Referral Lending and Mortgage Market Power: The Role of Realtors

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Abstract

This paper examines realtor-loan officer referral networks as a key source of mortgage market power. Despite the high level of competition in mortgage lending, significant price dispersion persists. We argue that realtors steer homebuyers toward a limited set of loan officers, restricting borrower choice even in competitive markets. Using a unique dataset that maps the entire realtor-loan officer network across 17 states and Washington, D.C., we document substantial concentration within these networks, with 85% of realtors likely referring their clients to a limited number of loan officers. Borrowers who work with high-concentration realtors pay 12 basis points higher mortgage rates, even after controlling for borrower and mortgage characteristics. Instrumental variable (IV) estimates confirm that referral-driven constraints impose a premium of 19.7 basis points (equivalent to \$2,722 in upfront costs) on homebuyers who choose referred loan officers. This premium primarily results from suboptimal lender selection and is particularly severe for Black, Hispanic, and financially constrained borrowers. While referred loan officers might improve the likelihood of mortgage approval and expedite mortgage processing (by 0.45 days), these benefits do not fully justify the higher borrowing costs. Our findings suggest that realtor referral networks reinforce mortgage market power, imposing significant financial burdens and raising equity concerns for borrowers.

Keywords: realtors, mortgage brokers, network, steering

JEL Classification Codes: L91, R13, R21

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1 Introduction

In the U.S. mortgage market, numerous studies have documented a significant price dispersion in mortgage rates (Bhutta et al., Forthcoming; Alexandrov and Koulayev, 2018), suggesting that mortgage lenders possess a certain degree of market power. However, the mortgage lending market is considered highly competitive, and existing literature has failed to find a relationship between mortgage rates and the concentration of local lender markets (Amel et al., 2018; Buchak and Jorring, 2021). This raises a fundamental question: What is the source of mortgage lenders' market power? We argue that a significant portion of this power originates in the home purchase process, which is largely intermediated by real estate agents, or realtors. Many realtors refer homebuyers to a limited set of loan officers,¹ effectively funneling them into a concentrated choice set of lenders, even in highly competitive lending markets.

Buying a home is one of the most complicated transactions that individuals undertake. Unlike most consumer purchases, housing transactions typically involve multiple intermediaries to help homebuyers navigate the intricate and high-stakes processes of purchasing a home. In the U.S., approximately 80% of home transactions involve realtors, contributing to a total transaction volume exceeding \$2.5 trillion in 2023. Once the purchase contract is signed, most homebuyers must secure a mortgage to finalize the transaction. Realtors play a crucial role in influencing homebuyers' choices, including their selection of loan officers. More than half of homebuyers consider realtors' recommendations important when shopping for mortgages, according to the National Survey of Mortgage Originations. One might argue that these referrals benefit homebuyers by reducing search costs and streamlining the home purchase process. However, the majority of realtors have a select group of lenders to whom they typically refer their clients (FreddieMac, 2016).² Relying on this narrow pool of recommended lenders may limit buyers' options, potentially resulting in higher interest rates and increased overall homeownership costs.

This paper present, to our knowledge, the first systematic evidence and quantification of the scope and impact of the realtor-mortgage loan officer referral network, as well as its contribution to mortgage market power and price dispersion. Using a unique dataset that tracks 126,598 realtors and their associated 280,245 loan officers in 17 states and Washington D.C. from 2018 to 2021, we map out the entire referral network between realtors and mortgage loan officers, and document the prevalence of referral networks between realtors and loan officers. Realtors tend to collaborate with a limited number of loan officers, even after accounting for transaction volume, compared to the broader pool of active loan officers within local markets. To identify possible referral networks, we calculate the share of each realtor's transactions handled by individual loan officers and use these shares to compute the loan officer concentration threshold of 0.7, and 85% exceed the medium-concentration threshold of 0.4. These realtors facilitated 22% (80%) of mortgage-financed home purchases. More interestingly, the high concentration of loan officers within realtors' referral networks per-

¹We use "loan officers" to refer to both in-house loan officers of mortgage lenders, and independent mortgage brokers.

 $^{^{2}}$ FreddieMac (2016) shows 84% of real estate professionals maintain a preferred network of lenders to whom they typically refer their clients. Among them, 73% work with just one to three lenders, while 24% collaborate with four to six.

sists and even increases, in markets with greater lender competition. This pattern suggests that, despite the presence of many lender options, homebuyers' actual mortgage choices remain constrained by realtor referral practices.

Do homebuyers pay higher mortgage rates when working with realtors who have highly concentrated loan officer networks? OLS results suggest they do. Borrowers working with top-quintile realtors (by CR4) pay 24.4 basis points more than those with bottom-quintile realtors, with rate differentials decreasing monotonically as concentration declines. Even after controlling for borrower and mortgage characteristics (e.g., LTV, DTI, FICO), the differential remains significant at 12 basis points and continues to decrease monotonically with the realtor concentration measure. This pattern stands in stark contrast to the broader mortgage market, where interest rates do not vary significantly with market-level lender concentration. This suggests that one reason that broader market competition does not meaningfully influence mortgage pricing is that realtor-driven referral networks constrain borrowers from shopping across the full range of lenders available in their local market. Within-realtor concentration appears to be a more relevant measure of market power, directly contributing to higher financing costs for homebuyers.

Nevertheless, this evidence alone does not establish the causal impact of the realtor-loan officer referral network, as certain borrowers may self-select lenders regardless of realtor recommendations. Since these recommendations are generally unobservable to researchers, referral networks are challenging to detect, leading to potential measurement errors. This can introduce attenuation bias in OLS estimates and risk misclassifying borrower-preferred loan officers, who often have large market shares and offer low rates, as referred loan officers—thereby underestimating the referral network effect.

To address these identification challenges, we employ an instrumental variable (IV) strategy. The IV is based on a borrower-preference-adjusted measure of loan officer concentration at the realtor level, reflecting the underlying likelihood of referrals. The IV penalizes loan officers' within-realtor mortgage shares by borrowers' estimated preferences, derived from a BLP model, and uses the adjusted shares to construct loan officer concentration measures (CR4). IV estimates show that homebuyers working with realtors who have strong referral networks and who use referred loan officers pay 19.7 basis points higher mortgage rates. For an average homebuyer, this translates to an additional \$567.12 in annual interest payments or \$2,722 in upfront costs to buy down the rate to levels without a referral network. Furthermore, our analysis suggests that this premium is primarily driven by the suboptimal selection of mortgage lenders within the local market. However, even within the same lender, we observe a 6.3 basis point rate differential between referred and non-referred borrowers, which translates to \$870 in upfront costs. This finding indicates that the referral network effect is not solely about lender choice but may also involve other factors influencing loan terms.

