estate agency the borrower uses. In both counterfactuals the average interest rate paid by borrowers falls, but the decline is larger in the second counterfactual. Overall welfare improves relative to the status quo in the both counterfactuals, as well.

This paper has three main contributions. First, it offers a novel channel to explain the price dispersion in mortgage pricing. Prior literature has documented that mortgage prices vary even for identical borrowers (Bhutta et al. (2020)). Subsequent papers have posited explanations for this dispersion, but a substantial residual remains unexplained (Bartlett et al. (2021), Bhutta and Hizmo (2021)). I contribute another partial explanation for the price dispersion in mortgage markets.

⁶Robles-Garcia (2019) and Benetton (2021) both deal with the U.K. mortgage market, and are looking at other questions than the one in this paper. This means that I have considerably simplified from the models in both papers.

Second, I am one of the first to study steering between real estate agencies and mortgage lenders. It is well documented that mortgage lenders steer buyers to loans which are most profitable for them (Guiso, Pozzi, Tsoy, Gambacorta and Mistrulli (2021), Agarwal, Amromin, Ben-David and Evanoff (2016)), and that real estate agencies steer buyers to homes which pay higher commissions (Barwick et al. (2017), Woodward and Hall (2012)).

To the best of my knowledge, Lopez et al. (2019) is the only paper that also links steering between real estate agencies and mortgage lenders. The authors study steering by sellers' agents on foreclosed homes in Las Vegas, NV. My data allow me to study a much broader geography, set of outcomes, and sample of home sales. Furthermore, I utilize variation at a level above the home transaction itself, and consider buyers' agents (who buyers are more likely to trust). I am the first to include a structural model to study regulatory counterfactuals and recover marginal costs.

Third and finally, I contribute to the discussion on whether, and how policy makers should regulate mergers involving banks and non-banks, as well as the consequences of the rise of non-banks and integration. I study far more mergers than the other papers in this literature with a broad set of potential outcomes. has shown that mergers in financial industries can have costs and benefits and influence pricing behavior (Berger et al. (1999), Stroebel (2016), Robles-Garcia (2019)). Related papers, such as Buchak et al. (2018), have documented the rise of non-banks in spheres traditionally occupied by banks.⁷

The rest of this paper is organized as follows. Section 2 provides institutional background for the setting of my paper. Section 3 presents survey evidence exploring the interaction between real estate agents, mortgage lenders, and borrower search behavior. Section 4 discusses a merger case study. Section 5 discusses my data; Section 6 presents the reduced form identification strategy, and Section 7 presents the results. Section 8 presents and estimates my structural model, and Section

⁷For a more general discussion of complementary goods mergers among non-financial products see Akgün, Caffarra, Etro and Stillman (2020), Choi (2008), and Ershov, Laliberté and Orr (2018).

9 concludes.

2 Institutional Background

This paper requires institutional background on real estate agencies, mortgage lenders, and the mortgage market. Beginning with real estate agencies, real estate agencies employ real estate agents to work with home buyers and sellers. 86% of buyers in the United States used a real estate agent in 2020.⁸ Buyers are generally satisfied with the quality of the service they receive from their real estate agent; 89% of buyers said they would use the same agent again or recommend the agent to others when asked.⁹ During the 2011-2019 years this paper studies, buyer's agents are paid out of the seller's agent's commission when the clients find a home.¹⁰ Agents are consequently not paid until after the client closes on a home. Besides helping buyers find homes and negotiate the purchase price of their home, real estate agents often recommend providers of related services to their clients, such as title companies and lenders.

Real estate agents cannot receive kickbacks from the firms they recommend to their clients under the Real Estate Settlements Procedure Act (RESPA), but they are allowed to share costs if the real estate office and another firm share expenses such as advertising or office space. Companies have violated this Act; in August 2023 the Consumer Financial Protection Bureau fined Freedom Mortgage for paying more than cost sharing to Revolve Realty. Similarly, ReMax has been fined for a kickback scheme with a mortgage lender.¹¹

Moving to mortgage lenders, mortgage lenders can attract consumers directly through their

⁸See: [here](#)

⁹See: [here](#)

¹⁰Recent 2023 and 2024 court rulings may change the compensation structure for real estate agents, but the compensation structure was fixed during the timing of this paper.

¹¹See: [here](#) and [here](#)

retail channel, but lenders can also work with mortgage brokers. Mortgage brokers are third party agencies that lenders can contract with to find more borrowers. Mortgage brokers contract with several lenders, and receive a commission from a lender when a buyer chooses that lender to originate their loan. Thus, borrowers going to a mortgage broker receive loan terms from several lenders, while borrowers going through a lender's retail channel will see only loans from that lender.

87% of buyers financed a home purchase with a mortgage in 2021.¹² The vast majority of mortgages in the United States are fixed rate mortgages, meaning that the rate on the mortgage will remain constant for the duration of the loan. Loans in the United States can either be originated through banks or non-bank lenders. Non-bank lenders originate the loans through lines of credit they hold with traditional banks (called warehouse lines), which the non-bank lender then securitizes and sells the loan. Most loans are backed by the Federal Housing Administration (FHA) or government sponsored entities, Fannie Mae and Freddie Mac. The government agencies backing mortgages provide detailed guidance on what the maximum value of the loan can be depending on the average home price in the area. In addition, the agencies give lenders a matrix of "Loan-Level Pricing Adjustments," which are increases to the interest rate lenders must charge based on the borrower's loan-to-value ratio (LTV) and credit (FICO) score.

Prior to the 2008 financial crisis, mortgage brokers originated over half of loans in the United States. Following federal regulations that made mortgage brokers less profitable, many mortgage brokers went out of business, and by 2019, mortgage brokers originated only 19% of loans in the United States. Now, lender cannot rely on mortgage brokers to help find borrowers for the lender to originate loans. Now, lenders must find another channel to find borrowers.

At the same time the share of borrowers finding loans through mortgage brokers is declining,

¹²See: [here](#)

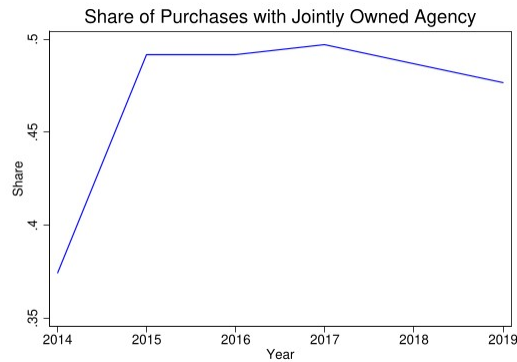
residential real estate agencies are merging with lenders and related services. Home purchases and mortgages are complementary goods; as the majority of buyers finance their home purchase with a mortgage, these two goods go hand in hand. Thus, mergers between residential real estate agencies and lenders can be profitable for both parties. Residential real estate agencies provide a set of customers for lenders who can no longer rely on mortgage brokers, and bringing a lender in house could simplify the loan search process for buyers, allowing buyers to close on a home, and the agent to get paid, more quickly.

While this paper focuses on mergers between lenders and residential real estate agencies, real estate agencies are also merging with other parts of the home buying process, such as title insurance. Gino Blefari, CEO of HomeServices of America, which owns multiple lenders, real estate agencies, and title insurance companies, said that “[c]reating a seamless all-inclusive shopping experience for a consumer’s real estate transaction – agency, mortgage, title & homeowners insurance is critical for both the best consumer experience and the best path to profitability,” suggesting that HomeServices of America sees the complementarities between real estate agencies, lenders, and title insurance companies and that merging improves overall firm performance.

Figures 1a, 1b, and 1c show how the real estate and mortgage markets have evolved over time. Figure 1a shows what share of home purchases are made using an agency that has a jointly owned lender, also referred to as a sibling lender. Since 2014, the share of home purchases made using a real estate agency with a sibling lender has increased by nearly 25%, and in 2019 almost half of home purchases used an agency with a sibling lender. Agencies that lenders are able to use as a distribution channel are a large fraction of the market and thus come with a large pool of buyers these lenders could attract.

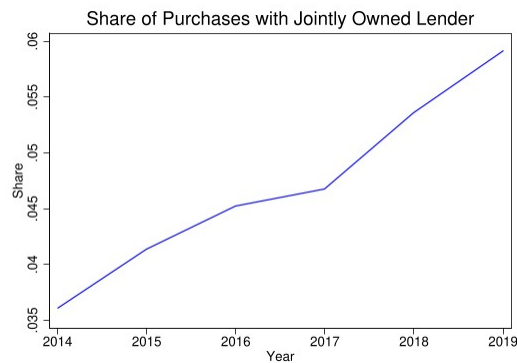
The story is similar when looking at lenders. In Figure 1b, we can see that the share of loans originated by lenders merged with agencies has increased from 3.5% in 2014 to 6% by 2019.

Although my data end in 2019, the share of loans originated by lenders with sibling real estate agencies has continued to increase in the intervening years. While real estate agencies are large players in the market, the lenders have considerably smaller market share. The small market share of lenders is consistent with state-level licensing to originate mortgages representing a high barrier to entry for lenders. Most lenders are geographically concentrated in at most a handful of states.



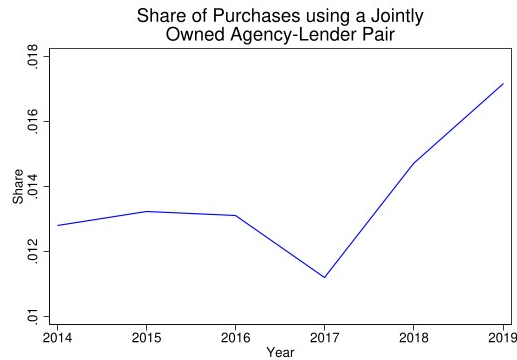
Notes: Figure shows share of home purchases which use a real estate agency that has a sibling lender at time of home purchase, regardless if lender originated the mortgage for that purchase or not.

Figure 1a: Share of Home Purchases with Conglomerate Agency



Notes: Figure shows share of purchase loan originations which use a lender that has a sibling real estate agency at time of home purchase, regardless if agency was involved in the transaction or not.

Figure 1b: Share of Loans Originated by Conglomerate Lender



Notes: Figure shows share of home purchases which use a jointly owned agency-lender pair for home purchase and mortgage financing.

Figure 1c: Share of Purchases using Conglomerate Agency - Lender Pair

In Figure 1c, I show the share of home purchases using a merged agency-lender pair. These are the purchases and loan originations that I am most interested in studying. The share of home purchases that are using a merged agency-lender pair is still small at 2% of my data, but given the growth of merged agencies and lenders in the previous figures, as well as the continued addition of new joint firms, the share of home purchases using a merged agency-lender pair is likely to grow over time. Furthermore, while 2% of all buyers is a small fraction, that is 33% of the market share of merged lenders, indicating that a sibling real estate agency is an important distribution channel for these lenders.

3 How Do Buyers Choose Lenders?

The National Survey of Mortgage Originations (NSMO) is a quarterly survey conducted by the FHFA and the CFPB asking recent home buyers a variety of questions about their home purchase and mortgage acquisition process. Questions include topics such as their understanding of mortgage terms, house price expectations, and how the buyer chose a lender. It is the questions on this

last topic which are relevant for this paper and which I discuss in this section.

When asked to select which features were not at all, somewhat, or very important to them, 34% of buyers said that the recommendation of their real estate agent was somewhat or very important.¹³ Moreover, 17% of buyers were introduced to their lender by an interested third party such as their builder or real estate agent. In addition, nearly half (49%) of buyers report only seriously considering one lender.

When restricting the survey data to first-time home buyers, 58% valued their real estate agent's recommendation, and 33% were directly introduced to their lender through an interested third party. Similar to the general population, 47% of first-time buyers only seriously look at one lender.

When looking at low credit score borrowers, even more, 64% of borrowers found their agent's recommendation somewhat or very important, 18% were introduced by an interested third party, and 51% only seriously consider one lender.

Taken together, the NSMO survey results indicate that, especially for low credit score and first-time home buyers, the recommendation of a buyer's real estate agent influences the lender the buyer ultimately chooses. As a result, lenders and real estate agencies merging has the potential to lead agents to recommend their sibling lender and ultimately the lender chosen by buyers. Thus, a real estate agency merging with a lender will likely increase the number of buyers coming to the lender from that agency. The effects on overall lender market share are unclear, however. If the lender treats these borrowers as perfect substitutes for other borrowers coming from non-merged real estate agencies, then overall market share will not increase, only the market share coming from the sibling real estate agency. However, if the lender treats the sibling borrowers as additional customers, without completely substituting away from buyers coming from agencies with whom they are not merged, then both the lender's market share within their sibling agency

¹³Other options include: rate (98%), lender reputation (71%), prior relationship with the lender (57%), local lender (50%), used lender before (39%), recommendation of a friend (36%), and lender is a friend (14%).

and their overall market share will increase.

Unfortunately, this survey data provides no evidence on price effects as interest rates are not available in the public use version of the NSMO. However, the lack of search by approximately half of borrowers leaves borrowers open to unknowingly paying higher prices as a result of the integration of real estate agencies and lenders and lack of search for mortgages by buyers as previously discussed.

