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

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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 study the welfare implications of mergers under counterfactual policies. I find that completely banning mergers harms consumers, while allowing mergers that promote competition can improve consumer welfare.

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1 Introduction

The increasing sophistication of technology has led to its integration in all aspects of life, including finance. Such "FinTech" advances have led to online-only banking, investing, and lending. With respect to mortgages, Buchak et al. (2018) documents that non-banks, including technology-rich online-only lenders, have gained significant market share in the post-crisis period. These non-banks lack the pre-existing customer base of traditional banks and thus must find a different way to reach customers. As a solution, some of these non-bank lenders have merged with real estate agencies. However, very little is known about how these mergers affect mortgage markets.

This paper studies the consequences of joint ownership between real estate agencies and mortgage lenders. For many households, a mortgage represents the largest debt and debt financing obligation they will face. When a real estate agency and a lender share a common parent company, understanding how this joint ownership affects how consumers access loan products and the ensuing competitive effects in the mortgage market will be crucial given the size and scope of the mortgage market. However, determining the consequences of joint ownership in this market is challenging due to identification and data issues. Beginning with data, the main challenge is that there is no single data set that contains all the information necessary to analyze the potential consequences of joint ownership. In terms of identification, 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.

First, to address the data issue, I 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 mergers involving real estate agencies and/or lenders into this data set to obtain the ownership structure over time. By constructing this data set, I am able to identify whether the lender and agency were jointly owned at any point in time in my data, including at the time of the home purchase and loan origination. I observe more than 100 mergers over the span of my data, and more than one million home purchases matched to the loan origination funding the purchase.

Second, to solve the identification issue, I exploit the fact that horizontal mergers between real estate agencies occur frequently, and that these horizontal mergers indirectly change which lenders are jointly owned with which real estate agencies, what I will call "indirect integration". If these mergers between agencies occur to consolidate the involved firms' agency businesses and the lender's books are not the primary concern, then these mergers create quasi-random variation in joint ownership from the perspective of the lender. Of the mergers I identify, 87 mergers fit these criteria. This large number of mergers and observations allow me to include rich fixed effects (over 50,000 total) to control for lender, agency, time, or geographic factors which could bias my results.

I use this data set and research design in a staggered difference-in-differences model to analyze the consequences of joint ownership between real estate agencies and mortgage lenders for market shares, prices, speed of transactions, characteristics of borrowers, and ex-post loan performance. Lender-agency pairs impacted by indirect integration are treated, while other lender-agency pairs that are never jointly owned function as a control group. To the best of my knowledge, this paper is the first to study this important class of mergers in a comprehensive manner.

Beginning with the market structure effects, I find that lenders jointly owned with a real estate agency more than double their loan share at that agency upon integration, consistent with the theory that jointly owned agencies direct buyers to their sibling lender. Doubling their loan share is a significant change for the lender's portfolio, and suggests that agencies direct buyers to the in-house lender when it exists, giving the lender market power over those consumers. When looking instead at the lender's market share in the core-based statistical area (CBSA), lenders jointly owned with a real estate agency gain only 0.54 percentage points higher market share. While this represents a 16% increase in the average lender market share, making it significant for the lender, the overall market structure is nearly unaffected due to the fragmented nature of the mortgage market.

With respect to interest rates, I find that buyers using a lender jointly owned with their real estate agency pay 9 basis points more on average, which is consistent with the theory that joint ownership allows lenders to "capture" some borrowers and charge these borrowers higher interest rates that dominate any cost reductions from joint ownership passed on to borrowers. This result holds even after accounting for the relationship between search behavior and interest rates, as documented by Bhutta et al. (2020). I argue that 9 basis points is a large effect in the context of mortgage rates; it is similar to the 7 basis point premium that minority buyers pay as found by Bartlett et al. (2021), more that 15% of the total interest rate dispersion documented by Bhutta et al. (2020), and amounts to an additional \$225 in interest payments per year on the average loan. In sum, joint ownership has important market share consequences for lenders and leads to higher interest rates for buyers.

While buyers pay more when going to a merged lender-agency pair, doing so does not change how fast they can close on their mortgage or the credit profile they need to get a loan. I find no evidence of the possibility suggested by theory that lenders are cream-skimming the best credit profiles from their jointly owned agency. The lack of change in borrower characteristics also suggests that lenders are not receiving additional information from the agency which the lender then uses to lend to riskier buyers, which is another possibility suggested by theory. I also find no effect on ex-post loan performance. This result contrasts with the findings in Stroebel (2016), where home buyers using a builder's lender were less likely to default on their mortgages.

I further enrich these reduced form results with a structural model of the mortgage market which allows me to test for marginal cost efficiencies from joint ownership and to run regulatory policy counterfactuals. I construct a logit demand model for loans with consumer-specific choice sets. To estimate the demand model, I first use maximum likelihood to recover mean utility for each loan product. I then use two stage least squares to recover the contribution of each product characteristic to a product's overall mean utility. The parameter estimates from this structural model are consistent with my reduced form findings that consumers value jointly owned agency-lender pairs, pre-existing relationships with lenders, and faster closing times. I pair this demand model with a supply model of profit-maximizing lenders offering differentiated mortgage products under Bertrand competition.

Using the estimates from my structural model, I study three different counterfactual regulatory policies the government could enact. All of these policies regulate lender behavior and consequently influence borrowers' access to loan products. In the first two, joint ownership between real estate agencies and mortgage lenders is banned, but the two differ in the choices available to buyers previously choosing the jointly owned products. In the third, joint ownership is permitted, but lenders are forbidden from offering different products to consumers based on what real estate agency they use. I find that banning mergers slightly decreases consumer welfare in both of the first two counterfactuals, but that welfare gains come from permitting mergers but requiring that lenders offer all products to all consumers. In short, a simple ban on mergers reduces welfare, while more nuanced regulatory policy can promote competition and thus improve welfare.

This paper contributes to several literatures within household finance and banking: First, I contribute to the literature on mortgage price dispersion and the role of steering in financial markets. This paper offers a novel channel to explain the dispersion in mortgage rates documented and partially explained in prior papers such as Bhutta et al. (2020), Bartlett et al. (2021), and Bhutta and Hizmo (2021). It also complements studies on other forms of steering in mortgage and home sales [Guiso et al. (2021), Agarwal et al. (2016), Barwick et al. (2017), Woodward and Hall (2012)]. I connect steering across mortgages and home purchases, and examine a particular kind of steering: bringing another good in-house. To the best of my knowledge, only one other paper looks at steering linking lenders and real estate agencies, that of Lopez et al. (2019). Relative to this earlier paper, I look at the buyer's agent (who buyers are more likely to trust) instead of the seller's agent, while including a much larger geography, additional outcomes, a different identification strategy that utilizes variation at a level above the transaction, and a structural model to estimate policy counterfactuals. Joint ownership is also common between car dealerships and auto lenders, another large household financing decision. Grunewald et al. (2020) find that the discretion given to dealers in these arrangements incentivizes them to increase the rate over the minimum specified by the lender. While the settings are not identical, the results in this paper on the mortgage market can provide insight into consequences in the auto lending market as well.

Lastly, this paper contributes to the literature on industrial organization and banking and to the debate 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. Prior literature 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. Here, I offer a rich study of the consequences of mergers in one particular financial market while studying a broad set of potential consequences with more mergers and richer outcomes than the current literature.[1]

[1] For a more general discussion of complementary goods mergers among non-financial products see Akgün et al. (2020), Choi (2008), and Ershov et al. (2018).