We then conduct a heterogeneous treatment analysis, which reveals that the mortgage rate differentials are even more pronounced for specific groups. Black borrowers face a referral effect of 20.9 basis points (\$2,888), while Hispanic borrowers endure an even larger effect of 28.8 basis points (\$3,980). Financially constrained borrowers, such as those with down payments under 5% or DTI ratios above 45%, experience referral effects of 25.3 basis points (\$3,496) and 25.8 basis points (\$3,565), respectively. These findings

suggest that the referral network may exacerbate existing inequities in mortgage lending, disproportionately affecting borrowers who are already more vulnerable in the housing market.

One possible rationale for relying on realtor-referred loan officers is their ability to expedite mortgage processing, thereby reducing the risk of closing delays. We find that homebuyers who use referred loan officers close their home purchases 0.45 days faster compared to a baseline of 40.3 days. While borrowers may benefit from these modest improvements in timeline efficiency, this gain is insufficient to justify the potentially higher borrowing costs associated with referral networks.

Another potential justification is that higher referral mortgage costs compensate for approval certainty, preventing purchase failures. If so, the premium reflects certainty rather than market power, but closing dates alone cannot confirm this. To address this, we analyze high-quality borrowers with minimal denial risk. Even among those with FICO higher than 780, LTV not above 80%, and DTI not above 36%, referred loans remain 16 basis points more expensive, suggesting that the improved potential approval certainty does not justify the referral premium.

Our paper contributes to three strands of literature. First, it adds to the growing body of research on price dispersion and market power in the mortgage market. Numerous studies have documented significant dispersion in mortgage rates (Bhutta et al., Forthcoming, 2020a; Agarwal et al., 2024; Alexandrov and Koulayev, 2018). However, existing research does not find a significant cross-sectional relationship between mortgage rates and the concentration of local lender markets (Amel et al., 2018; Buchak and Jorring, 2021), shifting the literature's focus toward factors beyond market power in explaining mortgage price dispersion. For instance, (Bhutta et al., Forthcoming) examines borrower sophistication, while (Agarwal et al., 2024) attributes part of the price dispersion to the adverse selection of borrowers resulting from the costly mortgage approval process. Additionally, (Gurun et al., 2016) illustrates how deceptive advertising contributes to mortgage price dispersion. From a policy perspective, the absence of a clear link between mortgage rates and local lender concentration has led the Federal Reserve to treat mortgage markets as national in scope, and overlook the influence of the banks mergers on local mortgage market concentration.

Our paper identifies the missing link between mortgage price dispersion and lending concentration. Traditional market-level lender concentration measures fail to meaningfully explain mortgage rate dispersion because realtor-driven referral networks constrain borrowers from shopping across the full range of lenders available in their local market. In reality, the market power of mortgage lenders stems from the home purchase process itself: many realtors steer homebuyers toward a limited set of loan officers, effectively funneling them into a constrained choice set of lenders, even in markets where lender competition is high. Therefore, withinrealtor concentration serves as a more relevant measure of market power, directly contributing to higher financing costs for homebuyers. Our findings complement the work of Allen et al. (2014) and Allen et al. (2019), who study the more concentrated Canadian mortgage market and attribute lender market power to search frictions and brand loyalty.

Second, our paper is also related to the small literature on referral networks. There are limited numbers of papers on referral networks – with the exception of labor market (Pallais and Sands, 2016; Chen-Zion

and Rauch, 2020), health care (Ho and Pakes, 2014; O'Malley et al., 2021; Sarsons, 2024) and education (Card and Giuliano, 2016; Cestau et al., 2017) referral networks – partly due to the informal nature of referral networks and the difficulties of measuring them. We provide to our knowledge the first set of evidence on the realtor and mortgage lender referral network.

Finally, our paper advances the literature on realtors and mortgage brokers. The previous studies have found that mortgage brokers will increase the cost of financing (Ambrose and Conklin, 2014; LaCour-Little, 2009; Ernst et al., 2008) and steer the borrowers to high-rate or risky types of mortgages (Spader and Quercia, 2011; Berndt et al., 2010). Woodward and Hall (2010) and Woodward and Hall (2012) provide direct evidence showing mortgage brokers retain a substantial proportion of the "yield-spread premium" as their profit. Robles-Garcia (2020), however, argues that the brokerage network provides an alternative distribution channel for small, new lenders with a limited branch network and lower brand recognition to access consumers, thus increases the mortgage market competition. Agarwal et al. (2021) finds that sole brokers respond to financial regulatory oversight by applying a more stringent screening process in conducting brokerage activities, hence achieving better loan performance. All existing papers, with the exception of Jorgensen (2024), study realtors separately from mortgage brokers. Jorgensen (2024) focuses on the 100 vertical integration of realtors and mortgage brokers and shows that home borrowers experience an increase of 6 basis points in borrowing costs after the merger. Our paper differs from existing studies in that it constitutes the first attempt in the literature to map out the entire referral network between these two types of important intermediaries and investigate the implications of these referral networks on mortgage loan outcomes experienced by mortgage borrowers in addition to interest rates, including the duration of the mortgage application process and loan costs.

The remainder of the paper is structured as follows. Section 2 describes the data sources and provides institutional background on realtor–loan officer referral networks. Section 3 presents stylized empirical facts characterizing the structure and prevalence of these networks. Section 4 examines the implications of referral networks for homebuyers' financing costs. Section 5 explores potential justifications for the use of referral networks. Section 6 concludes with a discussion of policy implications.

2 Institutional Background and Data

2.1 Institutional Background

Realtors, or real estate agents, play a vital role in the buying and selling of homes in the U.S. Their responsibilities combine market expertise, negotiation skills, marketing strategies, and a thorough understanding of legal requirements in real estate transactions. Realtors are legally and ethically bound to prioritize their clients' interests, offering advice with honesty, integrity, and transparency. This commitment builds trust and ensures that buyers and sellers are well-protected throughout the process.