4 Data

No pre-existing data set contains all the necessary pieces to the consequences of mergers between real estate agents and mortgage lenders: lender, real estate agency, and loan characteristics. Furthermore, corporate ownership structure plays a vital role in studying the consequences of mergers but is not readily matched to the lender, real estate agency, and loan characteristics. Thus assembling the data for this project is no small feat. The final data set represents a contribution to the field as it is useful for projects beyond this one. In all files, I restrict my sample to 2011-2019 so as to avoid contamination from either the 2008 financial crisis or the COVID-19 pandemic.

CoreLogic Deeds Data The CoreLogic Deeds data include details on residential properties at the time of sale, including the characteristics of the property, the deed transfer, and most notably for this project, the mortgage used to purchase the home. The mortgage details include, among others, the loan amount, the start date, loan term, interest rate, loan purpose and type, and lender. While all variables appear at least once in the data set, some, most notably interest rate, are missing the vast majority of the time. Lender name, however, is well populated, allowing me to see the lender who issued the loan. I will also restrict my analysis to purchase loans, since purchases are

when borrowers are most directly involved with a real estate agent, and when the influence coming from mergers between lenders and agencies is likely to be strongest. In comparison, at the point of refinancing, borrowers are not working directly with a real estate agent, and while the decision of a refinancing lender may be correlated with the the original choice of lender, the actual link is less clear and I leave to future research.

CoreLogic MLS Data CoreLogic also provides the Multiple Listing Service (MLS) data set which covers the MLS feeds for 138 MLSes across the United States. Similar to Zillow, a home listing on the MLS contains all fields from the listing of a home: list price, transaction price, date sold, date listed, home characteristics such as number of bedrooms and bathrooms, address, square footage, etc. It also contains information on the buyer's real estate agent, including the real estate agent's name and agency at the time of sale.¹⁴ I will use the terms agent and agency interchangeably.

CoreLogic LLMA Originations Data The CoreLogic Loan-Level Market Analytics (LLMA) Originations data come from a large loan servicer and contain individual loan characteristics at origination, including the interest rate, amount, origination month and year, property type, loan type, loan term, location, FICO score of borrower at origination, and loan-to-value-ratio at origination. The key variables I use from the LLMA data are the loan interest rate, borrower FICO score, and borrower LTV ratio.

CoreLogic LLMA Events Data The CoreLogic LLMA Events data track the major performance events of a loan including the date of the first 30, 60, and 90 day delinquency, the first date of a

¹⁴For this project, I utilize the agency as opposed to the individual agent. In cases of mergers, directives to recommend a given lender are likely to come from the parent company and affect all agents. Second, in cases where a team of agents work with a buyer, it is not clear who the purchase should be attributed to from the team. It is far more obvious which agency is responsible.

bankruptcy filing, and the first date of foreclosure filing. I use the LLMA Events data to compare the performance of loans by merged lender-agent pairs and those by other lenders who may have less soft information on which to base a lending decision.

CompuStat Transactions Data I use the CompuStat Transactions Data to identify mergers and infer ownership structure. The CompuStat Transactions data set records information on all mergers and acquisitions back to 2000: the target, the acquirer, the transaction date, and additional details. I identified all relevant transactions by hand.¹⁵ Due to the large number of real estate offices in the country, not all mergers are widely publicized. To the best of my knowledge, my data set is the most comprehensive that tracks mergers and acquisitions of solely real estate firms.

Home Mortgage Disclosure Act Data The Home Mortgage Disclosure Act (HMDA) public use data are redacted loan-level data originally provided to the federal government in order to ensure fair lending practices. Across all years of data, the HMDA data include borrower characteristics including as race and gender. For the last two years of my sample, the HMDA data also include loan fees and discount points.¹⁶ Loan fees are fees paid at origination to the lender, and are a function of the loan amount in most cases. Discount points are an additional fee paid at origination in order to reduce the interest rate on the loan. While two years of data are a limited time to view discount points and origination fees, it does provide some insight into other monetary considerations for borrowers beyond the interest rate, and the possible points-fees trade-off as documented in Bhutta and Hizmo (2021).

Summary statistics are reported in Table 1. I winsorize loan amount, time to close, and interest

¹⁵The similar nature of many real estate company names makes a fuzzy match or other algorithmic approach impossible.

¹⁶The addition of loan fees and discount points is due to a 2015 change in the reporting requirements which required reporting the additional variables beginning in 2018.

rate at the 5 and 95th percentiles to remove outliers. Just over half of my data come from purchases made with real estate agencies that ever have a sibling lender. Such a large share of purchases made with agencies that ever have a sibling agency occurs because the largest real estate firms in the United States are the ones that tend to have lending arms. However, only 5% of my sample uses a lender which ever merges with a real estate agency. I believe the share of buyers using lenders that are ever jointly owned is low due to three factors: first, lenders obtain licenses to originate mortgages in each state separately, and so not every lender is licensed in every state even if their eventual parent company has real estate agents in that state; secondly, because the large bank lenders do not have real estate agent arms, lenders with real estate agent arms are primarily non-bank lenders; and third, because lenders that merge later in the sample period are going to realize less growth from the merger within my sample window. 2% of purchases use a lender and agent pair that are ever merged, even if the lender and agent were not merged at the time of the purchase and origination.

Looking at the ownership structure at the time of origination, 32% of buyers use a real estate agency that has a sibling lending arm, while 5% use a lender that has a real estate agency sibling company. Again, 1.4% of borrowers use a merged agency-lender pair. This is not conditional on a lender being licensed in a given state, meaning the share of borrower able to use a merged agent-lender pair who use a merged agent-lender pair is larger than 1.4%. Nearly 40% of loans in my sample are classified as coming from an agent preferred lender, a definition I will explain in Section 6.2. The average interest rate is 4.08%, reflecting the fact that interest rates were generally low in my post-crisis study period of 2011-2019. The average FICO score in my sample is 736, with an average loan-to-value ratio (LTV) of 87%.

Table 1: Summary Statistics

	Mean	Std. Dev	Min	Max
Agent Ever Merged	0.5	0.5	0	1
Lender Ever Merged	0.05	0.21	0	1
Agent/Lender Ever Merged	0.02	0.12	0	1
Agent Merged	0.44	0.5	0	1
Agent/Lender Merged	0.01	0.12	0	1
Lender Merged	0.05	0.21	0	1
Agent Preferred Lender	0.37	0.48	0	1
Interest Rate	4.08	0.45	3.25	5.00
FICO Score	735	55	300	900
LTV Ratio	87	14	1	200
Time to Close	41	16	7	88

Notes: Real estate Office/Lender Ever Merged equals one if a buyer’s real estate agent and mortgage lender are ever merged, regardless of if they were at the time of the buyer’s purchase and origination. Real estate office preferred lender equals one if the lender meets the criteria I define for likely being a lender recommended by the buyer’s real estate agent.

4.1 Characterizing Mergers

I classify the mergers I observe in my data set involving real estate agencies based on whether there is a lender involved. I observe a total of 137 mergers involving at least one real estate agency. Of those, 87, or the majority occur between two agencies where at least one agency has a lending arm. These are the mergers which result in what I call “indirect integration.” A new agency gains an affiliated lender as a result of an agency-agency merger. Another 48 of the mergers are between two real estate agencies when neither one has a lending arm at the time of the merger. The mergers between two real estate agencies where neither agency has a lending arm do not cause indirect integration. Finally, I observe 2 cases where a lender and an agency merge directly.

Comparing the two types of agency-agency merger, agencies without sibling lenders have approximately the same market share regardless of if they are involved in a transaction that involves a lender or not. On average real estate agencies without lending arms involved in mergers have a

3-4% market share.

Table 2: Merger Breakdown Statistics

	N	Avg. Mkt Share	Std. Dev of Mkt. Share
Agency-Agency with Lender	87	0.04	0.06
Agency-Agency No Lender	48	0.03	0.03
Agency-Lender	2	0.001	0.0001

Notes: Agency-Agency with Lender mergers are those where one of the two real estate agencies merging has a sibling lender. Agency-Lender mergers are those where a lender and agency merge directly (ie: there is no second agency engaged in a horizontal merger). The average market share represents the average market share of the acquired firm.

5 Case Study

I will now present a case study to examine one merger closely for additional implications of mergers between real estate agencies and mortgage lenders beyond the consequences I test for in the reduced form and structural analyses.

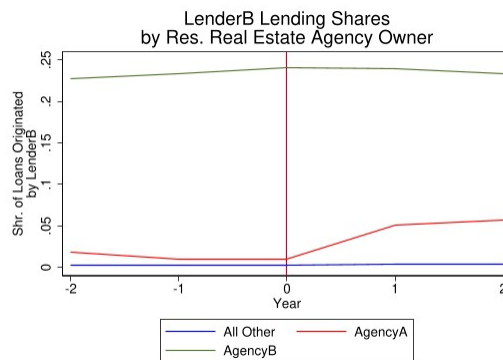
The real estate services subsidiary of a large conglomerate, BigFirm acquired AgencyA in July 20XX.¹⁷ BigFirm’s acquisition of AgencyA gave BigFirm significant residential real estate agency market share in portions of the United States. LenderA, a mortgage company and a subsidiary of AgencyA, was acquired along with AgencyA by BigFirm. Popular press and the company announcements of the merger suggest that the main reason for the merger was BigFirm gaining market share in the residential real estate agency market. Indeed, if the acquisition of LenderA was mentioned at all, it was later in the article, often as an afterthought.

Following the merger, BigFirm and it’s subsidiary real estate agencies were jointly owned with LenderA. Prior to the merger, BigFirm owned LenderB, another mortgage lender following

¹⁷Identifying details have been removed.

a merger with AgencyB in August 20XX.¹⁸ For the purposes of this case study, I will ignore LenderB.¹⁹

I begin by plotting the share of buyers who used LenderA to originate their mortgage, split by AgencyA, all other BigFirm buyers, and all other buyers in Figure 2. Prior to its merger with BigFirm, LenderA originated very few loans for home purchases made with any agencies other than AgencyA, consistent with the idea that AgencyA buyers were directed to LenderA even before the merger with BigFirm as AgencyA and LenderA were already jointly owned. Following the merger with BigFirm, there is no change in the number of mortgages LenderA originates to buyers from real estate agencies not owned by BigFirm, while the share of loans AgencyA originates to buyers from real estate agencies owned BigFirm share increases significantly.



Notes: Figure shows LenderA loan share at BigFirm agencies, AgencyA agencies, and all other agencies. Years are relative to merger year, denoted at 0 and with red line.

Figure 2: LenderA Loan Share by Real Estate Agency Owner

In Figure 3a, I map the market shares of BigFirm’s real estate agencies in 20XX, the year it acquired AgencyA and LenderA. BigFirm owned real estate agencies in most states in the year

¹⁸BigFirm has several subsidiary real estate agencies. For the purposes of this case study, I will use BigFirm to refer to all residential real estate agencies which were a subsidiary of BigFirm real estate services subsidiary in a given year.

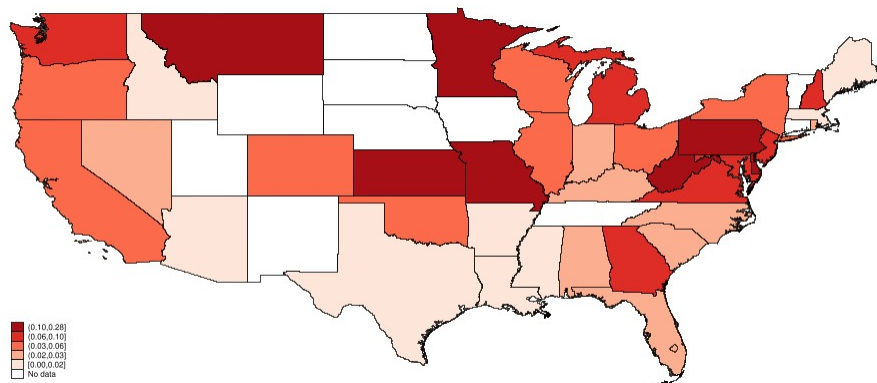
¹⁹Ignoring LenderB is not a major issue; LenderB was a very geographically concentrated lender, and wound down their origination business in my sample.

of the merger between AgencyA and BigFirm, with significant market shares in the Mid-Atlantic states as well as Minnesota, Missouri, and Kansas.

For comparison, Figure 3b shows the market share of LenderA in each state in 20XX, the year LenderA is acquired by BigFirm. LenderA had non-zero market share in only five states: Texas, Pennsylvania, Virginia, Maryland, and Delaware, reflecting the fact that lenders must be licensed in each state and LenderA was not licensed in most states in the year of the merger.

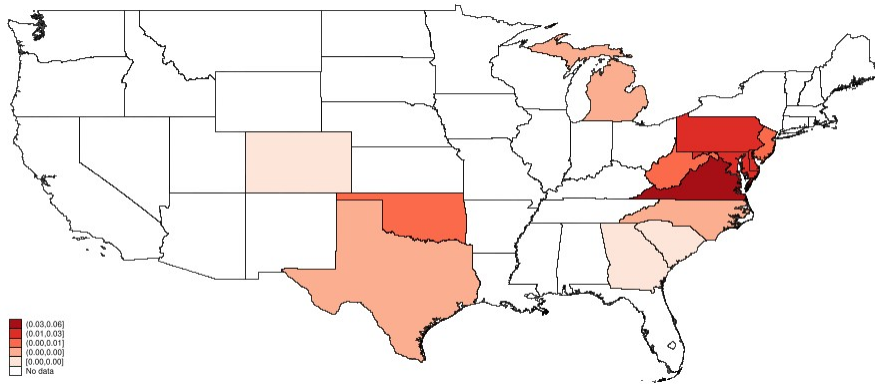
Lastly, in Figure 3c, I report the market shares of LenderA in each state two years after LenderA is acquired by BigFirm. Two years after the merger, LenderA was lending in considerably more states, and had gained sizable market share in some states, especially those where BigFirm already had a real estate agency.