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 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. In the United States, 86% of buyers used a real estate agent in 2020.[2] In general, buyers are satisfied with the quality of the service they receive from their real estate agent, with 89% saying they would use the same agent again or recommend the agent to others.[3] Buyer's agents are paid out of the seller's agent's commission when the clients find a home. Thus, agents are 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 will 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 firms share things such as advertising or office space. Companies have violated this; in August 2023 the Consumer Financial Protection Bureau fined Freedom Mortgage for violating this and paying more than cost sharing to Revolve Realty. Similarly, ReMax has

[2]See: https://www.nar.realtor/research-and-statistics/quick-real-estate-statistics
[3]See: https://www.nar.realtor/research-and-statistics/quick-real-estate-statistics

been fined in the past for oversharing with mortgage lenders.[4]

Moving to mortgage lenders, mortgage lenders can attract consumers directly through their retail channel, but they can also use mortgage brokers. Mortgage brokers are third party agencies which lenders can contract with to help them find more borrowers. Mortgage brokers contract with several lenders, and receive a commission from the lender when a buyer chooses that lender. 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.

When buying a home, 87% of buyers financed with a mortgage in 2021.[5]. 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 they then securitize and sell. Most loans are backed by the FHA or government sponsored entities, Fannie Mae and Freddie Mac. These agencies 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

[4]See:https://www.consumerfinance.gov/about-us/newsroom/cfpb-penalizes-freedom-mortgage-and-realty-connect-for-illegal-kickbacks/ and https://www.consumerfinance.gov/enforcement/actions/rgc-services-inc-dba-remax-gold-coast-realtors/

[5]See: https://www.nar.realtor/research-and-statistics/research-reports/highlights-from-the-profile-of-home-buyers-and-sellers

United States. Following federal regulations which made mortgage brokers less profitable, many mortgage brokers went out of business, and in 2019, mortgage brokers originated only 19% of loans in the United States. Thus, for lenders looking for borrowers, they cannot rely on mortgage brokers to find them. Now, lenders must find another channel through which to find borrowers.

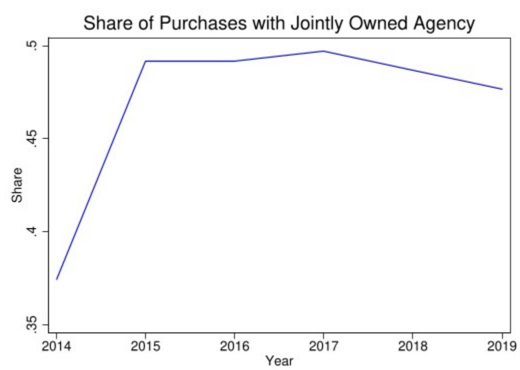
At the same time the share of borrowers finding loans through mortgage brokers is declining, residential real estate agencies are merging with lenders and related services. Home purchases and mortgages are complementary goods; as the majority of buyers finance their home purchase with a mortgage, these 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 them 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, these 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 merging firms see the complementarities between these goods and that merging them improves overall performance.

Figures 1a, 1b, and 1c show how the market has evolved over time. Beginning with Figure 1a, this 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, this share has increased by nearly 25%, such that in 2019 almost half of home purchases used an agency with a sibling lender. That is, the agencies which 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, this trend has not stopped in the intervening years. While the agencies are large players in the market, the lenders have considerably smaller market share. This is consistent with the state-level licensing to originate mortgages being a high barrier to entry for lenders. Most lenders are geographically concentrated in at most a handful of states.

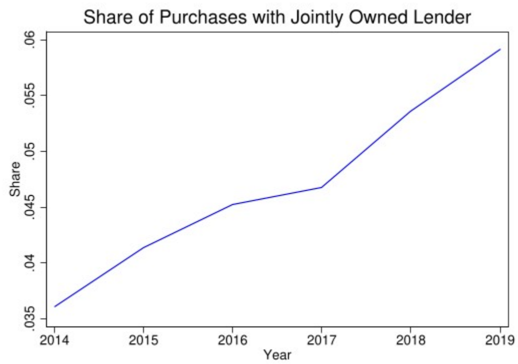
Lastly, in Figure 1c, I show the share of home purchases using a merged agency-lender



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.

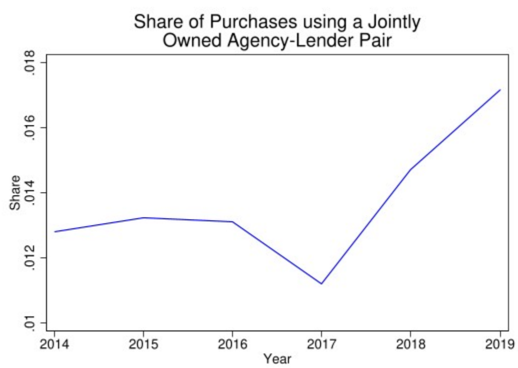
Figure 1a: Share of Home Purchases with Conglomerate Agency

pair. These are the purchases and loan originations which I am most interested in studying. The share of home purchases which 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, this share is likely to grow over



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 time. Furthermore, while 2% of all buyers is a small fraction, that is 33% of the market share of merged lenders, indicating that this is an important distribution channel for these lenders.

3 National Survey of Mortgage Originations

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.[6] 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 buyers only seriously look at one lender.

Similarly, 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 in-

[6] Other 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%).

terested third party, and 51% only seriously consider one lender.

Taken together, these survey results indicate that, especially for low credit score and first-time home buyers, the recommendation of the real estate agent influences the lender they ultimately choose. Thus, lenders and real estate agencies merging has the potential to lead agents to recommend their sibling lender, which has bearing on 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. However, the effects on overall lender market share are unclear. 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 go up, only the market share coming from the sibling firm. 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 and their overall market share will increase.

Similarly, 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 supracompetitive prices as a result of the integration and lack of search as previously discussed.

4 Data

The data to complete this analysis are difficult to compile. No pre-existing data set contains all the necessary pieces: lender, real estate agency, and loan characteristics. Furthermore, corporate ownership structure plays a vital role in this project but is not readily matched to the other pieces. Thus assembling the data explained below is no small feat and represents a contribution to the field as this data set 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. This includes characteristics of the property, the deed transfer, and most notably for this project, the mortgage used to purchase the home. The mortgage details include such fields as the amount, the start date, loan term, interest rate, loan purpose and type, borrower name, and lender. While these variables all 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 this 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 are 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 provides a second data product, the MLS data. This data set covers the MLS feeds for 138 MLSes across the United States. Similar to Zillow, this 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 additional fields, including information on the buyer's real estate agent, including their name and agency at the time of sale. [7] I will use the term agent and agency interchangeably.

[7] For 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.

CoreLogic LLMA Originations Data The CoreLogic LLMA Originations data, or Loan-Level Market Analytics Originations data come from a large loan servicer. This data 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. From here, the key variables I use are interest rate, FICO score, and LTV ratio.

CoreLogic LLMA Events Data The CoreLogic LLMA Events data track the major performance events of a loan including the first day of 30, 60, and 90 day delinquency, the first date of a bankruptcy filing, and the first date of foreclosure filing. I use these data to compare the performance of loans by merged lender-agent pairs and those by other lenders who may have less soft information to base their lending decision on.

CompuStat Transactions Data To identify mergers and back out ownership, I use the CompuStat Transactions Data. This data set records all mergers and acquisitions back to 2000, the target, the acquirer, the transaction date, and additional details. I have gone through this data and identified all relevant transactions by hand.[8] Due to the large number of real estate offices in the country, not all mergers are going to be widely publicized. To the best of my knowledge, my data set is the most comprehensive which tracks solely real estate firms.

Home Mortgage Disclosure Act 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, this includes borrower characteristics such as race and gender. For the last two years of my sample, this also includes

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

loan fees and discount points.[9] 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 is a limited time to view either of these, it does provide some insight into other monetary considerations for borrowers beyond the interest rate, and the possible points-fees tradeoff as documented in Bhutta and Hizmo (2021).