Mortgage loan officers, on the other hand, serve as intermediaries between borrowers and lenders, assisting clients in securing financing for home purchases. Their role involves guiding borrowers through every step of the mortgage process, from initial application to loan closing, ensuring a smooth and efficient experience.

Realtors and loan officers frequently collaborate during the home purchasing process. Realtors often refer clients to mortgage loan officers to facilitate financing, while mortgage loan officers may refer preapproved clients to realtors for property searches. This reciprocal referral system fosters a mutually beneficial relationship, driving business opportunities for both parties while enhancing the client experience.

While the Real Estate Settlement Procedures Act (RESPA) Section 8 prohibits kickbacks and unearned fees to realtors in mortgage lending, several common practices blur the line between realtors and loan officers. First, loan officers can give gifts to realtors. Although these gifts cannot be conditional on referrals, monitoring compliance is generally challenging. Second, loan officers can sponsor realtor events, providing financial support that may indirectly influence referral decisions.Finally, loan officers and realtors can engage in co-marketing, sharing advertising costs and potentially directing client flows in a way that raises compliance concerns. These practices create regulatory gray areas by potentially facilitating client steering from realtors to loan officers.

2.2 Data

CoreLogic Multiple Listings, Ownership Transfer, and Mortgage Data We link the CoreLogic Mortgage, Owner Transfer, and Multiple Listing Service (MLS) data products to create a panel of mortgages and their associated buyer agents. We restrict all datasets to records dated between July 1, 2017, and December 31, 2021. Geographically, we restrict to counties that meet three key criteria. First, over 80% of housing listings must originate from the same Multiple Listing Service (MLS), so we do not have to deal with cross listings on multiple platforms. Second, the dominant MLS must provide realtor IDs.³ Lastly, since we will need information on days to close after purchase contract is accepted (contract date), we restrict to counties where the dominant MLS include more than 50% of listings with non-missing fields for contract date. After applying all three filters, we are left with 559 counties from 17 states and Washington D.C.. Figure 1 highlights the counties on the map, and uses different colors to denote different MLSs.

We then proceed to clean the MLS data. First, we exclude rental listings and split property listings. Next, we group sequential listings for the same property that occur within 90 days into unique "listing events" to avoid duplication and capture only distinct sale attempts. Third, we retain only those listings that were successfully closed and financed with a mortgage. This restriction is necessary because, without a closed transaction, we cannot observe the buyer agent (realtor), and, without mortgage finance, we cannot observe the loan officer involved. Finally, we exclude transactions missing the loan officer's NMLS ID or buyer agent information in the MLS data, ensuring a reliable dataset.

³Surprisingly, many MLS systems lack buyer agent identifiers, which would force reliance on agent names instead—an approach that introduces significant challenges due to potential inconsistencies and ambiguities in name matching. By focusing on MLSs with complete buyer agent identifiers, we enhance the reliability and accuracy of the network construction process.

HMDA Data The detailed mortgage characteristics are from HMDA (Home Mortgage Disclosure Act), which report loan level information for the majority of mortgages in the U.S. The HMDA data underwent a significant transformation in 2018, resulting in a much more detailed disclosure of reported mortgages. Importantly, the new HMDA data includes mortgage interest rates, associated origination fees, as well as several additional attributes, such as loan-to-value ratio and debt-to-income ratio. We rely on HMDA panel data from 2018 through 2021 for our analyses.

We follow the standard method in the literature, and merge the originated HMDA mortgages with Core-Logic mortgage data with the overlapping information, i.e., lender name, loan amount, and property census tract. We focus on high-quality matches by only keeping the one-to-one matches.

Our core sample consists of mortgage-financed home purchases that were successfully matched to the HMDA data. It includes 1.53 million transactions, intermediated by 126,598 realtors.

Fannie Mae, Freddie Mac, Ginnie Mae Loan Performance Data In additional analyses, we incorporate borrower FICO score information from three major public institutions: Fannie Mae, Freddie Mac, and Ginnie Mae. Together, these entities guarantee over 70% of U.S. mortgages and publicly release origination and performance data—including credit scores—for securitized loans.

We merge this loan performance data with our core sample using overlapping mortgage characteristics. Approximately 40% of the mortgages in the core sample can be successfully matched to the loan performance data. We refer to this matched subsample as the "GSE sample" for the purpose of robustness analysis.

2.3 Summary Statistics

Table 1 presents summary statistics for the home purchase data used in this study. Column (1) reports statistics for the full sample. The upper panel summarizes the characteristics of realtors. On average, a realtor facilitates 34 mortgage-financed home purchases and collaborates with 18 loan officers.

The lower panel provides summary statistics on homebuyers and mortgages. The average home purchase price is \$331K, with an average house size of 2,111 ft^2 , 3.4 bedrooms, 2.5 bathrooms, and an average house age of 41 years. The average time to close (after the purchase contract is signed) is 40.94 days.

For mortgage characteristics, the average loan amount is \$288K. The average interest rate spread (relative to the benchmark rate for prime loans of comparable type) is 45 basis points. The average annual percentage rate (APR) spread, which incorporates origination fees and discount points, is 54 basis points. The average loan-to-value (LTV) ratio is 89%, and the average debt-to-income (DTI) ratio is 35%.

Regarding homebuyer demographics, the average buyer earns 1.46 times the median income of their county. Thirty-three percent of buyers are from minority groups, including 10% Black, 15% Hispanic, and 6% Asian. In the GSE sample, where mortgages are matched to performance data from government-sponsored enterprises, we also observe borrower credit scores. The average FICO score in this sample is 739.

3 Realtor-Loan Officer Referral Network

Since we cannot directly observe the referral actions between realtors and loan officers—such as explicit recommendations or referral agreements—we instead infer the existence of referral networks by examining the concentration of loan officer portfolios within individual realtors. The underlying logic is that, in the absence of steering, homebuyers would be expected to choose their mortgage lenders relatively independently, resulting in a more dispersed pattern of loan officer selection across a realtor's client base.

However, if a disproportionate share of a realtor's clients obtain financing from a small and recurring subset of loan officers, this suggests that the realtor may be systematically guiding clients toward certain loan officers. Such concentration serves as a proxy for referral behavior, capturing the degree to which a realtor's transactions are funneled through a limited set of financing channels.