Figures 3a, 3b, and 3c together suggest that LenderA expanded the most into the states where BigFirm had a substantial presence already. Thus, bringing LenderA in-house to BigFirm influenced the geographic expansion of LenderA.



Notes: Figure shows BigFirm's market share in each state immediately prior to acquiring AgencyA and LenderA. Darker states have higher market shares for BigFirm.

Figure 3a: BigFirm Agency Market Shares in Merger-Year by State



Notes: Figure shows LenderA's market share in each state immediately prior to being acquired by BigFirm. Darker states have higher market shares for LenderA.

Figure 3b: LenderA Market Shares in Merger-Year by State

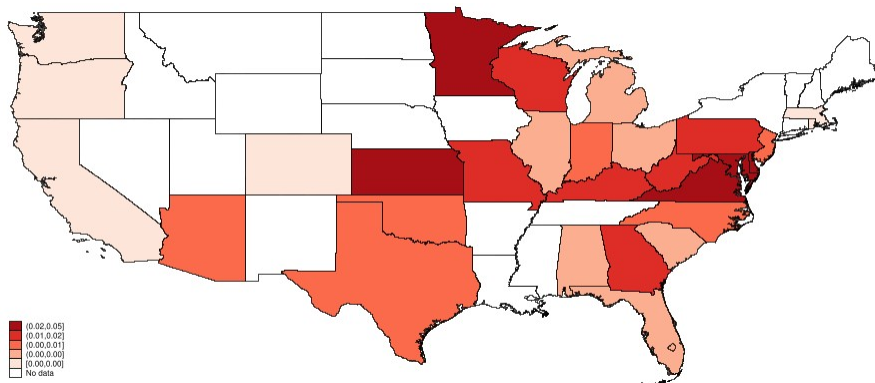


Figure 3c: LenderA Market Shares Two Years Post-Merger by State

Notes: Figure shows LenderA's market share in each state two years after acquisition by BigFirm. Darker states have higher market shares for LenderA.

6 Reduced Form Specification

6.1 Identification

In this paper, I am concerned with studying the economic consequences of mergers between real estate agencies and mortgage lenders for lenders and borrowers. To fix ideas, return to the 20XX merger between BigFirm and AgencyA discussed earlier. When BigFirm acquired AgencyA, AgencyA owned LenderA. Following the merger between AgencyA and BigFirm, is LenderA more likely to lend to buyers from BigFirm than before BigFirm was LenderA's parent company? How BigFirm's acquisition of LenderA affect the characteristics of the buyers coming to LenderA from BigFirm? How does LenderA's merger with BigFirm affect the loans buyers from BigFirm obtain?

The ideal experiment to estimate the causal effects of mergers between mortgage lenders and real estate agencies would randomly assign joint ownership between real estate agencies and lenders for a period of time, and then reassign ownership links to other real estate agency and lender pairs. Because randomly assigning and reassigning ownership structures is not a feasible research design, I will use a staggered differences in differences which exploits plausibly exogenous variation in ownership structure stemming from mergers and acquisitions.

Not all real estate agencies and mortgage lenders engage in merger activity, and not all mergers between real estate agencies and mortgage lenders that do occur occur at the same time. Therefore, there are groups of mortgage lenders who:

1. Are not merged with any real estate agency at the beginning of my sample, but are merged with a real estate agency at the end of my sample.
2. Are merged with a real estate agency for the duration of my sample.

3. Do not merge with any real estate agency for the duration of my sample.

Furthermore, there are buyers who use a given real estate agency and mortgage lender before and after the lender and agency merge because buyers have a choice in what real estate agency and mortgage lender they use.

I use the variation in lender-agency pairs chosen by buyers and merger activity in a staggered differences in differences. Specifically, I consider mergers which occur between two real estate agencies that incidentally also result in joint ownership between a lender and real estate agency, what I refer to as “indirect integration”.

Continuing with the example from the case study, I compare borrower characteristics and loan outcomes for mortgages originated by LenderA to borrowers using BigFirm real estate agents before BigFirm and LenderA merge to borrowers who use LenderA and BigFirm after BigFirm and LenderA merge in July 20XX. The borrowers who use BigFirm and LenderA before the July 20XX merger use an agency-lender pair that is not jointly owned while borrowers who use BigFirm and LenderA after the two firms merge use an agency-lender pair that is jointly owned.

The key assumption is in the motivation for the merger. If BigFirm’s desire to expand its real estate agency business drove BigFirm to acquire AgencyA, and BigFirm acquiring LenderA was incidental to the merger between AgencyA and BigFirm, then BigFirm and LenderA are indirectly integrated. From the perspective of LenderA, its merger with BigFirm is exogenous to LenderA’s books, but merging with BigFirm changes how LenderA acquires customers and which markets LenderA expands into, as is seen in the case study. I will make use of mergers like that between BigFirm and AgencyA which indirectly integrate real estate agencies and lenders. To further control for lender or agent-specific effects, I include fixed effects in all my specifications.

The first threat to causality with using variation stemming from indirect integration is that buyers who use merged agency-lender pairs are distinct from others, even after controlling for

observables, and that it is not joint ownership leading to the effects I find but rather these unobservable characteristics. To address this, I propose the following solution. First, I assume that buyers sequentially select a real estate agent and then a mortgage lender. Real estate agents often offer buyers a list of suggested lenders, and anecdotal evidence indicates that lenders on that list are most likely to return buyer calls, so it is likely that buyers do indeed begin with a real estate agent and then search for a lender. Even if buyers first choose a lender, it does not invalidate the effects I find, merely changes the interpretation. Now, instead of the agent referring buyers to a lender, it is the lender referring buyers to an agent. Either way, joint ownership is the channel allowing the referrals between real estate agents and lenders.²⁰

I further assume buyers pick a real estate agent based on characteristics of the agency/agent, **not** due to the presence of a sibling lender. Agents often provide a list of recommended services to buyers, including recommended mortgage lenders, regardless of merger status. Furthermore, many merged firms do not share common names, making it unlikely that buyers would be aware of the relationship between a given real estate agency and mortgage lender.²¹ Thus, buyers are selecting agents on criteria other than sibling lenders, and the change in status would not influence the type of buyers choosing to use a given real estate agency. I will further validate this assumption by showing that borrowers do not change on any observables following a merger.

The second threat to identification in this paper is misattributing the mechanism. Buyers who use a merged lender-agent pair are less likely to be searching for a lender, while buyers who go to a merged firm and **do not** use the sibling lender are more likely to be shopping around. The prior literature demonstrates that price dispersion is prevalent in consumer financial markets, and that search mitigates the dispersion [(Bhutta et al. 2020), (Woodward and Hall 2012)]. Thus, failing to

²⁰The set-up of my model requires that buyers choose an agent first, but the reduced form results do not.

²¹Merged firms often advertise for each other on their websites. However, they refer to each other as "partner" or "preferred," the text stating the nature of the relationship is fine print at the bottom, and likely ignored by most buyers.

control for search behavior could lead me to mistakenly attribute a price effect to a merger when in fact it is a result of lack of search, which is not the goal of this paper. To remedy this, I construct a proxy for lack of search, which I discuss below.

6.2 Proxy for Search (or Lack Thereof)

Most real estate agencies will offer buyers a list of recommended lenders. I will proxy for the list of recommended lenders supplied by real estate agents based on the lenders I observe buyers choosing. Survey data shows that buyers pay attention to agent recommendations, and therefore agent suggested lenders will originate more loans to borrowers from a agency recommending that lender than the lender's overall market share would suggest. I will thus use lender overall market shares and within-agency lending shares to construct the following measure of if a lender was likely recommended by the buyer's agent:

1. Within a real estate agency-year, calculate what share of loans each lender originates, conditional on originating at least one purchase loan. That is, lenders who do not originate any loans at an agency are not considered.
2. Within a CBSA-year, calculate lender market shares, conditional on a lender having a non-zero market share in that CBSA-year.
3. Define a lender as "recommended" by an agency if the lender's loan share within that agency is more than two standard deviations above the lender's loan share within the CBSA, **and** the lender originated at least eight loans in the CBSA-year.²²

²²Eight represents the bottom decile of lender-CBSA-year loan counts in my data. I have experimented with adjusting this threshold and the results are robust.

In other words, I define a lender as recommended by an agency if I can reject the null hypothesis that the lender’s share of loans within the CBSA-year and agency-CBSA-year are the same at the 95% confidence level. Using this criterion, 39% of loans in my sample are from agency recommended lenders, and 92% of loans which come from jointly owned pairs meet this criteria.

I will use this proxy for steering to restrict my sample when I look at borrower-level outcomes: borrower characteristics, time to close, and prices (interest rates).

7 Results

7.1 Lender Market Shares: Within Agency

I first examine if and how mergers between real estate agencies and mortgage lenders change the within real estate agency market share of lenders. I expect the within-agency share for the merged lender to increase at it’s sibling real estate agency post-merger if mergers lead real estate agencies to direct clients to the agency’s sibling company and this recommendation is influential. To test if mergers affect within-agency market share, I will use the specification:

$$Share_{ijkt} = \beta_0 + \beta_1 Treat * Post_{ijt} + \beta_2 Treat_{ij} + \gamma X_{ijkt} + \epsilon_{ijkt} \quad (1)$$

Here, $Share_{ijkt}$ is the share of purchases at agency i made with loans from lender j in CBSA k at time t , the time of loan origination. $Treat * Post_{ijt}$ is equal to one if agency i and lender j are merged at time t . $Treat_{ij}$ takes the value one if agency i and lender j are ever merged during my sample. X_{kt} is a vector of fixed effects including CBSA and year, along with other fixed effects in some columns.

Results can be found in Table 3. Before controlling for lender and agent fixed effects, the

Treat coefficient is negative and highly significant, but after controlling for lender and agent fixed effects in column (2), the magnitude drops and is statistically insignificant. There is no difference in the within-agency market share of lenders who will merge with a given real estate agency and the with-agency market share of a lender who will never merge after controlling for lender and agency-specific effects.

The coefficient on $Treat * Post$ is 0.15 in column (2), which indicates that following a merger, the share of loans originated by the sibling lender of a real estate agency increases by 15 percentage points above the mean of 0.133.

Merged lenders obtaining a larger market share from their sibling real estate agency post-merger is consistent with the idea that mergers change the referral pattern of real estate agencies. Following a merger, an agency refers more clients to its sibling lender than before the agency and lender were merged.

Recent literature has shown that staggered difference in difference specifications with two-way fixed effects are subject to unequal weighting of treatment cohorts, and that traditional two-way fixed effects models do not recover the average treatment effect. Thus, I employ the method suggested by Sun and Abraham (2021) as well. This method reports a coefficient for each relative time dummy included in the regression, which I aggregate to an average treatment effect. The last row of the table reports the average of the event study coefficients. The results using Sun and Abraham (2021) are stronger than standard staggered difference in difference. Now the coefficient on $Treat * Post$ is 0.28, or 28 percentage points and is consistent with the event study plot found in Figure 4.

While the effect on within-agency shares is interesting in its own right, it also provides the first stage result for later loan-level analysis. It demonstrates that mergers change the referral pattern of agents in a way that affects which lenders buyers choose. First, as agents now have an "inside

track” to the lender, agents may use this to help borrowers who otherwise struggle to get a loan; however, agencies may instead use this to ”cream skim” and send only the best borrowers to their sibling lender. Second, the lender may price loans to borrowers coming from a lender’s sibling real estate agency higher as the lender has a form of market power over the home buyer stemming from the lack of search on the part of buyers and the merger between the lender and real estate agency.

I will investigate the consequences of mergers on the characteristics of borrowers and the interest rate in subsequent sections.

Table 3: Within-Agency Lender Shares

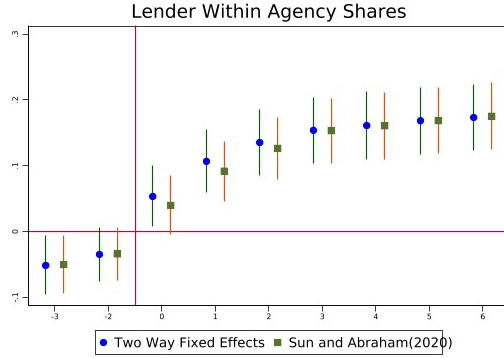
	(1)	(2)
Treat*Post	0.15*** (0.014)	0.15*** (0.012)
Treat	-0.10*** (0.011)	-0.0094 (0.0095)
Sun & Abraham (2020)	0.29*** (0.04)	0.28*** (0.04)
FE	CBSA, Year	CBSA, Year, Lender,Agency
R-squared	0.11	0.61
N	3,176,993	3,176,993

* 0.10 ** 0.05 *** 0.01

Notes: Dependent variable is a lender’s loan share within a CBSA-year-real estate agency. Unit of observation is a lender-agency-CBSA-year. Treat*Post represents the coefficient of interest and equals one if the lender and agency are a merged pair. Treat equals one for all lender-agency pairs which merge at any point in time. Standard errors are clustered at the agency level.