Summary statistics can be found in Table 1. Due to outliers, I winsorize loan amount, time to close, and interest rate at the 5 and 95th percentiles. Just over half of my data come from purchases made with real estate agencies that ever have a sibling lender. This 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 this is due to three things: 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 which merge later in the sample period are going to get less benefit from the merger that I observe. 2% of purhcases use a lender and agent pair that are ever merged, even if they 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 which has a sibling lending arm, while 5% use a lender who has a real estate agency sibling company. Again, 1.4% of borrowers use a merged pair. Similar concerns about the fact that these number are not conditional on licensing apply. Nearly 40% of loans in my sample are classified as coming from an agent preferred lender, a definition I will explain

[9] This change is due to a 2015 change in the reporting requirements which required reporting the additional variable beginning in 2018.

in Section 6.2. The average interest rate is 4.08%, reflecting the fact that interest rates were generally low in the post-crisis period I study. 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 Breakdown of Mergers

Here, I present a breakdown of the mergers I observe in my data set involving real estate agencies. 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." As a result of the merger that was consolidating agency business, the agency which previously did not have a sibling lender now does. Another 48 of the mergers are between two real estate agencies when neither one has a lending arm at the time of the merger. Thus, these 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, the lender-less agency involved in mergers which include a lending are are approximately the same size as the agencies involved in the mergers without a lending arm. On average the lender-less agencies 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 Studies

I will now present a case study to examine one merger more closely and see if there are additional implications beyond those I can analyze in the reduced form and structural analysis.

In July 20XX, the real estate services subsidiary of a large conglomerate, BigFirm acquired AgencyA.[10] This merger gave BigFirm significant market share in portions of the United States. At the time of the merger, LenderA, a mortgage company was a subsidiary of AgencyA, and was acquired in this merger 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 market. Indeed, if the acquisition of LenderA is mentioned at all, it is later in the article, often seeming like an afterthought.

Following the merger, BigFirm and it's subsidiary real estate agencies are jointly owned with LenderA. Prior to the merger, BigFirm owned LenderB, another mortgage lender fol-

[10] Identifying details have been removed.

lowing a merger with AgencyB in August 2013.[11] For the purposes of this case study, I will ignore LenderB.[12]

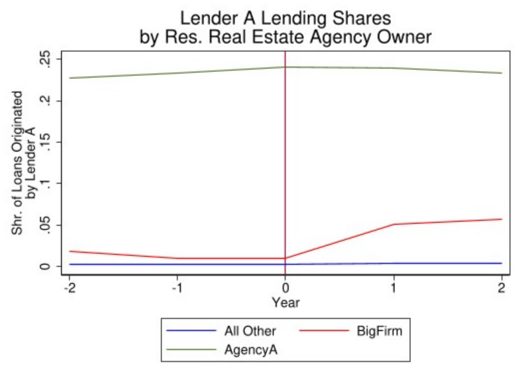
I begin by plotting the share of buyers who use LenderA to originate their mortgage, split by AgencyA, all other BigFirm buyers, and all other buyers in Figure 2. As can be seen here, prior to the merger, LenderA originated very few loans for purchases made with any agencies other than AgencyA, consistent with the idea that AgencyA buyers were already directed to LenderA as they were already jointly owned. Following the merger, we see no change in the number of buyers from agencies that are not owned by BigFirm, while the BigFirm share increases significantly. This graph also does not show the geographic expansion of LenderA following the merger. I have restricted this graph to only states in which LenderA is licensed before the merger, but following it's acquisition by BigFirm LenderA obtains licenses in many new states.

In Figure 3a, I map the market shares of BigFirm's real estate agencies in 20XX, the year it acquires AgencyA and LenderA. BigFirm had real estate agencies in most states in this year, 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 of the merger. LenderA has non-zero market share in only five states: Texas, Pennsylvania, Virginia, Maryland, and Delaware, reflecting the fact that lenders must be licensed in

[11] BigFirm 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.

[12] This is not a major issue; LenderB was a very geographically concentrated lender, with 80% of loans coming from the Philadelphia Metro area between 2015 and 2017 according to the Consumer Financial Protection Bureau.[13]. Furthermore, LenderB stopped originating new loans in late 2020, and the patterns in my data suggest that they were winding down their origination business before this. Lastly, Lender2 has been fined for discriminatory lending practices, making it a poor choice for a case study.



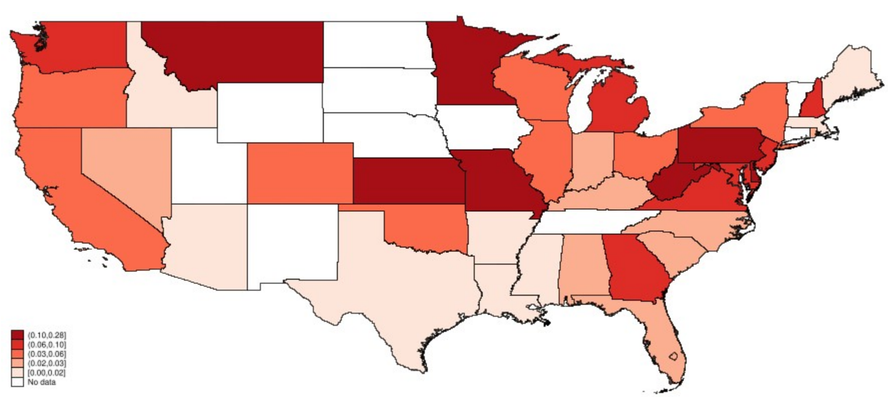
Notes: Figure shows LenderA loan share at BigFirm agencies, AgencyA agencies, and all other agencies. Years are relative to merger year, denoted at 0 and with red line.

Figure 2: LenderA Loan Share by Real Estate Agency Owner

each state and LenderA was not licensed in most states in the year of the merger.

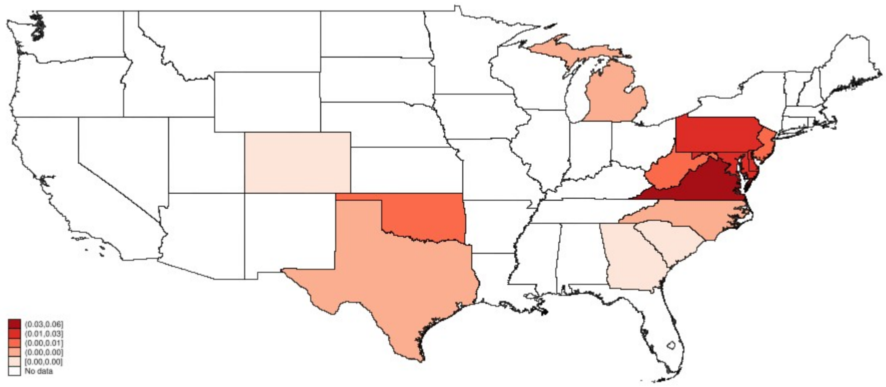
However, in Figure 3c, I report the market shares of LenderA in each state two years after the merger. Now, LenderA is lending in considerably more states, and has gained market share in some states that is sizable given the relatively small market share of most lenders.

These figures suggest that LenderA expanded into the states where BigFirm had a substantial presence already. Thus, bringing a lender in-house with a real estate agency influences the geographic expansion of the lender.



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

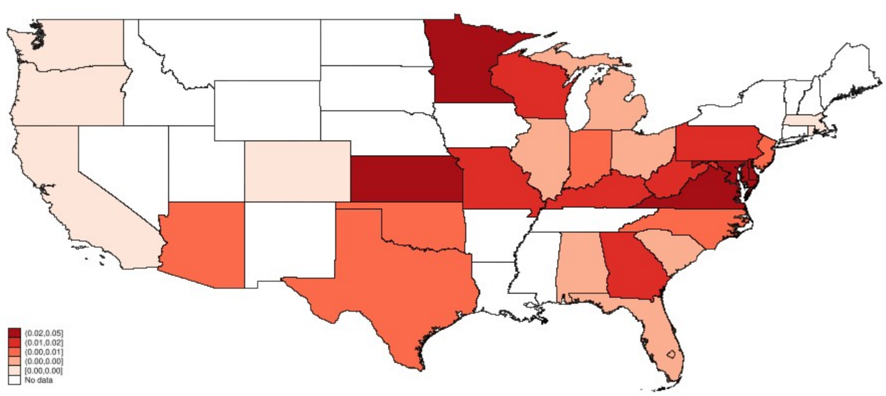


Figure 3c: LenderA Market Shares Two Years Post-Merger by State

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 section I will discuss how I intend to estimate the causal effects of mergers between mortgage lenders and real estate agencies. I will begin with a discussion of the identification strategy before moving into estimating the equations. I present the results in the next section.