Thus, we interpret high within-realtor concentration in loan officer usage (*CR*4 or *HHI*) as evidence of potential referral networks. This approach allows us to identify the realtor-loan officer refferral network, even in the absence of directly observable referral actions.

3.1 Prevalence of Referral Networks

Figure 2 presents the distribution of loan officer concentration measures for the 92,343 realtors in our sample. Panel (a) focuses on the four-firm concentration ratio (CR4), revealing substantial concentration within realtor-loan officer networks. Notably, 28% of realtors have a CR4 exceeding 0.7, meeting the conventional threshold for high concentration, while 85% exceed the medium-concentration threshold of 0.4.

The market relevance of these networks is further illustrated in Table 1. Realtors with high *CR*4 values facilitate 22% of all mortgage-financed home purchases in the sample, while those with medium concentration levels account for an additional 58%. These figures underscore not only the widespread presence of concentrated referral practices, but also their substantial footprint in the mortgage market. This raises important questions about the degree to which referral networks may shape lender competition, borrower choice, and ultimately, borrowing costs.

Panel (b) examines an alternative measure of concentration, the Herfindahl–Hirschman Index (*HHI*). The results mirror those of the *CR*4 metric: 39% of realtors exhibit an *HHI* above 1800, the benchmark for high market concentration, while 73% exceed the medium threshold of 1000. These consistent findings across both concentration measures reinforce the conclusion that referral networks are not only prevalent but also significantly concentrated.

Together, these results suggest that the structure of borrower-lender intermediation is far from neutral. The pervasiveness of such concentrated networks warrants deeper investigation into their implications for market efficiency, equity in borrower outcomes, and the distribution of market power within mortgage origination.

3.2 Characteristics of Realtors, Loan Officers, and Homebuyers in Referral Networks

Table 1, Columns (2)–(4), presents summary statistics for home purchases facilitated by realtors with high, medium, and low loan officer concentration, respectively. These groupings allow us to explore how the structure and composition of referral networks vary across different levels of intermediation intensity.

The upper panel summarizes characteristics of realtors. On average, a realtor facilitates 34 mortgagefinanced home purchases and works with 18 loan officers. Importantly, realtors with a lower transaction volume tend to exhibit higher loan officer concentration, suggesting that less active realtors are more reliant on a stable set of lending partners. This pattern is consistent with the idea that smaller-scale realtors may lack the visibility or client base to attract a wide range of lender relationships, and thus rely more heavily on established personal connections with specific loan officers. These tighter networks may also reflect long-term trust or informal arrangements that evolve in the absence of institutional oversight.

The middle panel provides descriptive statistics for the top four loan officers associated with each realtor, ranked by transaction volume. For realtors in the high-concentration group (high CR4), these top loan officers are especially likely to be mortgage brokers rather than bank employees or representatives of large national lenders. This pattern suggests that realtors with strong referral networks prefer loan officers who are more dependent on realtor-originated business. Mortgage brokers, in contrast to bank-affiliated officers, often lack direct consumer marketing channels, brand awareness, or established institutional pipelines, making them more reliant on external referrals to drive volume.

Conversely, loan officers affiliated with banks and large lenders are less prevalent in high-CR4 networks. These institutions can tap into existing client relationships through deposit accounts, cross-sold financial products, or employer-based partnerships, reducing their reliance on realtors as gatekeepers to borrower demand. This structural difference between broker-based and institutional lending models underscores the economic motivations behind referral dynamics and helps explain why certain types of loan officers are more embedded in high-concentration networks.

The lower panel describes the characteristics of homebuyers, stratified by the referral network strength of their realtors. Several important patterns emerge. First, homebuyers served by high-referral-concentration realtors tend to pay higher interest rates, despite receiving somewhat faster mortgage processing times. This tradeoff—between financial cost and processing efficiency—is explored in detail later in the paper.

Second, and perhaps more striking, are the socioeconomic and demographic patterns. Homebuyers associated with strong referral networks have lower relative incomes, as measured by their income-to-countymedian ratio, and tend to purchase less expensive, smaller, and older homes. These patterns suggest that referral-dependent lending is more prevalent among financially constrained households, who may face greater barriers to shopping broadly for mortgage financing.

Additionally, the data reveal that minority borrowers, particularly Hispanic homebuyers, are more likely to be represented in high-concentration referral networks. This may reflect multiple underlying mechanisms: reliance on community-based networks, language and informational barriers, or a higher level of trust in intermediaries such as realtors who share cultural or community ties. In such cases, the realtor may serve not only as a housing market intermediary but also as a key financial gatekeeper, shaping access to mortgage products and influencing borrowing outcomes.

3.3 Market-Level vs. Realtor-Level Lender Concentration

Figure 3 illustrates the relationship between market size, lender concentration, and within-realtor loan officer concentration. For each market (defined at the county-year level), we compute two measures: the average loan officer CR4 across all realtors (plotted as red dots in 100-binned scatter plots) and the market-level lender concentration (CR4) (plotted as blue triangles). This comparison allows us to disentangle the dynamics of lender competition at the market level from the concentration patterns embedded in realtor referral networks.

According to standard textbook entry models in industrial organization, as market size increases, entry by new firms intensifies competition, reducing market concentration. Consistent with this theory, we expect overall lender concentration to decline in larger markets, where more homebuyers attract more lenders, thereby weakening any single lender's market power. If realtors did not influence borrower-lender matches, we would expect a similar pattern within each realtor's network: as markets expand, within-realtor loan officer concentration should also decline, reflecting broader lender availability and borrower choice.

Panel (a) of Figure 3 confirms the decline in market-level lender concentration as the number of mortgage originations rises. This suggests that larger mortgage markets foster increased lender entry and competition, providing borrowers with more choices. At first glance, this appears to validate policies that focus on expanding market participation to erode lender market power.

However, when we shift focus from the market level to the realtor-borrower level, a different pattern emerges. Conditional on working with a given realtor, borrowers' loan officer choices remain highly concentrated, regardless of market size. In fact, within-realtor concentration increases with market size, contrary to the prediction of standard competition models. This indicates that in larger markets, a small subset of loan officers tends to dominate referral channels within realtor networks. Rather than matching with a broader pool of lenders, borrowers are steered toward a narrow set of preferred loan officers—implying that the competitive effects of larger markets are dampened by intermediary behavior.