7.2 Lender Market Shares: CBSA Level

In addition to market share effects at the real estate agency level, mergers may have an effect on the overall market shares for lenders. If, for example, mergers make lenders more efficient, this



Notes: Dependent variable is a lender’s loan share within a CBSA-year-real estate agency. Unit of observation is a lender-agency-CBSA-year. $Treat*Post$ coefficients are plotted. $Treat*Post$ represents the coefficient of interest and equals one if the lender and agency are a merged pair. Standard errors are clustered at the agency level.

Figure 4: Lender Agency Market Shares Event Study Plot

may allow lenders to process more loans in the same amount of time and attract more customers. Then, the lender’s market share overall may increase.

To test if mergers increase lenders overall market share, I use the following specification:

$$Share_{jkt} = \beta_0 + \beta_1 Treat * Post_{jt} + \beta_2 Treat_j + \gamma X_{jkt} + \epsilon_{jkt} \quad (2)$$

The left-hand side is the lender market share in a given CBSA-year, while $Treat * Post_{jt}$ and $Treat_j$ turn on if the lender is merged with *any* real estate agency at time t or at *any* point in time, respectively. This way, I am comparing lender market shares when a lender is always merged to lenders who merge at some point in my sample. The results for this can be found in Table 4.

There are no significant differences in lender market shares following a merger until I add in lender fixed effects. With the addition of lender fixed effects, merging results in a market share increase for a lender of 0.54 percentage points on average. The average lender market share in my sample is 3.3% overall, meaning that a 0.54 percentage point increase in market share represents

a 16% increase in market share, which is significant for the lender.²³ The fact that the increase in market share from a merger is only significant after the introduction of lender fixed effects is likely because lenders expand following mergers, as seen by the expansion of LenderA in the case study following the merger with BigFirm.

The event study plot version can be found in Figure 5. The results here are considerably noisier, in large part due to the relatively sparse data, especially after fixed effects are incorporated. However, the general pattern of the results match the results in the tables, and there are not obvious pre-trends. My results are even stronger after correcting for the biases of the two way fixed effects estimator, the effect on lender market share increases to 0.7 percentage points (21% of average lender market share and 18% of the average market share for lenders who are ever merged with a residential real estate agency.)

A 16% increase in market share is significant for the lender, but has relatively little impact on the overall market structure. While the jointly owned lender gains significant market share with respect to where it started, the lender does not dominate the market after a merger with a real estate agency. The broader market implications of this increase in market share are unclear. On the one hand, this additional market share could represent loans that would otherwise be provided by other lenders, and thus be business stealing by the now merged lender. Alternatively, if merging makes the lender more efficient so that it is profitable to originate more loans, the newly merged lender could gain market share without taking clients from other lenders. In this case, overall access to credit in the market will increase.

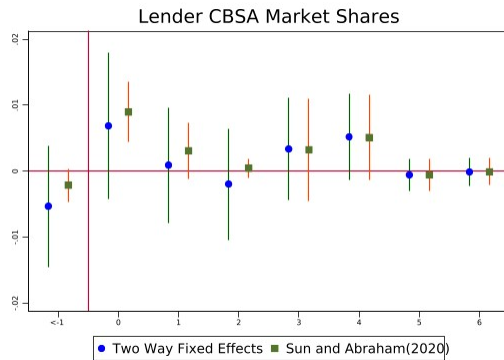
²³The market share for lenders who are ever jointly owned is 3.8% on average, so 0.54 percentage points represents a 14% increase in market share.

Table 4: CBSA Lender Market Shares

	(1)	(2)
Treat*Post	-0.0012 (0.0021)	0.0054* (0.0029)
Treat	0.0051*** (0.00072)	
Sun & Abraham (2020)	-0.001 (0.003)	0.007* (0.004)
FE	CBSA, Year	CBSA, Year, Lender
R-squared	0.63	0.64
N	415,764	415,764

* 0.10 ** 0.05 *** 0.01

Notes: Dependent variable is a lender’s market share within a CBSA-year. Unit of observation is a lender-CBSA-year. Treat*Post represents the coefficient of interest and equals one if the lender is merged with any agency at that point in time. Treat equals one for all lenders which are merged with an agency at any point in time. Standard errors are clustered at the lender level.



Notes: Dependent variable is a lender’s market share within a CBSA-year. Unit of observation is a lender-CBSA-year. Treat*Post coefficients are plotted. Treat*Post represents the coefficient of interest and equals one if the lender is merged with any agency at that point in time. Standard errors are clustered at the lender level.

Figure 5: Lender CBSA Market Shares Event Study Plot

7.3 Interest Rate

Interest rates are the “price” for mortgages and could be manipulated by lenders if joint ownership with a real estate agency confers market power to a lender. Prior work by Bhutta et al. (2020) documents that borrowers who apply to more than one lender pay 7 basis points less on average, and that “seriously considering” 3 or more lenders reduces rates by 9.5 basis points on average. I want to ensure that any effect of mergers between real estate agencies and mortgage lenders on interest rates I find is not caused by lack of search on the part of the buyers using merged pairs, but rather the ownership structure of the firms itself. Thus, I restrict my sample to only loans I flag as “agent recommended” as discussed in Section 6.2. Furthermore, in my main analysis, I restrict to loans coming from the lender’s retail channel, as theory suggests those are the buyers affected by joint ownership. Full sample results are available in the appendix.

The results for interest rate can be found in Table 5. All columns include lender, agency, CBSA, state, and year fixed effects, and I report the $Treat * Post$ coefficient from the Sun and Abraham (2021) methodology at the bottom of each column. The results are robust to Sun and Abraham (2021), and the event study plot can be found in Figure 6. The coefficient on $Treat * Post$ is positive and highly significant. Buyers who use a merged lender-agency pair and go directly to the lender pay 8 basis points more on average for their loan, consistent with the idea that buyers going to the retail lender who don’t search are most likely to be affected by the merger. When including FICO score and LTV in column (2), this increases to 9 basis points.

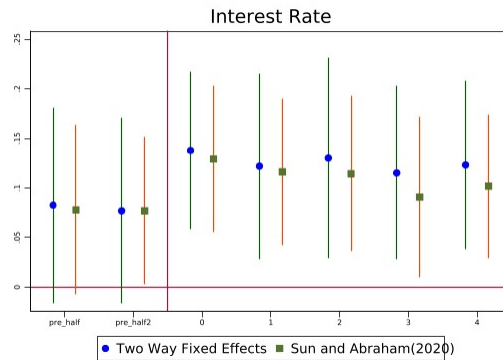
An interest rate effect of 9 basis points is quite large in the context of the literature. 9 basis points is similar to the premium paid by black borrowers compared to white borrowers found by Bartlett et al. (2021). Nine basis points is also approximately 15% of the dispersion between the 10th and 90th percentile of rates found by Bhutta et al. (2020). While their difference is significantly larger, they further document that search reduces this dispersion substantially. In the

Table 5: Interest Rate

	(1)	(2)
Treat*Post	0.079*** (0.019)	0.092*** (0.015)
Treat	-0.054*** (0.019)	-0.070*** (0.016)
FICO*LTV		0.00042*** (7.5e-07)
FICO Score		-0.005*** (0.0001)
LTV		-0.030*** (-0.001)
Sun&Abraham(2020)	0.122** (0.036)	0.138*** (0.036)
FE	CBSA,Year Lender,Agency	CBSA,Year Lender,Agency
R-squared	0.43	0.45
N	813,284	813,284

* 0.10 ** 0.05 *** 0.01

Notes: Dependent variable is the loan interest rate. Unit of observation is a loan matched to a home purchase. Treat*Post represents the coefficient of interest and equals one if the lender and agent are a merged pair. Treat equals one for any lender-agent pairs which ever merge. Standard errors are clustered at the agency level.



Notes: Dependent variable is the loan interest rate. Unit of observation is a loan matched to a home purchase. Treat*Post coefficients are plotted. Treat*Post represents the coefficient of interest and equals one if the lender and agent are a merged pair. Standard errors are clustered at the agency level.

Figure 6: Interest Rate Event Study Plot

case of my finding, I am analyzing a subset of consumers who were unlikely to search. Thus, the 9 basis point effect I find is not due to changes in shopping behavior of consumers, but solely the joint ownership of the lender and real estate agent the buyer happens to choose. This is not a fee for the convenience of not having to find a lender as most real estate agents will offer lender recommendations to consumers, so that premium is captured by studying only borrowers who do not search.²⁴ Furthermore, for affected buyers, nine basis points represents an extra \$225 per year in interest payments. In high cost of living areas, such as the Washington, DC metro, where loan amounts are higher, this rises to \$289 per year. The per year cost of using a jointly owned agent-lender pair will grow as home prices continue to rise.

7.4 Time to Close

One feature borrowers might be willing to pay a higher rate for is a loan which borrowers believe will process more quickly. In particular, in hot housing markets, the ability to receive financing quickly can be the difference between having an offer accepted and not. Merged firms might be able to originate loans more quickly due to the easier communication between lenders and agents.

I proxy for the time it take a borrower to obtain financing through details about the timing of transaction milestones. I observe both the date a property was under contract, that is on the day that the home had an offer accepted and was no longer up for sale, and the close date, the date on which the paperwork for the sale was signed and the home formally transfers from one owner to the next. I take the difference between these two values to obtain the length of time it takes for the property to move from under contract to closed, “time to close”. I use time to close as my left hand side variable in Table 6. In column (1), I use time to close directly. In column (2), I use the

²⁴The way in which agents recommend lenders to buyers is interesting in its own right, but I leave that analysis for a future paper.

probability that a purchase takes more than 45 days to close, 60 days in (3), and 75 days in column (4). I use only loans flagged as agent referred and obtained through the lender's retail channel, which is the sample that accounts for search intensity and which is most likely to be affected by a merger. I trim time to close at the 5 and 95 percentiles.

Beginning with column (1), using a merged pair reduces the time to close by 1.4 days or 3% of the mean. However, buyers may be less concerned with small changes in the level of time to close but far more concerned with avoiding a lengthy delay. Thus, I in columns (2) through (4) I put a dummy variable equal to one if the time to close is more than X days on the left hand side, making this a linear probability model. There is a 2.5 percentage point reduction in the probability that it takes more than 30 days for a purchase to close when using a merged lender-agent pair, but this is difference is not statistically significant. Moving to column (3) the effect for buyers going through the retail channel is statistically insignificant at 2.1 percentage point reduction in the probability it takes more than 45 days to close. In column (4), there a statistically significant reduction in the probability it takes more than 60 days to close of 1.9 percentage points.

Two days on a mean of 41 days is not a large effect, nor are any of the linear probability model results large. Thus, if there is any efficiency gain for buyers from choosing a lender merged with their real estate agency, I conclude that it is not through faster closing times.

7.5 Borrower Characteristics

Real estate agents and the agencies they work for have a considerable amount of information about their buyers and each buyer's ability to repay a loan. Thus, real estate agents can act as conduits of information between lenders and borrowers. A merger between a real estate agency and a lender legally codifies the information channel between the two, making information exchange even easier. There are two possible uses for information sharing between real estate agents and mortgage

Table 6: Time to Close

	(1)	(2)	(3)	(4)
	Days	30+ Days	45+ Days	60+ Days
Mean	42.0	0.72	0.35	0.16
Treat*Post	-1.2*	-0.022	-0.021	-0.019**
	(0.63)	(0.020)	(0.019)	(0.009)
Treat	0.81	0.032	0.017	-0.005
	(0.71)	(0.022)	(0.022)	(0.012)
Sun & Abraham (2020)	1.05	0.029	0.010	0.019
	(2.56)	(0.036)	(0.072)	(0.040)
FE	CBSA,Year	CBSA,Year	CBSA,Year	CBSA,Year
	Lender,Agency	Lender,Agency	Lender,Agency	Lender,Agency
R-squared	0.31	0.23	0.24	0.22
N	793,231	793,231	793,231	793,231

* 0.10 ** 0.05 *** 0.01

Notes: Dependent variable is the number of days between a home under contract and the home closing (column (1)), or indicator for if it took more than 30 days (column (2)), 45 days (column (3)), or 60 days (column (4)) to close. Unit of observation is a loan matched to a home purchase where loan is originated through the retail channel. Treat*Post represents the coefficient of interest and equals one if the lender and agency are a merged pair. Treat equals one for any lender-agency pairs which ever merge. Standard errors are clustered at the agency level. All columns include CBSA, Year, Lender, and Agency fixed effects.

lenders: assisting marginal borrowers or cream skimming. First, if an agency has soft information about prospective borrowers that lead the agency to believe that a borrower is a “better” risk than the borrower’s credit information may suggest, the agency can communicate this information to the lender and help the borrower get a loan. Marginal borrowers would be more likely to get loans from jointly owned agency-lender pairs if agents are communicating about soft information in this way. Second, the agency could selectively decide to refer only the best clients to its sibling lender, or cream-skim, if a merger results in an agent feeling financially invested in the performance of her sibling lender once the lender and agency are merged.