The ideal experiment to estimate the effects of mergers would to randomly assign agencies and lenders to be jointly owned for a period of time and then randomly reallocate them. This is not a feasible research design. Thus, I will exploit natural variations in the ownership structure of firms stemming from mergers and acquisitions.

As mergers occur at different points and not all firms merge, this creates a treatment group of lenders that are ever merged with real estate agents to compare with lenders who never merge, as well as the buyers who use a given agent and lender pair. To fix ideas, when Berkshire Hathaway (a large real estate agency that acquired a real estate firm with a lender, Prosperity) merges with another real estate agency, is Prosperity more likely to find borrowers through this link with the new agency? How does this affect the characteristics of the buyers coming to Prosperity from this agency as well as the loans these buyers obtain?

The identifying assumption is that the merger is motivated by Berkshire's desire to expand its real estate agency business, and not because Berkshire was interested in acquiring Prosperity specifically. In this case, the merger is exogenous as far as the lender is concerned, simply changing how it acquires customers and where it expands, as is seen in the case study. To further control for lender or agent-specific effects, I include fixed effects in all my specifications.

The main threat to causality 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 fix this, I propose the following solution. First, I assume that buyers select a real estate agent and then a mortgage lender. Given that all real estate agents offer buyers a list of suggested lenders, and anecdotal evidence indicates that only lenders on that list will return buyer calls, this is a reasonable assumption. Even if this direction does not hold, 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, the channel which allows this is joint ownership.[14]

Then, assuming that buyers first chose an agent, I assume that they pick this agent based on characteristics of the agency/agent, **not** due to a merger set up. Agents 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.[15] 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 most observables following a merger.

The second threat I face is misattributing the mechanism. Buyers who use a merged lender-agent pair are implicitly not searching while buyers who go to a merged firm and **do not** use the sibling lender may be shopping around. The prior literature demonstrates that price dispersion is prevalent in consumer financial markets, and that search mitigates this. Thus,

[14]The set-up of my model does require that buyers choose an agent first, but the reduced form results do not.

[15]Merged firms will 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, which is likely to be ignored by most buyers.

failing to 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 will discuss below.

6.2 Proxy for Search (or Lack Thereof)

No matter which real estate agency buyers go to, they will receive a list of recommended lenders. I do not have access to this list, but I can proxy for it based on outcomes. Since agent recommendations are something buyers pay attention to, the lenders agents suggest will comprise a larger share of the loans matched with purchases from those real estate agencies than agencies where they are not on the list of recommended lenders. Thus, I construct the following measure to determine if a lender is likely to be recommended by an 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. Withing 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 the agency is more than two standard deviations above the lender's loan share within the county, **and** the lender originated at least eight loans in the CBSA-year.[16]

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

[16]Eight 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.

meet this criteria.

With this set up, I will look at four outcomes: lender market shares at the CBSA level and within a agency, total number of loans originated in a county, borrower characteristics, and prices (interest rates). To estimate all of these outcomes, I will use one specification for the CBSA market shares, and another for everything else.

7 Results

7.1 Lender Market Shares: Within Agency

The first outcome of interest is lender market shares within a real estate agency. If mergers lead agencies to direct clients to their sibling company in a way that is not true without mergers, and this recommendation is influential, then we expect that the within-agency share for the merged lender to increase post merger. This leads to 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. $Treat * Post_{ijt}$ 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. X_{kt} is a vector of controls depending on the exact column in the table..

The results for this specification 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. This suggests that the firms which merge have lower within agency market shares merge, however, following the merger that these relationships are stronger.

This suggests that there is some strategy in which firms decide to merge; namely, firms which have less of a relationship strengthen that relationship by bringing it "in house." 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 already existing relationship.

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. Now, agencies are referring more clients to their sibling lender, which results in additional originations from the real estate agency for the lender.

Recent literature has shown that staggered difference in difference with two-way fixed effects are subject to unequal weighting of treatment cohorts and 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 have aggregated up to an average treatment effect. In the last row of the table, I report the average coefficient on the event study coefficients. This result is robust to the method suggested by Sun and Abraham (2021); in fact the results are stronger. Now the coefficient on $Treat * Post$ is 0.28, or 28 percentage points. This 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 the lenders buyers choose. First, as agents now have an "inside track" to the lender, they may use this to help borrowers who otherwise struggle to get a loan; however, they may instead use this to "cream skim" and send only the best borrowers to their sibling lender. Second, the lender may price loans to this group of home buyers higher as they have a form of market power over the home buyer stemming from the lack of search and the merger.

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

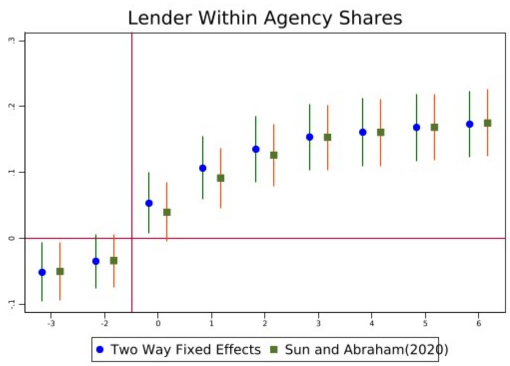
* 0.10 ** 0.05 *** 0.01
Notes: Dependent variable is a lender's loan share within a CBSA-year-real estate agency. Unit of observation is a lender-agency-CBSA-year. Treat*Post represents the coefficient of interest and equals one if the lender and agency are a merged pair. Treat equals one for all lender-agency 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 company level, mergers may have effects on overall market shares for lenders. If, for example, mergers make companies more efficient, this may allow them to process more loans in the same amount of time and thus attract more customers. Then, their market share overall may increase.

To test this possibility, I use the below specification:

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



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

Now, 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. Here, after controlling for CBSA trends, 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 of 0.54 percentage points. While the absolute value of this number is quite small, 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.[17] The fact that this is only significant after the introduction of lender fixed effects represents the fact that lenders expand following mergers, as seen in the case study.

The event study plot version can be found in Figure 5. The results here are considerably noisier. This is in large part due to the relatively sparse data, especially after fixed effects

[17] The 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.

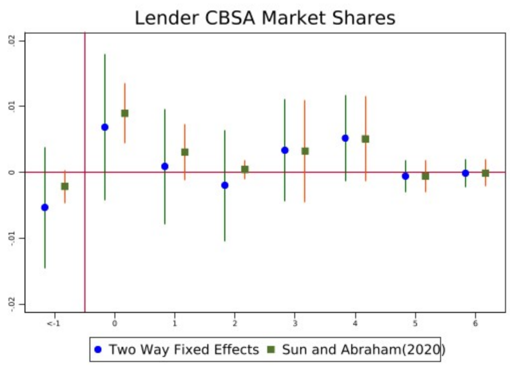
are incorporated. However, the general pattern of the results match the results in the tables, and there are not obvious pre-trends. My results are even stronger after correcting for the biases of the two way fixed effects estimator, the effect on lender market share increases to 0.7 percentage points (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.)

This 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, this is not making them dominant in the market. The broader market implications of this increase in market share are unclear. On the one hand, this could represent loans that would otherwise be provided by other lenders, and thus be business stealing. Alternatively, if merging makes the lender more efficient so that it is profitable to originate more loans, they could gain market share without taking clients from other lenders. In this case, the overall access to credit in the market will increase.

Table 4: CBSA Lender Market Shares

	(1)	(2)
Treat*Post	-0.0012	0.0054*
	(0.0021)	(0.0029)
Treat	0.0051***	
	(0.00072)	
Sun & Abraham (2020)	-0.001	0.007*
	(0.003)	(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

For mortgages, interest rates are analogous to prices, and thus could be manipulated by lenders if joint ownership with a real estate agency confers market power on them that does not exist otherwise. Studying interest rates is additionally complicated because 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 the effect I find is not caused by this lack of search, but rather the ownership structure of the firms selected. Thus, I restrict my sample to only loans I flag as agent recommended as discussed earlier 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.