Panel (b) presents a similar analysis, this time sorting markets by the number of active lenders rather than transaction volume. The pattern remains consistent: as the number of lenders increases, market-level lender concentration declines, consistent with rising competition. Yet, within-realtor loan officer concentration remains persistently high—and again, tends to increase in larger lender markets. These findings indicate that referral patterns are not merely a function of available market options; rather, they are shaped by institution-alized relationships between realtors and a subset of loan officers, who maintain dominant positions even in highly competitive environments.

These results carry important implications for mortgage market regulation and policy. Conventional antitrust and consumer protection strategies often focus on reducing market concentration by encouraging lender entry, assuming that broader participation will naturally weaken monopoly power. However, our findings suggest that such efforts may be insufficient. If realtor-driven referral networks persistently steer borrowers toward a narrow set of loan officers, then increasing the number of lenders does not guarantee greater borrower choice or improved mortgage pricing.

In this context, realtor-loan officer referral networks act as bottlenecks in the distribution of mortgage financing. They undermine the competitive potential of large markets by constraining borrower access to the full range of available lenders. As a result, policies aimed at enhancing transparency, limiting referral-based conflicts of interest, or improving borrower autonomy in lender selection may be more effective at curbing market power than those focusing solely on lender-side competition. The evidence thus points to a need for a more nuanced regulatory approach—one that addresses the intermediated structure of choice in mortgage markets.

3.4 Mortgage Interest Rates By Loan Officer Concentration of Realtors

To test the relevance of referral networks on borrowing costs, we first compare interest rates for transactions handled by realtors with more-concentrated lender networks versus those with less-concentrated networks, controlling for aggregate trends in interest rates and characteristics of loans, borrowers, and lenders. Using our sample of purchase mortgages, we estimate the following equation:

$$Y_{irl} = \sum_{q=2}^{5} \alpha_q Quintile_q(CR4_r) + X'_{irl}\gamma + \varepsilon_{irl}$$
(1)

Where mortgage *i* is associated with a loan officer *l* and realtor (buyer agent) *r*. *CR*4_{*r*} measures the level of concentration of realtor *r*'s loan officer network. The coefficients of interest, α_q , capture the differences in outcomes (*Y*_{*irl*}) between more-concentrated realtors and the omitted group of realtors (the bottom quintile in terms of *CR*4 in our baseline specifications). For outcomes (*Y*_{*irl*}), we examine the interest rate spread relative to the benchmark rate offered on prime mortgage loans of comparable types. The control variables (*X*_{*irl*}) include aggregate trends in interest rates (county*year-month fixed effects), borrower characteristics (e.g., income, age, and FICO score in additional analysis), and loan characteristics (e.g., loan amount, LTV, DTI, and a conforming loan dummy).⁴ This analysis focuses on first-lien, 30-year fixed-rate mortgages for owner-occupied, single-family, site-built properties, ensuring a consistent and relevant sample for examining these outcomes.

Table 2 presents estimates of Equation (1), examining the relationship between realtor-level loan officer concentration and mortgage interest rates.

Column (1) reports the raw differences in interest rate spreads across realtors segmented by the concentration of their loan officer networks. Borrowers working with top-quintile realtors (ranked by CR4) pay, on

⁴Applicant age bin FE include FE for the age bins reported in HMDA: <25, 25-34, 35-44, 45-54, 55-64, 65-74, >74. We define LTV ratio bins as 0-20, 20-40, 40-60, 60-80, 80-100, or 100+. For the GSE-matched sample, we group FICO scores into bins of approximately 40 points and include FE for these bins.

average, 24.4 basis points more than those working with bottom-quintile realtors. Moreover, the interest rate differential declines monotonically with decreasing loan officer concentration, providing suggestive evidence that greater within-realtor concentration is associated with higher borrowing costs.

To test the robustness of this pattern, we sequentially introduce control variables across columns. These include market-level fixed effects, borrower demographics (e.g., income, age), and loan characteristics (e.g., loan-to-value (LTV) and debt-to-income (DTI) ratios). By Column (5)—our baseline specification—we still observe a statistically and economically significant difference: borrowers working with top-quintile agents pay, on average, 11.9 basis points more than those working with bottom-quintile agents.

Given the average loan amount of \$287,880 in our sample, this 11.9 basis point premium translates into an additional \$343 in annual interest payments. Alternatively, to obtain the same lower interest rate as borrowers working with bottom-quintile realtors, a borrower would need to pay \$1,644 in upfront fees, assuming a point-to-rate reduction factor of 4.8 as estimated in Bhutta et al. (2020b). These results underscore the financial costs of participating in highly concentrated referral networks and highlight the potential for non-transparent steering to materially affect borrower outcomes.

In Column (6), we restrict the analysis to the GSE-matched sample, where mortgages are linked to loan performance data from Fannie Mae, Freddie Mac, and Ginnie Mae, allowing us to control for FICO scores. While the match rate is approximately 40%, the inclusion of FICO scores has little effect on the magnitude or significance of the estimated interest rate differential. This suggests that the observed pricing disparities are not primarily driven by differences in borrower creditworthiness. To maintain statistical power and broader generalizability, we continue using the core sample for the subsequent regression analyses.

3.5 Comparison with Market-Level Lender Concentration

Figure 4 visually compares the relationship between interest rate spreads and concentration measures at two different levels: within-realtor (Panel a) and market-wide (Panel b).

In Panel (a), we plot the results using within-realtor *CR*4 as the concentration metric. The black lines—both dotted and solid—represent estimates from the core sample, following the regression specifications in Table 2. The red line represents the GSE-matched sample results, which include FICO score bin fixed effects to further control for borrower risk profiles. The consistency between these specifications confirms that the absence of FICO scores in the core sample does not materially bias the findings.

By contrast, Panel (b) considers market-wide lender CR4. Here, we observe no systematic relationship between lender concentration and mortgage pricing, suggesting that broad market competition has little influence on borrower-level outcomes. This result echoes prior findings in Buchak and Jorring (2021) and Amel et al. (2018), both of which documented weak or insignificant effects of market-level lender concentration on mortgage interest rates.

These findings carry important policy implications. The Federal Reserve and other regulators often treat mortgage markets as national in scope, assuming that lender competition occurs across broad geographic boundaries. Consequently, local market concentration is viewed as largely irrelevant for assessing market power. However, this perspective may miss a key structural feature of mortgage intermediation: the persistence of referral-driven concentration within realtor networks.