Cream skimming or aiding marginal borrowers is most plausible following a merger. Now the agency and lender are working for the same parent company, and as such their incentives are aligned. Without the merger, the agency is primarily interested in getting a loan for its clients, not necessarily how well the clients will be able to repay, and likewise the lender is not interested in how easy it is for the agency to make a sale, so the lender is unlikely to want to “go the extra mile” to originate a loan. With the merger, both the lender and agency have reason to care about the others’ goals, making cream skimming and/or aiding marginal borrowers possible.

Borrower characteristics are the second set of results that may be correlated with search behavior. That is, borrower characteristics may be correlated with the propensity to shop around. As such, I report the specifications keeping only loans which I flag as agent referred and from the retail channel as discussed in the beginning of the empirical specification discussion. The full sample results are available in the appendix.

I report results for three ex-ante characteristics of borrowers: loan amount, FICO score at origination, loan-to-value ratio. In Table 7. In addition, I report results for ex-post loan performance, specifically the probability loans are 30, 60, and 90 days delinquent, to check if there are unobservables that are influencing interest rates as found by Stroebel (2016).

Results for ex-ante borrower characteristics and ex-post loan performance can be found in Table 7. All six columns are insignificant, suggesting that neither the ex-ante borrower characteristics, nor ex-post loan performance are different before and after merger. Thus, I find no evidence of cream-skimming or soft information helping marginal borrowers. If there were cream-skimming, I would expect an improvement in the borrower characteristics after merger. In reverse, if there were soft information helping marginal borrowers get loans who would otherwise be denied, I would expect the quality of borrower to decline following the merger.

Looking at Table 7, neither story appears to hold. The coefficient on loan amount is small in magnitude and statistically insignificant. The coefficient on LTV is similarly small and insignificant, at 2.2, or just under a 3% change. Similarly, the average FICO score in my data set is 735, but the coefficient on $Treat * Post$ is 10 points. While this is marginally significant, it does not represent a large change in the credit score of borrowers.

Moving to the loan performance results in columns (4) through (6), I again find no significant difference coming from merger. The performance of loans does not change with merger status, which is further evidence that the merger does not lead to soft information changing what type of borrowers are getting loans. It also helps put the interest rate results in context; the higher rates are not due to information leading to expected worse loan performance (at least not that is realized).

7.6 Heterogeneity

I test for heterogeneity in the effect of joint ownership over the distribution of the interest rate. It is possible that lenders are able to mark-up loans to borrowers using the lender's sibling agency differently at different points of the interest rate distribution. For example, buyers paying high baseline rates may be more sensitive to additional interest rate increases, and thus their relatively

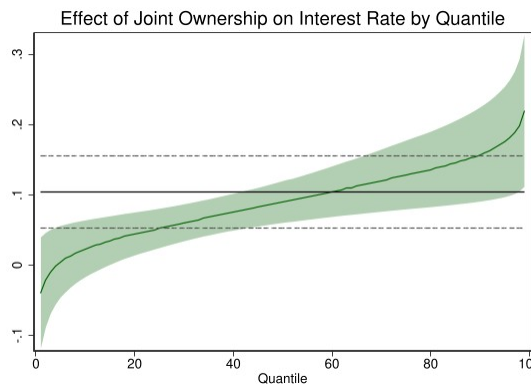
Table 7: Borrower Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Amount	LTV	FICO	30 Days	60 Days	90 Days
Mean	254,484	87.00	735	14.2%	7.8%	5.8%
Treat*Post	1,004 (6,658)	-2.2 (1.8)	10** (4.3)	-0.0006 (0.0081)	-0.0018 (0.0058)	0.0046 (0.0038)
Treat	-17,681** (7,830)	2.4 (1.8)	-11** (4.7)	0.015 (0.011)	0.0051 (0.0082)	-0.0036 (0.0062)
FICO*LTV				-0.000025*** (6.6e-07)	-0.000021*** (5.0e-07)	-0.000018*** (4.4e-07)
FICO Score				0.00054*** (0.000058)	0.00081*** (0.000044)	0.00080*** (0.000038)
LTV				0.020*** (0.00051)	0.017*** (0.00039)	0.015*** (0.00034)
Sun& Abraham (2020)	33,814** (14,645)	-8.78*** (1.76)	16.02*** (5.54)	-0.0824* (0.0422)	-0.0220 (0.0404)	-0.0497 (0.0377)
FE	CBSA, Year Lender, Agency	CBSA, Year Lender, Agency	CBSA, Year Lender, Agency	CBSA, Year Lender, Agency	CBSA, Year Lender, Agency	CBSA, Year Lender, Agency
R-squared	0.54	0.21	0.19	0.17	0.15	0.14
N	599,293	813,174	807,865	807,868	807,868	807,868

* 0.10 ** 0.05 *** 0.01

Notes: Dependent variable is loan amount (column (1)), loan-to-value ratio (column (2)), FICO (credit) score at origination (column (3)), or indicator for if loan is ever 30 days delinquent (column (4)), 60 days delinquent (column (5)), or 90 days delinquent (column (6)). Unit of observation is a loan matched to a home purchase where loan is originated through the retail channel. Treat*Post represents the coefficient of interest and equals one if the lender and agency are a merged pair. Treat equals one for any lender-agency pairs which ever merge. Standard errors are clustered at the agency level.

elastic demand leads lenders to charge lower premiums at the high end of the interest rate distribution. On the other hand, buyers at the high end of the interest rate distribution may actually be less elastic, as they are already selecting to buy a house at a higher interest rate. If buyers at high baseline interest rates are more inelastic, lenders will charge higher premiums to these borrowers. To test for heterogeneity in the effect of joint ownership at different interest rates, I run a quantile regression equivalent to column (2) in Table 5. I estimate this model at each percentile from 1% to 99%, and I plot the coefficients on $Treat * Post$ in Figure 7.



Notes: Regressions run at each quantile. Dependent variable is interest rate. Unit of observation is a loan matched to a home purchase where loan is originated through the retail channel. $Treat*Post$ represents the coefficient of interest and equals one if the lender and agency are a merged pair. $Treat$ equals one for any lender-agency pairs which ever merge. Standard errors are clustered at the agency level.

Figure 7: Quantile Regression of Joint Ownership on Interest Rate

The solid horizontal line in Figure 7 shows the coefficient in column (2) of Table 5, with the dashed lines showing the 95% confidence interval. The figure shows that the effect of joint ownership on the interest rate increases with the quantile of interest rate examined. In the right tail of the distribution, the effect of joint ownership on interest rate is quite small, and not statistically different than zero. However, at the median, the effect is similar to that reported in Table 5 column (2). As the interest rate increases, the effect of joint ownership grows, and is more than 20 basis points at the 99th percentile. This suggests that for buyers paying higher than median interest rates,

the effect of using a jointly owned agency-lender pair is actually larger than 9 basis points, and that the magnitude of the effect increases with the interest rate.

8 Model

The reduced form results above discuss the implications of mergers between agencies and lenders for consumers, mortgage market structure, and lender market shares but are unable to examine any potential cost savings for the lender and test policy counterfactual scenarios. Thus, I combine a logit demand model for mortgages with Bertrand differentiated product competition supply to recover lenders' marginal costs and estimate counterfactuals.

8.1 Household

First, I begin with the household, who are choosing a specific loan product. Each household i in market t has a choice set C_{it} from which the household selects one loan, j . The household receives utility from a loan product based on the product characteristics. For a given product j , the indirect utility household i receives can be written as:

$$V_{ijt} = -\alpha r_{jt} + \beta x_j + \xi_{jt} + \epsilon_{ijt} \quad (3)$$

where r_{jt} represents the interest rate paid by the household, and x_j is a vector of product characteristics observed by the econometrician. ξ_{jt} is the characteristics of the product which are observable to the household, but unobservable to the econometrician. ϵ_{ijt} is the error term. I will define the product characteristics included in the indirect utility function in when discussing model estimation.

Then, household i chooses the product in their choice set C_{it} which maximizes their indirect utility.

8.2 Lender

Second, each lender l offers products j which have different rates and different marginal cost in every market t . I assume that if a lender is jointly owned, it offers two product in a given market: one to buyers from its sibling agency and another to all other buyers in the market.

For a given product j which is sold in market t , the lender has profit:

$$\Pi_{jlt}^S = (r_{jlt} - \kappa_{jlt})s_{jlt} \quad (4)$$

where r_{jlt} is the interest rate, and κ_{jlt} is the marginal cost of selling that product. s_{jlt} represents the choice probability for product j . Thus, the overall profit for firm l in market t is:

$$\Pi_{lt} = \sum_{j \in J_t} (s_{jlt} \Pi_{jlt}) \quad (5)$$

where s_{jlt} is the market share for product j . Then, the lender chooses the interest rate r_{jlt} for each product to maximize their profit function. The first order condition for the optimal rate on good j from lender l in market t , r_{jlt}^* is:

$$r_{klt}^* = \kappa_{klt} - \frac{s_{klt}}{\frac{\partial s_{klt}}{\partial r_{klt}}} - \sum_{j \neq k \in J_t} \frac{r_{jlt} - \kappa_{jlt} \frac{\partial s_{jlt}}{\partial r_{klt}}}{\frac{\partial s_{klt}}{\partial r_{klt}}} \quad (6)$$

9 Model Estimation

9.1 Household Demand

Each household i belongs to a market t . I define a market as a CBSA-year-above/below median credit score-above/below median loan-to-value ratio-loan type (Non-conforming, conforming, or jumbo). In standard logit demand, households in the same market have the same choice set, and the logit model can be written as a two stage least squares equation. However, in this case, not all households in a given market have access to the same products; buyers using an agency with a sibling lender have access to a different loan product than borrowers using a different real estate agency. Household-specific choice sets mean that the standard logit-estimation strategy using market shares will not work, and instead I will exploit the micro data.

I do not observe the options in a household's choice set, so I will construct it. First, I separate all loans into above and below median credit score, and then above and below median loan-to-value-ratio. Then, I define a product as a combination of lender, and if the loan went to buyers from jointly owned agency-lender pairs. That is, even with the same credit score, loan-to-value ratio, and lender, I consider a loan a different product if the household i came from the lender's sibling residential real estate agency or not.

I assume that buyers in market t have access to loans issued in market t that required the same credit score bin (as defined by above/below median), loan type, and loan-to-value ratios (above/below median) from all lenders operating in market t . However, if a lender is jointly owned with the buyer's real estate agency, the buyer will only have access to that lender's jointly-owned product for a given credit score x loan to value ratio, and vice versa. I construct the outside option, $j = 0$, by combining all products from lenders who have a 0.05% market share or less, and normalize the outside option to have mean utility of zero.

My specification for the choice set does not take into account heterogeneity in search costs. For example, large firms may advertise more aggressively, and gain larger market shares as a result. To account for potential bias, I include lender fixed effects. Assuming that conditional on observables borrower composition is not correlated with product attributes, including the dummy for being a linked lender, not accounting for search costs is unlikely to drive my results. In the reduced form I find little effect of mergers on borrower characteristics, making this assumption plausible.

Recall that a household i 's indirect utility from product j in market t can be written as :

$$V_{ijt} = -\alpha r_{jt} + \beta x_j + \xi_{jt} + \epsilon_{ijt} \quad (7)$$

where r_{jt} is the average rate, and x_j are the observable product characteristics: joint ownership, time to close, and lender fixed effects, and ξ_{jt} are unobservables. I assume that ϵ_{ijt} is distributed Extreme Value Type-I. Then, a consumer i chooses the product j from their choice set C_{it} which maximizes their indirect utility. That is, if household i chooses product j , then:

1. Product $j \in C_{it}$
2. $V_{ijt} > V_{ikt} \forall k \in C_{it}$

Among all products in its choice set, C_{it} , the household will choose the product which maximizes its indirect utility. In other words, if household i choose product j from lender l in market t , that implies that:

1. Product j is in the household's choice set C_{it}
2. $V_{ijt} > V_{ikt} \forall k \in C_{it}$

Then, the conditional choice probability of household i in market t choosing product j is:

$$s_{ijt} = Pr(j|C_{it}) = \frac{\exp(\delta_{jt})}{\sum_{k \in C_{it}} \exp(\delta_{ikt})} \quad (8)$$

Where δ_{jt} can be written as:

$$\delta_{jt} = \alpha r_{jt} + \beta X_{jt} + \xi_{jt} \quad (9)$$

To rephrase, δ_{jt} is the indirect utility with the ϵ_{ijt} integrated out. δ_{0t} is normalized to zero.

The above conditional choice probability leads to household i 's likelihood function:

$$\mathcal{L}_i = \prod_{j \in C_{it}} s_{ijt}^{\mathbb{1}(\text{product } j \text{ chosen})} \quad (10)$$

Taking logs yields household i 's log-likelihood function:

$$\ln(\mathcal{L}_i) = \sum_{j \in C_{it}} \ln(s_{ijt}) \mathbb{1}(\text{product } j \text{ chosen}) \quad (11)$$

I estimate the demand parameters from the log-likelihood in two steps. First, I use a non-linear optimization to find the δ_t which maximizes the likelihood for all households. Second, I use two stage least squares to decompose δ_t into each of the contributing product characteristics. I cannot recover the demand parameters directly from standard OLS because it is possible $cov(r_{jt}, \xi_{jt}) \neq 0$. For example, one element of ξ_{jt} could be quality. It makes sense that higher quality products would have higher prices, so $cov(r_{jt}, \xi_{jt}) > 0$. Thus, failing to account for the endogeneity between r_{jt} and ξ_{jt} will lead to biased estimates.