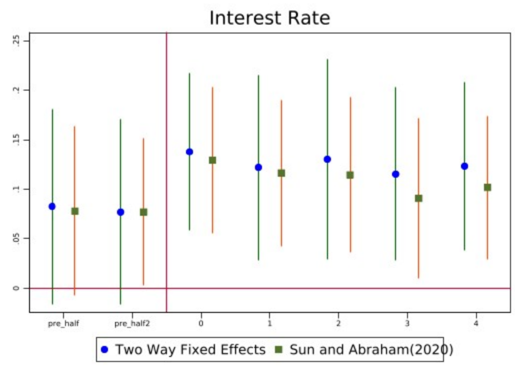
The results for this variable can be found in Table 5. All columns include lender, agency, CBSA, state, and year fixed effects, and I report the $Treat * Post$ coefficient from the Sun and Abraham (2021) methodology at the bottom of each column. The results are robust to this, and the event study plot can be found in Figure 6. the coefficient on $Treat * Post$ is positive and highly significant. This means that buyers who use a merged lender-agency pair and go directly to the lender pay 8 basis points more on average for their loan. This is 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.

Table 5: Interest Rate

	(1)	(2)
Treat*Post	0.079***	0.092***
	(0.019)	(0.015)
Treat	-0.054***	-0.070***
	(0.019)	(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**	0.138***
	(0.036)	(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.

An interest rate effect of 8-9 basis points is quite large in the context of the literature. This is similar to the effect found by Bartlett et al. (2021) for the premium paid by black borrowers over white borrowers. It is also approximately 15% of the interest rate dispersion found by Bhutta et al. (2020) between the 10th and 90th percentile of rates. While their difference is significantly larger, they further document that search reduces this dispersion substantially.



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

In the case of my finding, I am analyzing a subset of consumers who I believe did not search. Thus, the effect I find is not due to changes in shopping behavior of consumers, but solely the legal structure of the company they happen to choose. As most real estate agents will offer lender recommendations to consumers, this is not a the fee for the convenience of not having to find a lender, any effect from that is already included.[18] This effect is due purely to the organizational structure of the firms in question. Furthermore, for affected buyers, this is not a small effect. On the average loan in my sample, it 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. As home prices continue to rise, these numbers will grow.

7.4 Time to Close

One feature borrowers might be willing to pay for in the form of higher rates is a loan which they believe will close 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

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

between lenders and agents.

I cannot directly observe the time it takes for a borrower to receive financing; however, I am able to proxy for it. 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. The results of this analysis can be found in Table 6. In column (1), I use time to close directly. In column (2), I use the probability that a purchase takes more than 45 days to close, 60 days in (3), and 75 days in column (4). In column, 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 before calculating each variable.

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 the 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 2.3% reduction in the probability that it takes more than 45 for a purchase to close when using a merged lender-agent pair, but this is not statistically significant. Moving to columns (3) the effect for buyers going through the retail channel is statistically significant at 2.1% reduction in the probability it takes more than 60 days to close. In column (4), there is no significant change in the probability it takes more than 75 days to close. This is due in part because less than 10% of transactions take more than 75 days to close.

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

Table 6: Time to Close

	(1)	(2)	(3)	(4)
	Days	45+ Days	60+ Days	75+ Days
Mean	42.0	0.35	0.16	0.09
Treat*Post	-1.4**	-0.025	-0.023	-0.021**
	(0.59)	(0.020)	(0.019)	(0.0088)
Treat	0.97	0.034	0.020	-0.0037
	(0.68)	(0.021)	(0.022)	(0.012)
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 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 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.

7.5 Borrower Characteristics

Real estate agents and the agencies they work for have a considerable amount of information about their clients and their ability to repay a loan. Thus, they can act as conduits of information between lenders and borrowers. Following the merger, this channel is legally codified, making the exchange even easier. There are to two possible uses for this channel: assisting marginal borrowers or cream skimming. In the first case, suppose the agency has soft information about applicants which lead it to believe that they are a ”better” risk than their credit information may suggest. They can communicate this to the lender and help them get a loan. In the second case, the agency could selectively decide to refer only the best clients to its sibling lender.

While both of the above cases could be true for agencies and lenders who have a relationship that is not legally codified, its existence is more 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 they 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 is unlikely to want to "go the extra mile" to originate a loan. With the merger, both have reason to care about the others' goals, making one or both channels possible. I will now discuss results for three ex-ante characteristics of borrowers: loan amount, FICO score at origination, loan-to-value ratio. In addition, I have results for loan performance, to check if there are some unobservables which are influencing interest rates as found by Stroebel (2016). For these, I test the share of loans which are ultimately 30, 60, and 90 days delinquent.

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.

These results 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. This suggests that the performance of loans does not change with merger status. This is further evidence that the merger does not lead to soft information changing loans. It also helps put the eventual 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).

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	402	-2.2	10*	-0.012	-0.0048	0.0013
	(7,118)	(1.5)	(5.5)	(0.011)	(0.0075)	(0.0051)
Treat	-14,694*	2.5*	-11*	0.023*	0.0065	-0.0044
	(8,318)	(1.5)	(5.7)	(0.013)	(0.0095)	(0.0070)
FICO*LTV				-0.000025***	-0.000021***	-0.000019***
				(6.3e-07)	(4.9e-07)	(4.3e-07)
FICO Score				0.00054***	0.00081***	0.00080***
				(0.000056)	(0.000043)	(0.000037)
LTV				0.020***	0.017***	0.015***
				(0.00049)	(0.00038)	(0.00033)
FE	CBSA,Year	CBSA,Year	CBSA,Year	CBSA,Year	CBSA,Year	CBSA,Year
	Lender,Agency	Lender,Agency	Lender,Agency	Lender,Agency	Lender,Agency	Lender,Agency
R-squared	0.54	0.21	0.19	0.17	0.15	0.13
N	606,238	830,385	824,923	824,821	824,821	824,821

* 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.

8 Model

While the reduced form results above discuss the implications of mergers between agencies and lenders for consumers, mortgage market structure, and lender market shares, they are unable to examine any potential cost savings for the lender, as well as unable to test policy counterfactual scenarios. Thus, I have constructed a logit demand model for mortgages as well as Bertrand differentiated product competition supply so as to recover marginal cost and estimate counterfactuals.

8.1 Household

Each household i in market t has a choice set C_{it} from which they select one loan, j. For a given product j, the indirect utility household i receives can be written as:

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

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

8.2 Lender

A given lender l offers products j. 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:

$$\Pi^S_{jlt} = (r_{jlt} - \kappa_{jlt})s_{jlt} \tag{4}$$

where r_{jlt} is the interest rate, and κ_{jlt} is the marginal cost of selling that product. Thus, each product the lender offers is allowed to have a different rate and a different cost in every market. s_{jlt} represents the choice probability for product j. Thus, the overall profit for firm l in market t is:

$$\Pi_{lt} = \sum_{j \in J_{lt}} (s_{jlt}\Pi_{jlt}) \tag{5}$$

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:

$$r^*_{klt} = \kappa_{klt} - \frac{s_{klt}}{\frac{\partial s_{klt}}{\partial r_{klt}}} - \sum_{j \neq k \in J_t} \frac{r_{jlt} - \kappa_{jlt}\frac{\partial s_{jlt}}{\partial r_{klt}}}{\frac{\partial s_{klt}}{\partial r_{klt}}} \tag{6}$$

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. However, in this case, not all households in a given market have access to the same products. 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 vertically integrated broker-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.

Now, 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 the lender is jointly owned with the buyer's real estate agency, they will only have access to that lender's vertically integrated product for a given credit score x loan to value ratio, and vice versa. I construct the outside option, $j = 0$, by setting it to all lenders who have a 0.05% market share or less, and normalize it to have mean utility of zero.

This 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 this, I will include lender fixed effects. Then, 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.