Even in markets with numerous competing lenders, realtor-driven steering may constrain borrower choice, leading to persistent concentration in loan officer relationships. Thus, regulatory efforts that focus solely on promoting lender entry and aggregate market competition may fail to improve borrower outcomes if intermediaries continue to limit access to the broader set of financing options. These results call for greater regulatory attention to the microstructure of referral networks and the institutional incentives that sustain them.

4 Implication of the Referral Network on Mortgage Rates

The preceding evidence indicates that realtor-loan officer referral networks have a tangible effect on homebuyers' financing costs. In this section, we aim to quantify the causal impact of these referral networks on mortgage interest rates, thereby providing direct evidence on how intermediary relationships can shape borrower outcomes in the mortgage market.

4.1 OLS Regressions

Motivated by the results in Section 3, we use the following indictor to capture referral network between realtor r and loan officer l,

$$Referral_{rl} = \begin{cases} 1 & \text{if } CR4_r \ge 0.7 \text{ and } l \text{ is a top 4 loan officer} \\ 0 & \text{otherwise.} \end{cases}$$
(2)

A $CR4_r \ge 0.7$ indicates that the realtor has a high degree of loan officer concentration, strongly suggesting the existence of a referral network. The second condition, where the homebuyer opts to borrow through one of the top 4 loan officer *l*, implies that the homebuyer likely follows the realtor's recommendation to use a referred loan officer. Together, these conditions provide evidence of referral practices influencing the borrower's choice of lender.

With this single indicator of referral network, we can estimate the referral effect using the following specification:

$$Y_{irl} = \alpha Referral_{rl} + X'_{irl}\delta + \varepsilon_{irl}$$
(3)

Table 3 presents the estimation results for the effect of realtor-loan officer referrals on mortgage costs, based on specification (3). Column (1) estimates the interest rate spread by regressing it solely on the referral indicator, yielding an effect of 9.3 basis points. In this specification, the control group includes all borrowers working with realtors who have low to medium loan officer concentrations, some of whom may still be influenced by referral networks. As such, the estimate in Column (1) likely represents a lower bound for the

referral effect. To improve statistical power, Column (3) refines the analysis by isolating "likely referrals," defined as mortgages processed by one of a realtor's top four loan officers in cases where the realtor has medium loan officer concentration. This more targeted approach increases the estimated referral effect to 12.1 basis points, underscoring the impact of referral networks on borrower costs. Column (5) utilizes the GSE-matched sample and incorporates FICO scores as additional controls. The results remain highly consistent with those from the core sample.

4.1.1 Suboptimal Choice of Lenders or Other Factors

In Table 3, Column (2) incorporates market*lender fixed effects, enabling a comparison of mortgages closed by referred loan officers with non-referred mortgages from the same lender. Even with this control, we find a 2.8-basis-point referral effect within the same lender, indicating that part of the cost differential is due to borrowers being referred to specific loan officers ("wrong loan officers") rather than potentially more competitive alternatives within the same lender.

The majority of the referral effect, however, stems from the suboptimal selection of lenders ("wrong lenders"), which accounts for most of the observed cost differential. This indicates that the higher borrowing costs associated with referred loan officers are primarily driven by borrowers being directed to less competitive lenders. These findings suggest that borrowers could reduce their mortgage costs by putting more effort into shopping for the best lender, rather than relying on referrals alone.

4.1.2 Mortgage Origination Costs

Columns (7)-(10) focus on the APR spread, which accounts for both the mortgage rate and origination costs. The results indicate a referral effect that is 0.8–1.2 basis points higher than the effect observed on interest rates alone. This incremental effect arises from differences in mortgage origination costs, such as higher processing fees or reduced lender credits for borrowers who use referred loan officers. These findings suggest that referral networks not only affect interest rates but also contribute to higher overall borrowing costs through additional fees.

4.2 Identification through an IV Approach

The estimates from the OLS regressions alone are insufficient to establish the causal impact of the realtor-loan officer referral network due to potential measurement errors in identifying the referral network. Misclassification or alternative explanations for observed patterns in borrowing behavior could bias the results and obscure the true effect.

For instance, consistently observing that a realtor's clients borrow from a small group of loan officers does not necessarily indicate the existence of a referral network. Such patterns might instead be explained by other factors. One possibility is market dominance, where the bank affiliated with these loan officers holds a

dominant position in the local market. In this case, borrowers may naturally gravitate toward the loan officers from that bank, irrespective of any realtor recommendations.

Another explanation could be geographic or relational proximity. Loan officers might have closer physical locations or pre-existing relationships with the realtor's clients, which could independently drive borrowers' choices. This proximity, rather than a formal referral, could lead to higher loan officer concentration among a realtor's transactions.

These complications requires a more sophisticated method accounting for those confounding factors to accurately measure and isolate the referral network's causal effects.

To address these identification challenges, we employ an instrumental variable (IV) strategy designed to capture the underlying likelihood of referrals. The ideal IV would accurately measure the propensity of borrowers to use referred loan officers, independent of other confounding factors.

In a simple model, the underlying likelihood of referral would be perfectly correlated with the realtor's loan officer concentration (e.g., *CR*4) if all loan officers were homogeneously preferred by the realtor's clients. However, in reality, borrowers often have heterogeneous and endogenous preferences for loan officers, influenced by factors such as personal relationships, geographic proximity, or lender characteristics. This heterogeneity complicates the interpretation of loan officer concentration as a direct measure of referral likelihood.

To address this issue, we propose an IV that adjusts for borrower preferences, aiming to recover the actual underlying likelihood of referrals. Specifically, we construct a borrower-preference-adjusted measure of loan officer concentration, which penalizes the concentration score for borrower-driven preferences. This adjustment ensures that the measure more accurately reflects the extent to which referrals, rather than borrower choice, drive loan officer concentration.

The formula for this borrower-preference-adjusted concentration measure is as follows:

$$\widehat{CR4}_r = \sum_{k=1}^{4} \widehat{S}_{rl(k)}^{(k)}$$
(4)

where $\hat{S}_{rl(1)}^{(1)} \ge \hat{S}_{rl(2)}^{(2)} \ge ...$ and

$$\hat{S}_{rl} = \frac{\sum_{rl} 1/p_{rli}}{\sum_{r} 1/p_{rli}}$$
(5)

where p_{rli} is the probability of borrower *i* choosing loan officer *l* without a referral.