To address the endogeneity of ξ_{jt} , the unobservables which may be correlated with price, I use the annual average 10-year Treasury bond rate as the instrument interacted with the average number of lenders in the market over the course of my sample. Mortgage rates are often tied to

the treasury rate; when the Treasury rate increases, mortgage rates increase. The degree to which lenders can increase mortgage rates is limited by the number of lenders in the market. Since the level of the treasury rate is absorbed into the year fixed effects and the number of lenders is absorbed into the CBSA fixed effects, the interaction term is the only term which appears in my first stage; the interaction term is measuring the degree of pass-through from lenders to borrowers following a change in the Treasury rate.

The first stage results can be found in Appendix Table D1. The first stage finds that the degree of pass-through from lenders to borrowers increases with the Treasury Rate. The first stage is also strong with an F-statistic of 49.07.

Moving to the demand estimation using the above instrument, the coefficients on the product characteristics can be found in Table 10. The coefficient on interest rate is -45.11. The negative coefficient is consistent with the idea that borrowers prefer to pay lower interest rates, all else equal. The coefficient on Merged Pair is positive. This positive coefficient is consistent with the reduced form results in Table 3. When a lender is merged with the borrower's real estate agent, the borrower is more likely to choose that lender, which can be thought of as the additional "brand premium" that a lender receives when a lender is jointly owned with a real estate agent. The Merged Pair effect is large relative to the magnitude of the lender fixed effects, which mirrors the findings in Table 3 that when a lender and real estate agent are jointly owned, the borrower is significantly more likely to choose the jointly owned lender, that is, there is quite a bit of additional brand premium.

Table 8: Mean Utility Parameters

Rate	-45.11***
	(5.803)
Merged Pair	2.96**
	(0.77)
Time to Close	0.013*
	(0.006)
FE	Lender, CBSA, Year
Observations	338,658

* 0.10 ** 0.05 *** 0.01

Notes: Mean utility parameters recovered from logit run on a 25% random sample of data. Unit of observation is a given loan product j in a market t . Merged Pair is a dummy variable equal to 1 if the residential real estate agency and lender are part of the same conglomerate. Time to close is the number of days between contract and close. Standard errors bootstrapped on 500 random samples at market level.

9.2 Supply

Using the first order condition for profit-maximizing pricing, I can solve for the marginal cost of product k in market t , κ_{kt} . Using the results from the demand estimation, I can compute conditional choice probabilities s_{jnt} for all products, as well as the partial derivatives. In every market, I am left with a system of J_t equations with J_t unknowns, so the system is just identified, and a unique set of marginal costs exists.

Summary statistics for marginal cost can be found in Table 9. The average marginal cost on non-merged loans is 4.09%, while that on merged loans is 3.53% of loan amount. The magnitude of the marginal cost on these loans is qualitatively similar to those found in the UK mortgage market by Robles-Garcia (2019). Furthermore, a two-sample t-test rejects that the marginal cost of merged and non-merged loans is the same. Loans originated for borrowers from a lender's sibling real estate agency are cheaper to originate than loans to other borrowers.

This makes the reduced form result that buyers using the lender jointly owned with their real estate agent pay 9 basis points higher interest rates even more stark. The loans being originated for

buyers who are using a lender’s sibling real estate agency are *cheaper* to originate than other loans, but the lender is charging more. Thus, these loans are more profitable for lenders, and lenders are utilizing the captured nature of borrowers from the lender’s sibling real estate agency to markup these loans more than the loans the lender is originating for other buyers.

Table 9: Marginal Cost

	Marginal Cost
Non-Merged	4.09 (0.03)
Merged	3.53 (0.91)

Notes: Average marginal cost calculated from model. Unit of observation is a product j in market t . Non-Merged products are those available to buyers not coming from the sibling residential real estate agency of a lender while merged products are only available to buyers coming from the lender’s sibling agency. Results calculated using a 25% random sample of markets. Standard errors bootstrapped on 500 random samples at market level.

10 Counterfactual

I find that merged loans are cheaper to originate yet cost buyers 9 basis points more in interest payments, which suggests that regulation may improve borrower utility. The fraction of borrowers choosing a given loan product influences how much the lender can adjust the price, which also influences the choice probability of borrowers. The relationship between market power and price means that if the mergers between real estate agencies and mortgage lenders were regulated, and consumers were choosing loan products in the counterfactual world, prices would not necessarily fall by 9 basis points. To analyze how policies regulating mergers between real estate agencies and mortgage lenders would affect the mortgage market, I run counterfactuals using the demand parameters and marginal cost values I previously estimated. I run a total of two counterfactuals. In the first, I estimate a counterfactual equivalent to breaking up the merged real estate agencies

and lenders. All merged products are removed from the market so only the unmerged products are left; borrowers who previously chose merged products now choose from the remaining loan options. Keeping the utility parameters from the demand estimation and the recovered marginal cost, I solve for the optimal interest rate for each product using the lender's first order condition for profit maximization:

$$r_{klt}^* = \kappa_{klt} - \frac{s_{klt}}{\frac{\partial s_{klt}}{\partial r_{klt}}} - \sum_{j \neq k \in J_t} \frac{r_{jlt} - \kappa_{jlt} \frac{\partial s_{jlt}}{\partial r_{klt}}}{\frac{\partial s_{klt}}{\partial r_{klt}}} \quad (12)$$

In the second counterfactual, I assume the government has allowed joint ownership between real estate agencies and mortgage lenders, but that the lender cannot offer different products to consumers based on which real estate agency the borrower chose; the lender must offer the same menu of products to all consumers with the same credit characteristics. All consumers keep the product they actually selected in their choice set, but the overall size of the choice set increases.

The results of both counterfactuals can be found in Table 10. In each column, I report the average of each product characteristic, weighted by market share, the resulting average utility, and the change in basis points which would result in the same utility change relative to the status quo. I also report the same information for the status quo for comparison.

Beginning with the first counterfactual, banning mergers but allowing consumers to pick between all options in the market and the outside option slightly decreases the interest rate from 4.092% to 4.077%. However, buyers lose the brand premium from choosing joint ownership, choose products with less desirable unobservable characteristics (ξ decreases from an average of 2.17 to 2.10), and choose from lenders which provide a higher brand premium. Overall, welfare increase, by an amount equivalent to that from an interest rate decrease of 1.4 basis points, or a welfare gain of \$35 at the mean loan amount.

In the second counterfactual, consumers now have access to two products from jointly owned lenders: the one previously offered to customers coming from the lender's sibling agency and the one offered to all other customers. The additional competition decreases rates, but by less than in the first counterfactual. A similar share of consumers choose the jointly owned product with its brand premium, but choose products from less desirable brands and with less desirable unobservable characteristics. These choices combined mean that consumer welfare increases by \$13 on average relative to the status quo, equivalent to a rate decrease of 0.5 basis points.

In both counterfactuals, regulation improves consumer welfare slightly. The decrease in the average interest rate is small, but it is coupled with changes in other product characteristics which combined improve consumer welfare. The currently small share of consumers affected by joint ownership makes the changes small. As more consumers continue to use a merged agency-lender pair, the welfare benefits to regulating mergers between real estate agencies and mortgage lenders, and regulating how lenders may offer products to borrowers, will continue to grow.

Table 10: Counterfactual Results

	Status Quo	Merger Ban	Competition
Interest Rate	4.092	4.077 (0.028)	4.086 (0.017)
Time to Close	39.90	39.85 (0.19)	39.90 (0.21)
Jointly Owned	0.01	0.00 (0)	0.01 (0.002)
ξ	2.17	2.10 (0.48)	2.12 (0.40)
Lender FE	0.87	0.89 (0.11)	0.84 (0.08)
Utility	3.50	4.15 (0.58)	3.77 (0.16)
Equivalent Rate Change(bp)		-1.4 (0.02)	-0.5 (0.01)
Utility Change (Dollars)		35 (0.45)	13 (0.24)

Notes: Results of counterfactual simulation on a 25% random sample of markets. Unit of observation is a product j in a market t . Dollar utility calculated by computing the change in the interest rate which corresponds to the same change in utility and then multiplying that by the average loan amount. Results are weighted by the product market share in the counterfactual. Standard errors bootstrapped on 500 random samples at market level

11 Conclusion

In the post-crisis era, technologically adept non-bank lenders have a significant presence in the mortgage market. Recent literature has worked to examine the consequences increasing market share for non-bank lenders on a variety of economic outcomes but has remained relatively silent on how relationships between non-bank lenders and other players in the real estate market may influence both mortgage market structure and borrower outcomes. In this paper, I study the consequences of mergers between non-bank lenders and real estate agencies on lender market shares and a variety of borrower outcomes.

I construct a novel data set of home purchases matched to the loans which funded the home purchases, and use 100+ mergers I hand-matched in a staggered differences design that exploits mergers which indirectly integrate lenders and real estate agencies. I find that real estate agents from jointly owned firms direct clients to their agency's sibling lender, and that lender market shares more than double at the lender's sibling real estate agency following a merger. I next find that mergers between real estate agencies and mortgage lenders do not substantially reduce competition in the mortgage market, with lenders only gaining about 0.54% market share on average.

Using a merged lender-agency pair increases the rate affected borrowers pay by 9 basis points, with larger effects at higher quantiles of the interest rate distribution. Borrowers using jointly owned agency-lender pairs are not closing on their homes more quickly, nor do borrowers using merged pairs differ on observable ex-ante creditworthiness or ex-post loan performance from other borrowers. The 9 basis points appears purely due to the market power a sibling lender has on the borrowers from the lender's sibling real estate agency.

I supplement my reduced form findings of higher market shares for lenders and higher interest rates for buyers with a structural model of supply and demand for loans. I use a logit demand model for mortgages with consumer-specific choice sets characteristics and a supply model where

lenders are profit maximizing under Bertrand differentiated product competition. The recovered utility parameters from the demand model confirm my reduced form results that buyers prefer jointly owned agency-lender pairs, faster closing time, and that there is a significant "known brand" premium. I recover marginal costs by combining the demand estimates with the supply model and find cost efficiencies from lender-agency mergers, making the 9 basis point interest rate effect I find even more stark. Finally, I estimate two regulatory policy counterfactuals, both of which lead to an interest rate decrease and improved welfare.

Real estate agencies and mortgage lenders are generally studied separately, despite both lender and agents being intimately involved in the home buying process. I study the consequences of mergers between two portions of the home buying process, real estate agencies and mortgage lenders, in a low interest rate environment. In the years following my data, interest rates rose considerably, and mergers between real estate agencies and mortgage lenders continue to occur. The effects found in this paper likely represent a lower bound on the ultimate effects as more real estate agency and mortgage lender mergers occur and in a high interest rate environment where remaining borrowers may be more inelastic. Finally, new policy regulations which allow an individual licensed as both a real estate agent and mortgage lender to operate in both capacities and receive compensation for each task may further strengthen the ties between jointly owned lenders and real estate agencies, and thus the consequences for borrowers.²⁵ Future study will be necessary to examine how the consequences of mergers between non-bank lenders and real estate agencies change as non-bank lenders continue to grow, new mergers occur, and the macroeconomic conditions and regulatory environment evolve.

²⁵The FHA proposed allowing dual compensation in early 2023.

References

- Agarwal, Isha, Malin Hu, Raluca A Roman, and Keling Zheng**, “Lending by servicing: Monetary policy transmission through shadow banks,” 2023.
- Agarwal, Sumit, Gene Amromin, Itzhak Ben-David, and Douglas D Evanoff**, “Loan product steering in mortgage markets,” Technical Report, National Bureau of Economic Research 2016.
- Akgün, Uğur, Cristina Caffarra, Federico Etro, and Robert Stillman**, “On the welfare impact of mergers of complements: Raising rivals’ costs versus elimination of double marginalization,” *Economics Letters*, 2020, 195, 109429.
- Bartlett, Robert, Adair Morse, Richard Stanton, and Nancy Wallace**, “Consumer-lending discrimination in the FinTech era,” *Journal of Financial Economics*, 2021.
- Barwick, Panle Jia, Parag A Pathak, and Maisy Wong**, “Conflicts of interest and steering in residential brokerage,” *American Economic Journal: Applied Economics*, 2017, 9 (3), 191–222.
- Benetton, Matteo**, “Leverage Regulation and Market Structure: A Structural Model of the U.K. Mortgage Market,” *The Journal of Finance*, 2021, 76 (6), 2997–3053.
- Berger, Allen N, Rebecca S Demsetz, and Philip E Strahan**, “The consolidation of the financial services industry: Causes, consequences, and implications for the future,” *Journal of Banking & Finance*, 1999, 23 (2), 135–194.