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

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

where r_{jt} is the average rate, and x_j are the observable product characteristics: vertical integration 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. That is, 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:

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

Where δ_{jt} can be written as:

$$\delta_{jt} = \alpha r_{jt} + \beta X_{jt} + \xi_{jt} \tag{9}$$

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

Then, then household i's likelihood function is:

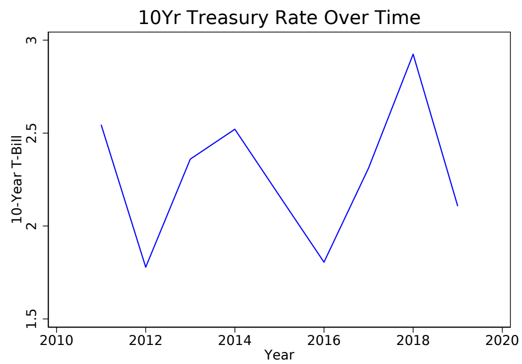
$$\mathcal{L}_i = \prod_{j \in C_{it}} s_{ijt}^{\mathbb{1}(\text{product } j \text{ chosen})} \tag{10}$$

This gives the log-likelihood for household i as:

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

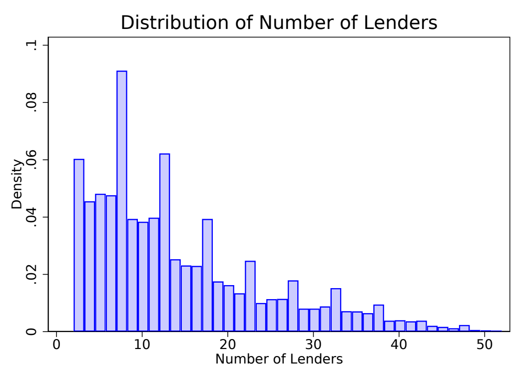
I estimate this in two steps. First, I use a non-linear optimization to find the δ_t which maximizes the likelihood for all households. Then, I use two stage least squares to decompose δ_t into each of its pieces. This cannot be done with standard OLS because it is possible $cov(r_{jt}, \xi_{jt}) \neq 0$. For example, one element of ξ_{jt} could be quality. Then, 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 deal with the endogeneity of ξ_{jt}, the unobservables which may be correlated with price, I use the 10-year Treasury bond rate interacted with the number of lenders in the market. The intuition behind this IV is that mortgage rates are often tied to the treasury rate. However, the degree to which lenders can pass on changes in the federal funds rate to buyers is dependent on the degree of competition in the market. With rate increases, in more competitive markets lenders cannot pass as much of the treasury rate increase on to borrowers. I have plotted the 10-year Treasury rate in each year in Figure 7. The rate varies over time, lending time variation to my IV. Furthermore, the number of lenders in a market varies year over year; only 11% of my markets have the same number of lenders from one year to the next, providing additional time variation. There is also significant variation in the number of lenders in a market within a given year, providing geographic variation. A histogram with the distribution of number of lenders can be found in Figure 8.



Notes: Figure shows the annual average of the 10-year Treasury rate over sample period (2011-2019).

Figure 7: 10-Year Treasury Rate over Sample Period



Notes: Figure is histogram of number of lenders in market year over sample period (2011-2019).

Figure 8: Histogram of Number of Lenders in Market-Year

The first stage results can be found in the appendix in Table 11. The coefficients on the product characteristics can be seen in Table 10. The coefficient on interest rate is -8.26. This is consistent with the idea that borrowers prefer to pay less interest, all else equal. The coefficient on Merged Pair is positive. This 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. This can be thought of as the additional "brand premium" that a lender receives when they are jointly owned with a real estate agent. However, the lender fixed effects are considerably larger, on the order of 40. Thus, the premium for being jointly owned is not large in comparison. This matches the reduced form results where the effect on CBSA market share is relatively small.

The coefficient on time to close is negative. This suggests that borrowers prefer to close quickly, which is again consistent with theory.

Table 8: Mean Utility Parameters

Rate	-8.26^{***}
	(1.74)
Merged Pair	2.20^{**}
	(0.23)
Time to Close	-0.020^{***}
	(0.004)
Observations	16,024

* 0.10 ** 0.05 *** 0.01

Notes: Mean utility parameters recovered from nested 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 optimal pricing, I can solve for the marginal cost of product k in market t, κ_{kt}. Then, using the results from the demand estimation, I can compute conditional choice probabilities s_{jnlt} for all products, as well as the partial derivatives. Then, 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 4.00%, while that on merged loans is 3.98%. I cannot reject that these two are the same, but it is suggestive that merged loans are cheaper to originate than non-merged loans. The magnitude of the marginal cost on these loans is qualitatively similar to those found in the UK mortgage market by Robles-Garcia (2019).

Table 9: Marginal Cost

	Marginal Cost	Markup
Non-Merged	4.00	0.018
	(0.03)	(0.07)
Merged	3.98	0.02
	(0.06)	(0.011)

Notes: Average marginal cost and markups over 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

Now that I have recovered the demand parameters and marginal cost for each type of loan, I can run counterfactuals. I run a total of three counterfactuals. In the first, I estimate a counterfactual equivalent to breaking up the merged agencies and lenders, but not allowing borrowers to choose new loan products other than the outside option. All merged products are removed from the market so only the unmerged products are left; borrowers who previously chose merged products now choose the outside option. 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 pricing equation:

$$r^*_{klt} = \kappa_{klt} - \frac{s_{klt}}{\frac{\partial s_{klt}}{\partial r_{klt}}} - \sum_{j \neq k \in J_t} \frac{r_{jlt} - \kappa_{jlt} \frac{\partial s_{jlt}}{\partial r_{klt}}}{\frac{\partial s_{klt}}{\partial r_{klt}}} \tag{12}$$

In the second counterfactual, I again assume that the government has banned joint ownership, but now I allow the affected buyers to choose any product, instead of just the outside option. Again, I hold the mean utility parameters and all product characteristics other than rate fixed and re-solve the lender's problem. These first two counterfactuals, the main change is the composition of the consumer's choice sets, but the size is fairly constant.[19]

In the third counterfactual, I assume the government has allowed joint ownership, but now the lender cannot offer different products to consumers based on which real estate agency they chose, they must offer both products to all consumers. Thus, this counterfactual can be thought of as increasing the size of the choice set but all consumers keep the product they chose in the status quo in their choice set.

The results of these counterfactuals can be seen in Table 10. In each column, I report the weighted average of each product characteristics in that counterfactual as well as the utility implied. These values are weighted by the product market shares in that simulation. I also report the status quo for comparison.

Beginning with the first counterfactual, banning mergers but sending all affected consumers to the outside option decreases rates by 1 basis point on average. However, because consumers now choose products without the brand premium boost from joint ownership and with slightly lower unobservable quality, overall utility decreases slightly.

Moving to the last counterfactual, banning mergers but allowing consumers to pick between all options in the market and the outside option results in higher interests rates on average, increasing from 4.09% to 4.14%. However, buyers compensate for this by choosing products which close slightly faster, with higher unobservable characteristics (ξ increases from an average of 0.99 to 1.32), and from lenders which provide a higher brand premium. However, these positive characteristics are not enough to offset the disutility from a higher

[19] There are a handful of markets where the choice set does change size because the jointly owned lender does not offer both a jointly owned and a non-jointly owned product in that market, but correcting for this does not substantively change the results.

rate, so welfare decreases. The welfare decrease is equivalent to that from an interest rate increase of 0.3 basis points, or welfare loss \$9 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. In this instance, rates do not change relative to the status quo, but buyers substitute to different products. Fewer consumers choose the jointly owned product, 1% instead of 2%, but choose products with higher quality, faster closing, and more preferred lenders. This means that consumer welfare increases by \$18 on average.

Taken together these counterfactuals suggest that regulating the product offerings of lenders jointly owned with real estate agents would increase consumer welfare if it is done carefully. Simply banning mergers would harm consumers, but requiring all consumers be offered the same products rather than banning joint ownership increases consumer welfare on average.