Estimating p_{rli} with a BLP Model To construct the borrower-preference-adjusted *CR*4, we first estimate the probability of borrowers choosing specific loan officers. For this, we employ the classic Berry-Levinsohn-Pakes (BLP) model to capture borrower preferences.

Our analysis begins with a discrete choice framework to model how borrowers select mortgage lenders. To simplify the model, we abstract away from factors such as loan size, which are primarily driven by borrowers'

wealth and financial needs and are less likely to be influenced by realtor recommendations. Instead, we concentrate on the utility borrowers derive from choosing a particular lender, focusing on lender-specific characteristics and borrower preferences. Suppose the utility of borrower i who secures a loan from lender j in market m is the following:

$$u_{ijm} = X'_{im}\beta_1 + X'_{ijm}\beta_2 + \xi_{jm} + \varepsilon_{ijm},\tag{6}$$

 X_{jm} is a vector of lender-market-specific characteristics. We include dummies for whether lender j is a bank, a fintech firm⁵, or an out-of-state lender (defined as having no branches within-state); and dummies for whether lender j is the first, second, or third-largest lender in market m. ξ_{jm} represents an unobserved vertical component specific to lender j in market m.

 X_{ijm} is a vector of borrower-lender-market-specific characteristics. We include the distance between borrower *i*'s property and lender *j*'s nearest branch; interactions between a dummy for whether borrower *i* is 65+ years old and the "bank" and "fintech" dummies; interactions between FICO score bins and the "bank", "fintech", and "top 1/2/3 lender" dummies; and interactions between loan-to-value ratio bins and the "fintech" and "top 1/2/3 lender" dummies.

Finally, ε_{ijm} is a Type I Extreme Value shock. Aggregating over all consumers delivers lender *j*'s market share s_{jm} and the concentration ratio in market *m*: *HHI*_m. We estimate (β_1 , β_2) via maximum likelihood with a nested fixed-point. For each guess of β_2 , we invert ξ_{jm} so that the model-predicted lender shares are equal to the observed lender shares in each market. We estimate the model separately for each state in our data, on an analogous sample of refinance loans. We use refinances rather than purchase loans because our prior is that realtor steering is likely to be stronger for the former, since consumer search may be a more salient force in the latter. Thus, we believe that estimating the model parameters using refinancing choices helps isolate consumers' preferences from realtors' referrals.

Caveat Ideally, we would use the predicted probability of each borrower selecting a specific loan officer. However, given the large number of loan officers in the dataset, this approach places significant computational demands on the BLP model, making it impractical.

Instead, we use the predicted probability of a borrower selecting the loan officer *l*'s affiliated lender b(l) as a proxy.

$$p_{rli} = p_{b(l)i}^{BLP} \tag{7}$$

This approach assumes that there is no competition among loan officers within the same lender, allowing the lender-level predicted probabilities to serve as a reasonable approximation for borrower preferences at the loan officer level. While this simplification introduces some abstraction, it enables the model to remain

⁵We use the list of fintech firms from Fuster et al. (2019), available at https://pages.stern.nyu.edu/~pschnabl/data/ data_fintech.htm.

computationally feasible while still capturing the essential dynamics of borrower preferences and competition.

IV Results Table 4 presents the instrumental variable (IV) estimates of the referral network effect on mortgage costs. The results show that homebuyers who work with realtors having strong referral networks and use referred loan officers pay, on average, 19.7 basis points higher mortgage rates compared to borrowers outside such networks. For an average homebuyer in our sample, this translates to an additional \$567.12 in annual interest payments, based on the average loan size of \$287.88K. Alternatively, borrowers would need to pay approximately \$2,722 in upfront costs to buy down the interest rate to levels comparable to those without a referral network.

Our analysis reveals that the majority of this premium is driven by the suboptimal selection of mortgage lenders within the local market. Borrowers working with referred loan officers are often directed to less competitive lenders, leading to higher overall borrowing costs ("wrong lenders"). However, the findings also show a 6.3 basis point rate differential between referred and non-referred borrowers within the same lender. This "wrong loan officer" effect suggests that the impact of referral networks is not limited to the choice of lender but extends to other aspects of the loan process, such as loan officer-specific pricing strategies or negotiation dynamics.

These findings highlight the potential drawbacks of referral networks in the mortgage market. While such networks may offer benefits like reduced search costs and expedited loan processing, they also impose significant financial costs on borrowers, driven by both suboptimal lender selection and less favorable loan terms even within the same lender. This underscores the need for greater transparency and borrower awareness when navigating realtor-loan officer relationships.

Column (3) and (4) utilize the GSE-matched sample and incorporates FICO scores as additional controls. The results remain highly consistent with those from the core sample.

Columns (5) and (6) analyze the APR spread, which incorporates both the interest rate and origination costs, and reveal an additional 1.7 basis points effect (\$235) for borrowers working with referred loan officers. This incremental cost reflects higher origination expenses, such as processing fees or reduced lender credits, associated with using referred loan officers. These findings suggest that the financial impact of referral networks extends beyond interest rates, further increasing the overall cost of borrowing.

4.3 Heterogeneous Effects

Table 5 examines the referral effect across specific subsets of borrowers, using the IV strategy. The results reveal that the impact of referral networks is more pronounced for certain financially vulnerable or historically disadvantaged groups, underscoring significant disparities in the costs borne by these borrowers.

For Black borrowers, the referral effect is 20.9 basis points, translating into an additional \$2,888 in upfront costs. Hispanic borrowers face an even greater impact, with a referral effect of 28.8 basis points, amounting to \$3,980 in extra costs. These findings point to significant equity concerns, as borrowers from minority groups are disproportionately affected by the financial implications of referral networks.

Financially constrained borrowers also experience heightened effects. Borrowers with down payments less than 5%, an indication of cash constraints, incur a referral effect of 25.3 basis points, resulting in \$3,496 in added costs. Similarly, borrowers with debt-to-income (DTI) ratios above 45%, indicative of lower income, face a referral effect of 25.8 basis points, translating to \$3,565 in additional costs.

These results suggest that referral networks not only impose higher costs on all borrowers but disproportionately affect those who are financially vulnerable or belong to historically marginalized groups. This raises important policy and ethical questions about the fairness and transparency of referral practices in the mortgage market.