- Bhutta, Neil and Aurel Hizmo**, “Do minorities pay more for mortgages?,” *The Review of Financial Studies*, 2021, 34 (2), 763–789.
- , **Andreas Fuster, and Aurel Hizmo**, “Paying too much? Price dispersion in the US mortgage market,” 2020.
- Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru**, “Fintech, Regulatory Arbitrage, and the Rise of Shadow Banks,” *Journal of Financial Economics*, 2018, 130 (3), 453–483.
- Cabral, Luís and Gabriel Natividad**, “Cross-selling in the US home video industry,” *The RAND Journal of Economics*, 2016, 47 (1), 29–47.
- Choi, Jay Pil**, “Mergers With Bundling In Complementary Markets,” *The Journal of Industrial Economics*, 2008, 56 (3), 553–577.
- CoreLogic Deeds Data**. Philadelphia, Montgomery, Delaware, and Bucks Counties, 2011-2019.
- CoreLogic Loan-Level Market Analytics Data**. Philadelphia, Montgomery, Delaware, and Bucks Counties, 2011-2019.
- CoreLogic MLS Data**. Philadelphia, Montgomery, Delaware, and Bucks Counties, 2011-2019.
- Draganska, Michaela, Daniel Klapper, and Sofia Villas-Boas**, “A Larger Slice or a Larger Pie? An Empirical Investigation of Bargaining Power in the Distribution Channel,” *Marketing Science*, 2010, 29 (1), 57–74.
- Ershov, Daniel, Jean-William Laliberté, and Scott Orr**, “Mergers in a model with complementarity,” 2018.

Fuster, Andreas, Matthew Plosser, Philipp Schnabl, and James Vickery, “The Role of Technology in Mortgage Lending,” *The Review of Financial Studies*, 04 2019, 32 (5), 1854–1899.

Grunewald, Andreas, Jonathan A Lanning, David C Low, and Tobias Salz, “Auto Dealer Loan Intermediation: Consumer Behavior and Competitive Effects,” Working Paper 28136, National Bureau of Economic Research November 2020.

Guiso, Luigi, Andrea Pozzi, Anton Tsoy, Leonardo Gambacorta, and Paolo Emilio Mistrulli, “The cost of steering in financial markets: Evidence from the mortgage market,” *Journal of Financial Economics*, 2021.

Irani, Rustom M, Rajkamal Iyer, Ralf R Meisenzahl, and José-Luis Peydró, “The Rise of Shadow Banking: Evidence from Capital Regulation,” *The Review of Financial Studies*, 09 2020, 34 (5), 2181–2235.

Jiang, Erica, Gregor Matvos, Tomasz Piskorski, and Amit Seru, “Which Banks are (Over) Levered? Insights from Shadow Banks and Uninsured Leverage,” Working Paper 26903, National Bureau of Economic Research March 2020.

Jiang, Erica Xuewei, “Financing Competitors: Shadow Banks’ Funding and Mortgage Market Competition,” *The Review of Financial Studies*, 04 2023, 36 (10), 3861–3905.

Lopez, Luis A, Shawn McCoy, and Vivek Sah, “Steering Consumers to Affiliated Financial Services: Evidence from Mortgage Referrals and Cost of Credit,” *Available at SSRN 3365347*, 2019.

National Survey of Mortgage Originations. 2013-2017.

Robles-Garcia, Claudia, “Competition and incentives in mortgage markets: The role of brokers,”
Unpublished working paper, 2019.

Sichelman, Lee, “Feds investigating Quicken Loans’ real estate affiliate for illegal kickbacks,”
Miami Herald, 2021.

Stroebel, Johannes, “Asymmetric Information about Collateral Values,” *The Journal of Finance*,
2016, 71 (3), 1071–1112.

Sun, Liyang and Sarah Abraham, “Estimating dynamic treatment effects in event studies with
heterogeneous treatment effects,” *Journal of Econometrics*, 2021, 225 (2), 175–199. Themed
Issue: Treatment Effect 1.

Villas-Boas, Sofia Berto, “Vertical Relationships between Manufacturers and Retailers: Inference
with Limited Data,” *The Review of Economic Studies*, 2007, 74 (2), 625–652.

Woodward, Susan E and Robert E Hall, “Diagnosing consumer confusion and sub-optimal
shopping effort: Theory and mortgage-market evidence,” *American Economic Review*, 2012,
102 (7), 3249–76.

Internet Appendix

A Merging the Data

A.1 MLS to CoreLogic Property Data

I begin by matching the CoreLogic MLS data to the CoreLogic Property data. I first merge on APN and county FIPS code. However, there are a number of properties in the MLS which do not have APN numbers. Thus, I take all unmerged properties in both the MLS and Property data after the APN and FIPS code merge, and merge them on address text.

After the first merge, I have a data set of basic property characteristics merged to the MLS data, including APN number, FIPS, and tax account number. Now, I can merge the data to the CoreLogic Mortgage data on APN, FIPS and tax account number. This is an imperfect merge, and APN, FIPS and tax account number do not uniquely identify observations. To avoid inflating the size of my data set by double counting observations, I use a random number generate to drop all but one of each combination of APN, FIPS and tax account number.

Now, I have a data set of MLS listings matched to property records, including the mortgage provider. I now clean the names of the real estate agencies and lenders. This is a nontrivial process, requiring much hand checking. However, without this, it is not possible to have consistent firm names.

A.2 Merging in the LLMA Data

There are very few unique identifiers in the LLMA data that are shared with my MLS-CoreLogic Property data set. I merge first on origination year-month, loan amount, and zip code. Then, I use

a random number generator to keep one observation of each of the observations matched on these three variables.

I next take the unmatched LLMA and MLS-CoreLogic Property data, and merge on just year-month and zip code. Again, I use a random number generator to keep a unique observation from each match.

After merging in the LLMA Originations data, it is easy to merge in the events data. There is a unique loan-level identifier which can be matched.

A.3 Merging in the HMDA Data

Similar to the other inexact matching steps, I iteratively match the HMDA data, relaxing the match quality with each iteration. Data are first matched between the CoreLogic Property Records and HMDA on tract, exact loan amount, and lender name. Then, a random number generator is used to keep one observation from each match. Next, the data are matched just on tract and exact loan amount, and a unique observation from each match is kept. Next, the loan amount is allowed to vary sequentially more each iteration from $\pm\$1,000$ up to $\pm\$10,000$ in increments of 1,000. At each iteration, the previous two steps are repeated. That is, first tract, loan amount, and lender name are used. Then, after a unique observation is kept lender name is dropped and the process is repeated with just tract and loan amount before moving on to the next iteration with a higher loan range.

B Results for All Agent Preferred Loans

Below, I report the same borrower and loan-level outcomes I report in the main paper, but keeping all loans I flag as agent preferred, instead of just the retail channel loans. In general, the results

are robust to including more loans: there is little to no impact on time to close, ex-ante borrower characteristics, or ex-post loan performance.

The one set of results which do substantively change are those on interest rate in Table B. Here, the coefficient on $Treat * Post_{jlt}$ is positive and significant in my main sample before including credit characteristics, but not when looking at all loans. The insignificant effect in column (1) and marginally significant result in column (2) is consistent with the fact that the full sample includes distribution channels that are unlikely to be subject to price effects from the merger, such as mortgage brokers, which will attenuate the effect size.

Table B1: Time to Close

	Days	30+ Days	45+ Days	60+ Days
Mean	42.0	0.72	0.35	0.16
Treat*Post	-2.0*** (0.54)	-0.034*** (0.013)	-0.032* (0.019)	-0.014 (0.011)
Treat	1.6** (0.61)	0.035** (0.014)	0.025 (0.022)	-0.0012 (0.013)
FE	CBSA,Year Lender,Agency	CBSA,Year Lender,Agency	CBSA,Year Lender,Agency	CBSA,Year Lender,Agency
R-squared	0.29	0.22	0.22	0.20
N	1,132,834	1,132,834	1,132,834	1,132,834

* 0.10 ** 0.05 *** 0.01

Notes: Dependent variable is the number of days between a home under contract and the home closing (column (1)), or indicator for if it took more than 45 days (column (2)), 60 days (column (3)), or 75 days (column (4)) to close. Unit of observation is a loan matched to a home purchase. Treat*Post represents the coefficient of interest and equals one if the lender and agency are a merged pair. Treat equals one for any lender-agency pairs which ever merge. Standard errors are clustered at the agency level. All columns include CBSA, Year, Lender, and Agency fixed effects.

Table B2: Borrower Characteristics

	Amount	LTV	FICO	30 Days	60 Days	90 Days
Mean	\$254,484	87.00	736	14.2%	7.8%	5.8%
Treat*Post	-8,356 (6,161)	-0.38 (0.84)	6.9*** (2.4)	-0.00079 (0.0082)	0.0043 (0.0058)	0.0018 (0.0036)
Treat	1,268 (6,710)	-0.030 (0.84)	-5.2* (2.7)	0.0050 (0.010)	-0.0050 (0.0079)	-0.0060 (0.0056)
FICO*LTV				-0.000025*** (5.4e-07)	-0.000022*** (4.2e-07)	-0.000019*** (3.7e-07)
FICO Score	0.00050***	0.00084***	0.00083***	(0.000049)	(0.000037)	(0.000032)
LTV				0.020*** (0.00042)	0.017*** (0.00032)	0.015*** (0.00028)
FE	CBSA, Year Lender, Agency	CBSA, Year Lender, Agency	CBSA, Year Lender, Agency	CBSA, Year Lender, Agency	CBSA, Year Lender, Agency	CBSA, Year Lender, Agency
R-squared	0.52	0.20	0.18	0.17	0.14	0.13
N	835,405	1,162,098	1,072,172	1,072,003	1,072,003	1,072,003

* 0.10 ** 0.05 *** 0.01

Notes: Dependent variable is loan amount (column (1)), loan-to-value ratio (column (2)), FICO (credit) score at origination (column (3)), or indicator for if loan is ever 30 days delinquent (column (4)), 60 days delinquent (column (5)), or 90 days delinquent (column (6)). Unit of observation is a loan matched to a home purchase. Treat*Post represents the coefficient of interest and equals one if the lender and agency are a merged pair. Treat equals one for any lender-agency pairs which ever merge. Standard errors are clustered at the agency level.

Table B3: Interest Rate (Mean = 4.09%)

	(1)	(2)
Treat*Post	0.026 (0.032)	0.054* (0.030)
Treat	-0.021 (0.033)	-0.041* (0.025)
FICO*LTV		0.000042*** (6.7e-07)
FICO Score		-0.005*** (0.0001)
LTV		-0.030*** (0.001)
Sun&Abraham(2020)	0.067*** (0.009)	-0.032 (0.034)
Sample	All	All
FE	CBSA,Year Lender,Agency	CBSA,Year Lender,Agency
R-squared	0.41	0.43
N	1,162,386	1,162,386

* 0.10 ** 0.05 *** 0.01

Notes: Dependent variable is loan interest rate. Unit of observation is a loan matched to a home purchase where loan is originated through the retail channel. Treat*Post represents the coefficient of interest and equals one if the lender and agency are a merged pair. Treat equals one for any lender-agency pairs which ever merge. Standard errors are clustered at the agency level.

C Robustness Checks

C.1 Placebo Test

In Table 5, I show that buyers who use the retail channel to obtain their mortgage pay higher interest rates, consistent with the story that buyers who use the retail channel are most captured by the one-stop shopping model and thus charged the higher rate by lenders.

By similar logic, buyers who use a mortgage broker should be the least captured by a merged agency-lender pair, and I would not expect there to be an effect of using a merged agency-lender pair for buyers who obtain a loan through a mortgage broker. To that end, running my specification on buyers who use the mortgage broker distribution channel is a placebo test.

I report the effect of using a merged agency-lender pair on interest rate for buyers using a mortgage broker in Table C1. As can be seen, the result is insignificant. Even if it were significant, the point estimate is negative, suggesting that buyers who use mortgage brokers pay *less* following a merger between real estate agency and mortgage lender. The null effect is consistent with the idea that mortgage brokers present loan options from multiple lenders, so the lender does not have market power stemming from the merger in the same way.

C.2 Points Paid

One way that my identifying assumption would be violated is if borrowers not exposed to a merged lender-agent pair behave differently than the borrowers exposed to a merged lender-agent pair. I have shown in Section 7.5 that borrowers using merged lender-agent pairs and borrowers not using merged lender-agent pairs do not differ substantially on observable borrower characteristics that are plausibly determined prior to the loan contract (namely, loan amount, FICO score, and loan-

Table C1: Interest Rate for Mortgage Broker Intermediated Loans

	(1)
Treat*Post	-0.144 (0.200)
Treat	-0.211 (0.178)
Sun&Abraham(2020)	-0.44 (0.057)
Sample FE	Mtg.Broker CBSA,Year Lender,Agent
R-squared	0.63
N	7,032

* 0.10 ** 0.05 *** 0.01

Notes: Dependent variable is the loan interest rate. Unit of observation is a loan matched to home purchase. Treat*Post represents the coefficient of interest and equals one if the lender and agent are a merged pair. Treat equals one for any lender-agent pairs which ever merge. Standard errors are clustered at the agency level.

to-value ratio), nor do the two groups of borrowers differ on ex-post loan performance. However, borrowers can decide to pay points at origination, where borrowers trade an upfront fee (called "discount points") in exchange for lowering the interest rate on the loan. Bhutta and Hizmo (2021) document that the apparent gap in interest rates paid by white vs. minority borrowers can be explained by the fact that white borrowers tend to pay more points in exchange for a lower interest rate.