Table 10: Counterfactual Results

	Status Quo	Merger Ban, No Re-Sort	Merger Ban	Competition
Interest Rate	4.09	4.08	4.14	4.11
		(0.01)	(0.01)	(0.01)
Time to Close	39.99	39.95	39.79	39.64
		(0.19)	(0.23)	(0.33)
Jointly Owned	0.02	0.00	0.00	0.01
		(0.00)	(0.00)	(0.001)
ξ	0.99	0.96	1.32	1.21
		(0.19)	(0.16)	(0.18)
Lender FE	44.65	44.68	44.73	44.69
		(0.03)	(0.05)	(0.04)
Utility	11.09	11.05	11.06	11.15
		(0.19)	(0.21)	(0.18)
Equivalent Rate Change(bp)		0.5	0.3	-0.7
		(0.34)	(0.29)	(0.69)
Utility Change (Dollars)		-12	-9	18
		(23)	(16)	(35)

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 150 random samples at market level

11 Conclusion

In this paper, I construct a novel data set of home purchases matched to the loans which funded them, and exploit the 100+ mergers I hand-matched to examine the consequences of jointly owned real estate agencies and mortgage lenders which has been previously unstudied in the literature. Of these more than 100 mergers, 87 occur between real estate agencies and indirectly integrate a lender with one of the two agencies. I use this indirect integration in a staggered difference-in-differences design to analyze the consequences of joint ownership between real estate agencies and mortgage lenders for lenders and borrowers.

Beginning with the effects on market share, I find that joint ownership has a small impacts on a lender's market share in a CBSA, and larger effects on their market share within sibling residential real estate agencies. This suggests that when an agency and a lender share a parent company, the agent directs clients to her sibling lender, and this increases the lender's market share. While this increase in market share represents a significant increase in market share for the lender, the effect on overall market competition is small.

Third, after documenting that mergers change the lender chosen by buyers using a merged real estate agency, I investigate if interest rates change as a result of using a jointly owned agency-lender pair, and I find that borrowers going directly to a lender pay 9 basis points more in interest than borrowers with similar characteristics did before the merger, even when the lender was recommended by the agency in both cases, so search intensity has not changed.

Fourth, I examine if mergers facilitate easier communication between agencies and lenders, leading buyers close on their mortgage faster, which buyers may be willing to pay for. While I find a two day reduction in the time to close, this is small relative to the average time to close. Furthermore, there is only slight evidence that joint ownership decreases the probability of an unusually long time to close. I therefore conclude that joint ownership does not get home buyers into their homes faster.

Fifth, I examine how mergers change borrower characteristics. By strengthening the ties between lenders and agencies, mergers could facilitate information exchanges which benefit marginally qualified borrowers or result in jointly owned lenders taking only the best borrowers ("cream-skimming"). When looking at FICO score, LTV, and loan amount, I find no large significant effects. The fact that lenders do not change behavior with respect to FICO and LTV scores is consistent with the fact that these are GSE-insured loans where little of the riskiness of the borrower is borne by the lender. Similarly, I find no evidence of differential loan performance after origination.

Finally, 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. Using a logit demand model for mortgages, I estimate mean utility parameters for product characteristics which 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 couple this demand model with a supply model where lenders are profit maximizing, face exogenous marginal cost, and must choose an interest rate for each loan product. From this supply model paired with my demand model results, I recover marginal costs. I fail to reject that marginal cost is identical for merged and non-merged loans. Using this model, I next estimate three policy counterfactuals for what could happen if joint ownership between real estate agencies and mortgage lenders were further regulated.

In the first counterfactual, I assume that joint ownership is banned and force all of the buyers choosing jointly owned loan products to choose the outside option. In this case, interest rates fall, but so does average utility. In the second counterfactual, I again assume joint ownership is banned, but now consumers can re-sort among all products, not just consumers who previously chose jointly owned products, and not just to the outside option. In this case, the decrease in competition increases interest rates, but consumers are able to choose products that have other desirable characteristics, so while utility falls, it falls by less than in the first counterfactual. In the third and final counterfactual, I assume that joint ownership is permitted, but that jointly owned lenders must offer all their products to consumers, regardless of real estate agency chosen. In this case, prices go up very slightly, but consumers choose products with other characteristics, that overall utility and welfare go up by $18 per person on average.

These results open several avenues of future research. First, there could be heterogeneous effects by borrower characteristics; perhaps first-time, minority, and/or female borrowers are impacted differently than other borrowers. Second, understanding how agencies recommend lenders, independent of common ownership is important to understanding this market. Third, local market conditions may make change the ability of conglomerate lenders to adjust their prices, and thus change the penalty impacted borrowers pay. Extensions to the model would incorporate limited consideration sets for buyers, or more complex or dynamic pricing decisions by lenders. I leave these analyses to future papers. Finally, the data set I constructed for this project are useful for other projects which may want to link loans and the associated home purchase, or which want to exploit variation in corporate ownership structure of real estate firms over time.

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A Matching 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 data sets, and attempt to mere them on address.

This gives me a data set of basic property characteristics merged to the MLS data. Now, I can merge the data to the CoreLogic Mortgage data. This merge is an imperfect merge on APN number, FIPS, and tax account number. However, as this is not a unique match, I restrict this sample to cases where the ownership data match.

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. Thus, this is a very inexact match. 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, this process is an iterative match. 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 Model Results

Below are the first stage results for the instrumental variables in the logit demand. I use one instruments: the 10-year Treasury Rate interacted with the number of lenders in the market.

The results of this estimation are reported below. The coefficient on *Merged Pair* is positive but insignificant, which is consistent with the reduced form results. Furthermore, the

Table 11: First Stage

	Interest Rate
Treasury Rate * Num. Lenders	0.004***
	(0.0002)
Jointly Owned Pair	0.016
	(0.016)
Time to Close	−0.001***
	(0.0002)
FE	Lender
F-Statistic	40
Observations	162,667
R^2	0.200

* 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.

C 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. In general, the results are robust to this change in specification: 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 C. Here, the coefficient on $Treat * Post_{jlt}$ is positive and significant in my main sample, but not when looking at all loans. This 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.

Table 12: Time to Close

	Days	30+ Days	45+ Days	60+ Days
Mean	42.0	0.72	0.35	0.16
Treat*Post	-2.0***	-0.034***	-0.032*	-0.014
	(0.54)	(0.013)	(0.019)	(0.011)
Treat	1.6**	0.035**	0.025	-0.0012
	(0.61)	(0.014)	(0.022)	(0.013)
FE	CBSA,Year	CBSA,Year	CBSA,Year	CBSA,Year
	Lender,Agency	Lender,Agency	Lender,Agency	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 13: 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	-8,213	-0.55	3.1*	-0.0072	0.0051	0.0012
	(5,923)	(0.71)	(1.8)	(0.011)	(0.0062)	(0.0043)
Treat	2,692	0.28	-2.1	0.016	-0.0067	-0.0076
	(6,431)	(0.74)	(2.1)	(0.013)	(0.0084)	(0.0062)
FICO*LTV				-0.000025***	-0.000022***	-0.000019***
				(5.3e-07)	(4.1e-07)	(3.6e-07)
FICO Score				0.00053***	0.00087***	0.00083***
				(0.000047)	(0.000036)	(0.000031)
LTV				0.020***	0.017***	0.015***
				(0.00041)	(0.00032)	(0.00028)
FE	CBSA,Year	CBSA,Year	CBSA,Year	CBSA,Year	CBSA,Year	CBSA,Year
	Lender,Agency	Lender,Agency	Lender,Agency	Lender,Agency	Lender,Agency	Lender,Agency
R-squared	0.52	0.20	0.18	0.16	0.14	0.13
N	846,338	1,189,050	1,096,155	1,095,983	1,095,983	1,095,983

* 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 14: Interest Rate (Mean = 4.09%)

	(1)	(2)
Treat*Post	0.026	0.054*
	(0.032)	(0.030)
Treat	-0.021	-0.041*
	(0.033)	(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***	-0.032
	(0.009)	(0.034)
Sample	All	All
FE	CBSA,Year	CBSA,Year
	Lender,Agency	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.