If borrowers who use merged lender-agent pairs after the merger are paying fewer points than their pre-merger counterparts, I would misidentify the higher post-merger interest rates as being due to the merger when in fact the higher rates are due to a change in borrower behavior.

Unfortunately, the LLMA data do not include points paid. However points paid are reported in HMDA data beginning in 2018 following a rule change in 2015. I merge in HMDA and observe both the interest rate and points paid for the last two years of my data. Sample size prevents me

from restricting to just agent referred lenders, however earlier versions of my results were robust to either sample, so that is not driving these results.

In Table C2, I make points paid the dependent variable in columns (1) through (3). The first two columns are for all loans, while the third column restricts to just retail channel loans. Beginning with the first column, we see that the coefficient on $Treat * Post$ is both very small in magnitude and insignificant. This holds with the inclusion of credit metrics in column (2), and when restricting the sample to just retail loans in column (3). All in all, a change in buyer behavior with respect to points paid cannot explain the higher interest rates I find for buyers using a merged agent-lender pair.

C.3 Total Origination Costs

It is possible that after the merger, buyers pay lower origination costs in exchange for higher interest rates. While the LLMA data do not include origination costs, the same rule change which required lenders to report any discount points paid also required lenders to report total origination costs. I use the last two years of my data to test for differences in total origination costs by merged and unmerged lender-agent pairs.

I report these results in Table C3. In columns (1) and (2) I include all loans while column (3) considers only retail channel loans. Beginning with column (1), there is no relationship between origination costs and merged status. I continue to find a null effect when including credit score, loan-to-value ratio, and the interaction of loan-to-value ratio and credit score in column (2) and when subsetting to retail channel loans in column (3). In all three specifications the coefficient on $Treat*Post$ is insignificant. Furthermore, the coefficient on $Treat$ is also insignificant, suggesting that even before the merger buyers using eventually merged lender-agent pairs were not paying different origination costs than other buyers. In short, origination costs do not explain the interest

Table C2: Discount Points

	(1)	(2)	(3)	(4)
Treat*Post	1.2e-08 (4.8e-08)	1.4e-08 (5.6e-08)	-2.3e-09 (5.8e-08)	-6.0e-09 (5.8e-08)
Treat	-1.9e-08 (4.7e-08)	-2.3e-08 (5.5e-08)	-7.4e-09 (5.8e-08)	-2.4e-09 (5.8e-08)
FICO*LTV		6.4e-12*** (5.7e-13)		9.3e-12*** (6.5e-13)
FICO		-7.6e-10*** (5.1e-11)		-9.4e-10*** (5.8e-11)
LTV		-6.0e-09*** (4.3e-10)		-8.1e-09*** (5.0e-10)
Sample	All	All	Retail	Retail
FE	CBSA, Year, Lender, Agency	CBSA, Year, Lender, Agency	CBSA, Year, Lender, Agency	CBSA, Year, Lender, Agency
R-squared	0.14	0.15	0.14	0.14
N	690,167	651,645	469,841	469,293

* 0.10 ** 0.05 *** 0.01

Notes: Dependent variable is the amount of discount points paid at origination. Unit of observation is a loan matched to home purchase. Treat*Post represents the coefficient of interest and equals one if the lender and agent are a merged pair. Treat equals one for all lender-agency pairs which merge at any point in time. Standard errors are clustered at the agency level.

rate effects I find in Table 5.

Table C3: Total Origination Costs

	(1)	(2)	(3)	(4)
Treat*Post	251 (317)	84 (379)	185 (459)	39 (455)
Treat	-223 (308)	-82 (364)	-204 (440)	-94 (433)
FICO*LTV		-0.19*** (0.0049)		-0.22*** (0.0057)
FICO		12*** (0.42)		16*** (0.48)
LTV		165*** (3.7)		188*** (4.3)
Sample	All	All	Retail	Retail
FE	CBSA, Year, Lender, Agency	CBSA, Year, Lender, Agency	CBSA, Year, Lender, Agency	CBSA, Year, Lender, Agency
R-squared	0.29	0.33	0.33	0.35
N	714,475	674,194	481,761	481,177

* 0.10 ** 0.05 *** 0.01

Notes: Dependent variable is the total origination costs. Unit of observation is a loan matched to home purchase. Treat*Post represents the coefficient of interest and equals one if the lender and agent are a merged pair. Treat equals one for all lender-agency pairs which merge at any point in time. Standard errors are clustered at the agency level.

C.4 Only Agency-Agency Mergers

Another concern with my identification strategy is that mergers do not occur randomly. Specifically, residential real estate agencies and mortgage lenders will strategically decide to merge in a way that changes lender behavior.

First, I do not believe this is a major issue, as more than half of the mergers in my data set are actually horizontal between two residential real estate agencies where one of the two agencies

happens to already have a lending arm. Thus, it seems that the exposure to the lender is occurring quasi-randomly. However, to be sure, I re-run my main analysis keeping only those mergers which are agency-agency, removing all observations which are affected by an agency-lender merger. The results from including only agency-agency mergers can be found in Table C4. As can be seen, if anything the results are stronger than my main specification. My results are not driven by strategic mergers between lenders and real estate agencies.

Table C4: Only Exogenous Mergers

	(1)	(2)	(3)	(4)
	Lender CBSA Share	Within Agency Share	Interest Rate	Interest Rate, Retail Only
Treat*Post	0.0072** (0.0013)	0.14*** (0.011)	0.086*** (0.0091)	0.089*** (0.014)
Treat		-0.0096 (0.0082)	-0.093*** (0.014)	-0.090*** (0.016)
FICO*LTV			0.000041*** (6.7e-07)	0.000041*** (7.5e-07)
FICO			-0.0049*** (0.000059)	-0.0049*** (0.000067)
LTV			-0.030*** (0.00052)	-0.030*** (0.00058)
Sample			All	Retail
FE	CBSA, Year, Lender	CBSA, Year, Lender, Agency	CBSA, Year, Lender, Agency	CBSA, Year, Lender, Agency
R-squared	0.62	0.61	0.43	0.45
N	414,265	3,175,875	1,056,558	796,412

* 0.10 ** 0.05 *** 0.01

Notes: Treat*Post represents the coefficient of interest and equals one if the lender is merged (column (1)) or if a lender and agent are a merged pair (columns (2) through (4)). Treat equals one for any lender-agent pairs which ever merge. Standard errors are clustered at the lender level in column (1) and at the agency level in columns (2) through (4).

C.5 Stacked Event Study

Retrospective merger studies commonly construct a control group for each merger, generate a merger-specific ID, and then stack each of these mergers in an event study using the merger-IDs as fixed effects. This way, each merger is considered individually, and the issues with staggered DiD do not apply. Because I observe over 100 mergers, I can exploit a similar approach in my data, and I include it as a robustness test.

For each merger, I construct a control group of all unmerged lender-agent pairs at time t in counties where I also observe the merging lender-agent pair. In other words, for each merger, my sample for that merger consists of all loans for a given merger and all loans from the same counties the lender operated in that were belong to lender-agency pairs which never merge. Each merger has its own control group, avoiding the issues of staggered differences in differences. I report the results of the stacked event study for each of my main regression specifications in Table C5.

The stacked event study results in C5 are largely consistent with the main results, with the exception of the lender's CBSA market share. The main results finds that lenders who merge with residential real estate agencies gain 0.54 percentage points of market share, while the stacked event study finds that merged lenders lose 0.53 percentage points of market share after merging. The rest of the results mirror their main specification counterparts.

With the exception of the lender CBSA market shares, the results in Table C5 are stronger than my main results. However, as the stacked event study results are dependent on the particular control group used, I choose to keep the stacked event study as a robustness check instead of as the main specification.

Table C5: Stacked Event Study

Dependent Variable	(1) CBSA Share	(2) Agency Share	(3) Rate	(4) Rate
Treat*Post	-0.0053* (0.0030)	0.20*** (0.013)	0.055 (0.047)	0.11*** (0.031)
Treat		0.015** (0.0069)	-0.047 (0.046)	-0.091*** (0.026)
FICO*LTV			0.000043*** (7.4e-07)	
FICO			-0.0050*** (0.000066)	
LTV			-0.030*** (0.00056)	
Sample	All	All	All	Retail
FE	CBSA, Year, Lender	CBSA, Year, Lender, Agent	CBSA, Year, Lender, Agent	CBSA, Year, Lender, Agent
R-squared	0.41	0.72	0.45	0.47
N	2,465,198	24,701,215	14,777,831	11,301,873

* 0.10 ** 0.05 *** 0.01

Notes: Treat*Post represents the coefficient of interest and equals one if the lender is merged (column (1)) or if a lender and agent are a merged pair (columns (2) through (4)). Treat equals one for any lender-agent pairs which ever merge. Standard errors are clustered at the lender level in column (1) and at the agency level in columns (2) through (4).

C.6 Additional Fixed Effects

Below, I report the interest rate result using CBSAxYear fixed effects, FIPStYear fixed effects, and Zip-Year fixed effects. In general, the results are robust to the fixed effects specification I choose, and of similar magnitude.

Table C6: FIPS-Year Fixed Effects

	(1)	(2)	(3)	(4)
Treat*Post	0.021 (0.039)	0.037 (0.036)	0.069** (0.028)	0.079*** (0.025)
Treat	-0.0085 (0.039)	-0.019 (0.037)	-0.040 (0.029)	-0.052** (0.026)
FICO*LTV		-0.000012*** (1.5e-06)		0.00004*** (7.4e-07)
FICO		0.00018 (0.00013)		-0.0049*** (0.00007)
LTV		0.011*** (0.0011)		-0.030*** (0.0006)
Sample	All	All	Retail	Retail
R-squared	0.42	0.47	0.44	0.46
N	1,188,913	1,095,474	829,938	824,220

* 0.10 ** 0.05 *** 0.01

Notes: Dependent variable is the loan interest rate. Treat*Post represents the coefficient of interest and equals one if the lender and agent are a merged pair. Treat equals one for any lender-agent pairs which ever merge. Standard errors are clustered at the agency level. Fixed effects included in all columns are FIPStYear, FIPS, Year, Lender, Agency.

Table C7: CBSAxYear Fixed Effects

	(1)	(2)	(3)	(4)
Treat*Post	0.020 (0.040)	0.044 (0.034)	0.071** (0.028)	0.081*** (0.024)
Treat	-0.0088 (0.040)	-0.024 (0.035)	-0.041 (0.029)	-0.053** (0.026)
FICO*LTV		0.000041*** (6.5e-07)		0.000042*** (7.4e-07)
FICO		-0.0049*** (0.000057)		-0.0049*** (0.000066)
LTV		-0.030*** (0.00050)		-0.030*** (0.00057)
Sample	All	All	Retail	Retail
R-squared	0.41	0.44	0.44	0.46
N	1,189,092	1,095,646	830,157	824,442

* 0.10 ** 0.05 *** 0.01

Notes: Dependent variable is the loan interest rate. Treat*Post represents the coefficient of interest and equals one if the lender and agent are a merged pair. Treat equals one for any lender-agent pairs which ever merge. Standard errors are clustered at the agency level. CBSAxYear, CBSA, Year, Lender, Agency.

Table C8: Zipx Year Fixed Effects

	(1)	(2)	(3)	(4)
Treat*Post	0.036 (0.042)	0.053* (0.031)	0.074*** (0.019)	0.087*** (0.015)
Treat	-0.033 (0.044)	-0.050 (0.034)	-0.056** (0.028)	-0.067*** (0.025)
FICO*LTV		0.000039*** (9.2e-07)		0.000039*** (1.0e-06)
FICO		-0.0047*** (0.000081)		-0.0047*** (0.000091)
LTV		-0.028*** (0.00070)		-0.028*** (0.00078)
Sample	All	All	Retail	Retail
R-squared	0.44	0.46	0.46	0.48
N	622,278	572,097	428,953	425,511

* 0.10 ** 0.05 *** 0.01

Notes: Dependent variable is the loan interest rate. Treat*Post represents the coefficient of interest and equals one if the lender and agent are a merged pair. Treat equals one for any lender-agent pairs which ever merge. Standard errors are clustered at the agency level. ZIPxYear, ZIP, Year, Lender, Agency.

D Demand Estimation First Stage Results

Below are the first stage results for the instrumental variable in the logit demand. I use one instrument: the annual average 10-year Treasury Rate interacted with the average number of lenders in the market over my sample.

The first stage results are reported in Table D1. The coefficient on *Merged Pair* is positive and significant, which is consistent with the reduced form results that borrowers who use a jointly owned agent-lender pair pay higher interest rates. The coefficient on the instrument is positive, suggesting that the degree of pass-through from lender to borrower increases with the interest rate. The F statistic is 49.07, making the first stage strong.

Table D1: First Stage

	Interest Rate
Treasury Rate * Number of Lenders	0.001*** (0.0002)
Jointly Owned Pair	0.057*** (0.01)
Time to Close	0.0003 (0.0001)
FE	Lender, CBSA, Year
F-Statistic	49.07
Observations	33,886
R ²	0.556

* 0.10 ** 0.05 *** 0.01

Notes: Results of first stage regressions on a 25% random sample of data. Unit of observation is a loan product j in a market t . Standard errors calculated on 500 bootstraps of random sample at market level.