D Robustness Checks

D.1 Placebo Test

In Table 5, I show that the effect is statistically significant for buyers who use the retail distribution channel. This is 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 similar logic, buyers who use a mortgage broker should be the least captured by a merged pair, and thus, I would not expect to see an effect on the interest rate. To that end, running my specification on buyers who use the mortgage broker distribution channel is a placebo test for my results.

I report that specification in Table 15. 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* after the merger. These results are consistent with the story I have put forth.

D.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 not exposed to a merged lender-agent pair. I have shown in Section 7.5 that on observable borrower characteristics that are plausibly determined prior to the loan contract (namely, loan amount, FICO score, and loan-to-value ratio), borrowers do not differ substantially in most respects. However, it is possible that borrowers change their behavior within the loan contract. Specifically, in deciding to pay discount points. Borrowers can decide to pay points at origination, where they trade an upfront fee (called "points") in exchange for lowering the interest rate on the

Table 15: 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	Mtg.Broker
FE	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.

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 merger are paying fewer points than their pre-merger counterparts, that would appear as higher interest rates post-merger, which is not truly a consequence of the joint ownership.

Unfortunately, the LLMA data do not include points paid. However, due to a rule change, points paid are reported in HMDA data beginning in 2018. Thus, for the last two years of my data, I can merge in HMDA and observe both the interest rate and points paid. Due to the small nature of this sample, I am not able to restrict to just agent referred buyers, however earlier versions of my results were robust to either sample, so that is not driving these results.

In Table 16, 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, points paid cannot explain my main results.

Table 16: Discount Points

	(1)	(2)	(3)	(4)
Treat*Post	1.2e-08	1.4e-08	-2.3e-09	-6.0e-09
	(4.8e-08)	(5.6e-08)	(5.8e-08)	(5.8e-08)
Treat	-1.9e-08	-2.3e-08	-7.4e-09	-2.4e-09
	(4.7e-08)	(5.5e-08)	(5.8e-08)	(5.8e-08)
FICO*LTV		6.4e-12***		9.3e-12***
		(5.7e-13)		(6.5e-13)
FICO		-7.6e-10***		-9.4e-10***
		(5.1e-11)		(5.8e-11)
LTV		-6.0e-09***		-8.1e-09***
		(4.3e-10)		(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.

D.3 Total Origination Costs

Similarly to the discussion above, 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. Thus, for the last two years of my data I can test for differences in total origination costs by merged and unmerged lender-agent pairs.

I report these results in Table 17. 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. This continues to be true when including credit score, loan-to-value ratio, and their interaction in column (2) and 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. In short, origination costs do not explain the interest rate effects I find in Table 5.

Table 17: Total Origination Costs

	(1)	(2)	(3)	(4)
Treat*Post	251	84	185	39
	(317)	(379)	(459)	(455)
Treat	-223	-82	-204	-94
	(308)	(364)	(440)	(433)
FICO*LTV		-0.19***		-0.22***
		(0.0049)		(0.0057)
FICO		12***		16***
		(0.42)		(0.48)
LTV		165***		188***
		(3.7)		(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.

D.4 Only Agency-Agency Mergers

One concern about my identification strategy is that mergers are not exogenous. Specifically, residential real estate agencies and mortgage lenders will strategically decide to merge. In other words, mergers not occur randomly.

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 happens to 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. These results can be found in Table 18. As can be seen, if anything the results are stronger than my main specification. Thus, this cannot explain the results.

Table 18: Only Exogenous Mergers

	(1)	(2)	(3)	(4)
	Lender CBSA Share	Within Agency Share	Interest Rate	Interest Rate, Retail Only
Treat*Post	0.0072**	0.14***	0.086***	0.089***
	(0.0013)	(0.011)	(0.0091)	(0.014)
Treat		-0.0096	-0.093***	-0.090***
		(0.0082)	(0.014)	(0.016)
FICO*LTV			0.000041***	0.000041***
			(6.7e-07)	(7.5e-07)
FICO			-0.0049***	-0.0049***
			(0.000059)	(0.000067)
LTV			-0.030***	-0.030***
			(0.00052)	(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).

D.5 Stacked Event Study

A common way to study mergers retrospectively is to 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 about staggered DiD do not apply. This is similar to the approach taken in prior merger retrospective papers. 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, and who come from a county where I also observe the merging lender-agent pair. In other words, for each merger, my sample for that merger consists of all observations for a given merger as well as all observations from that county that are never treated. In this way, each merger-ID compares the effects of that merger to observations never treated by a merger that creates sibling lender-agent pairs. This specification avoids the issues of staggered difference-in-difference by giving each merger its own control group. I report the results of this for each of my main regression specifications in Table 19. Due to sample size, I omit the mortgage broker results.

As can be seen below, the results are largely consistent with the main specification, with the exception of the lender's CBSA market share. Now, this specification finds that lenders that merge with residential real estate agencies lose 0.53 percentage points of market share after merging, in contrast to the 0.54 percentage point gain found in my main specification. However, the result in column (2) that a lender's within-agency market share increases by 0.20 percentage points when they merge with a residential real estate agency is consistent with the main finding of 0.15 percentage points. Likewise, the positive but insignificant 5 basis point effect from using a merged lender-agent pair in column (3) and the significant effect of 11 basis points when restricting to only buyers going directly to the lender in column

(4) mirror the results in the main section of the paper.

With the exception of the lender CBSA market shares, the results in Table 19 are stronger than my main results. However, as this is dependent on the particular control group used, I choose to keep this as a robustness check instead of as the main specification.

Table 19: Stacked Event Study

	(1)	(2)	(3)	(4)
Dependent Variable	CBSA Share	Agency Share	Rate	Rate
Treat*Post	-0.0053*	0.20***	0.055	0.11***
	(0.0030)	(0.013)	(0.047)	(0.031)
Treat		0.015**	-0.047	-0.091***
		(0.0069)	(0.046)	(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).

D.6 Additional Fixed Effects

Below, I report the interest rate result using CBSAxYear fixed effects, FIPSxYear 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 20: FIPS-Year Fixed Effects

	(1)	(2)	(3)	(4)
Treat*Post	0.021	0.037	0.069**	0.079***
	(0.039)	(0.036)	(0.028)	(0.025)
Treat	-0.0085	-0.019	-0.040	-0.052**
	(0.039)	(0.037)	(0.029)	(0.026)
FICO*LTV		-0.000012***		0.00004***
		(1.5e-06)		(7.4e-07)
FICO		0.00018		-0.0049***
		(0.00013)		(0.00007)
LTV		0.011***		-0.030***
		(0.0011)		(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 FIPSxYear, FIPS, Year, Lender, Agency.

Table 21: CBSAxYear Fixed Effects

	(1)	(2)	(3)	(4)
Treat*Post	0.020	0.044	0.071**	0.081***
	(0.040)	(0.034)	(0.028)	(0.024)
Treat	-0.0088	-0.024	-0.041	-0.053**
	(0.040)	(0.035)	(0.029)	(0.026)
FICO*LTV		0.000041***		0.000042***
		(6.5e-07)		(7.4e-07)
FICO		-0.0049***		-0.0049***
		(0.000057)		(0.000066)
LTV		-0.030***		-0.030***
		(0.00050)		(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 22: ZipxYear Fixed Effects

	(1)	(2)	(3)	(4)
Treat*Post	0.036	0.053*	0.074***	0.087***
	(0.042)	(0.031)	(0.019)	(0.015)
Treat	-0.033	-0.050	-0.056**	-0.067***
	(0.044)	(0.034)	(0.028)	(0.025)
FICO*LTV		0.000039***		0.000039***
		(9.2e-07)		(1.0e-06)
FICO		-0.0047***		-0.0047***
		(0.000081)		(0.000091)
LTV		-0.028***		-0.028***
		(0.00070)		(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.