5 Possible Justifications for Using Referral Networks

While the evidence presented thus far shows that realtor-loan officer referral networks are associated with higher mortgage costs for borrowers, it is important to consider whether these networks offer offsetting benefits that might justify their existence. In particular, referral networks may provide informational or procedural advantages—especially for borrowers who are inexperienced, face language or financial barriers, or are navigating complex transactions. If so, the observed cost premium might reflect value-added services or reduced risks, rather than market power. This section investigates two such possibilities: whether referral networks improve efficiency by reducing closing times, and whether they serve as a tool for securing financing among borrowers who might otherwise face denial risk. By assessing these justifications, we seek to understand whether the referral premium is compensatory or distortionary in nature.

5.1 Days to Close

In the mortgage market, borrowing is not only costly but also risky. Some borrowers, particularly those unfamiliar with the financing process or facing structural barriers, may benefit from leveraging their realtor's referral network to secure timely loan approval and reduce uncertainty.

Table 6 presents instrumental variable (IV) estimates for the number of days to close a home purchase, measured as the time between the purchase contract date and the closing date. Column (2) shows that, conditional on successful closing, homebuyers who use referred loan officers complete their purchases 0.45 days faster, on average, compared to a baseline of 40.3 days. This finding suggests that referral networks may offer modest efficiency gains by streamlining the mortgage process.

Such gains may arise because referred loan officers often have established working relationships with realtors, enabling smoother communication, quicker document handling, and more responsive processing. These officers may also possess deeper knowledge of local lending practices and be better equipped to navigate administrative bottlenecks, leading to faster closings.

Column (4) further shows that the probability of a transaction taking more than 30 days to close falls by 3.6 percentage points, from a baseline of 72%. This indicates that referral networks are particularly helpful

in avoiding moderate delays. However, Column (6) reveals that the likelihood of a closing taking more than 45 days remains unaffected, suggesting that referral networks do not mitigate more substantial or systemic delays.

Together, these findings imply that while referred loan officers may expedite the closing process modestly, especially for moderately delayed transactions, the effect is limited when it comes to avoiding significant delays. Thus, borrowers may gain some convenience from referral networks, but the benefits are relatively small and must be weighed against the higher borrowing costs documented in earlier sections.

5.2 Mortgage Denial Risk

Another possible justification for the higher cost of referred mortgages is that referral networks may provide value through certainty—helping borrowers avoid mortgage denial and ensuring that transactions close successfully. If true, the higher interest rates associated with referral networks might reflect a risk premium, not market power.

However, this explanation can be tested by focusing on borrowers unlikely to face credit risk. If even low-risk borrowers pay more when working with referred loan officers, then the premium cannot be explained by approval risk mitigation alone.

To examine this, Table 7 explores the effect of referral networks across high-quality borrower subsamples. In Column (2), we restrict the sample to high-FICO borrowers, who generally face a low risk of denial. These borrowers still experience elevated mortgage costs when using referred loan officers, suggesting that credit quality does not fully account for the pricing differential.

Column (5) further narrows the sample to very low-risk borrowers—those with FICO scores above 780, LTV ratios below 80%, and DTI ratios below 36%. Even within this stringent group, referral networks are associated with a significant cost premium of 16.3 basis points, reinforcing the view that the referral effect is not driven by credit risk concerns.

These results point to a structural explanation: the referral process itself constrains borrower choice, funneling them into narrower lender pools that charge higher rates. Rather than compensating for risk, the price premium reflects reduced competition—a result of steering in referral networks that persists even among the most creditworthy borrowers.

6 Conclusion

This paper provides the first systematic evidence on the existence, structure, and consequences of realtor–loan officer referral networks in the U.S. mortgage market. We demonstrate that while the mortgage lending industry is characterized by a high degree of institutional competition, real-world borrower choices are constrained by the intermediation of realtors who routinely refer clients to a limited set of loan officers. These referral networks create locally concentrated lender access, even in otherwise competitive markets, and play a crucial

but underexamined role in shaping borrower outcomes.

Using a novel dataset covering over 1.5 million mortgage-financed home purchases from 2018 to 2021, we map out the full scope of referral relationships between 126,598 realtors and 280,245 loan officers across 17 states and Washington, D.C. We find that referral concentration is pervasive: over 28% of realtors operate within highly concentrated networks, and 85% exceed a medium concentration threshold. These networks are not passive byproducts of matching efficiency or borrower preferences; rather, they persist—and even intensify—in larger, more competitive markets, indicating a structural source of market power embedded in the home purchase process.

We show that referral networks impose real financial costs on homebuyers. Borrowers working with highly concentrated realtors pay significantly higher mortgage interest rates—with IV estimates indicating a causal impact of nearly 20 basis points, or \$567 annually on the average loan. This premium is economically meaningful and persists even among borrowers with low credit risk and those matched to the same lenders, suggesting that the referral effect operates through both constrained choice sets and reduced bargaining power. Moreover, these costs are not evenly distributed: minority and financially constrained borrowers face disproportionately higher rate differentials, exacerbating existing inequalities in mortgage access and affordability.

While referral networks offer some procedural benefits, such as modest reductions in time to close, these gains are not large enough to justify the observed increase in borrowing costs. Even among high-quality borrowers with minimal default risk, referral loans remain more expensive. These results challenge the conventional narrative that referral relationships are merely efficiency-enhancing and suggest instead that they may serve as a channel through which market power is exercised and maintained.

Our findings contribute to the literature on mortgage price dispersion, intermediary market power, and informal referral networks. We uncover a previously underexplored mechanism—realtor-driven steering—that helps explain why competitive supply conditions fail to translate into competitive pricing at the borrower level. This also has broader implications for how researchers and regulators conceptualize competition in retail financial markets, where intermediaries play a pivotal role in mediating access.

From a policy perspective, our results call for greater scrutiny of intermediary behavior, especially in how referral incentives are structured and disclosed. While existing regulation (e.g., RESPA Section 8) prohibits kickbacks and unearned fees, our evidence suggests that informal and opaque referral practices may continue to distort borrower choices and reduce effective competition. Future policy efforts may need to rethink transparency requirements, strengthen enforcement mechanisms, and consider reforms that enhance borrower autonomy in selecting mortgage financing options.

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Figures



Figure 1: Geographic Coverage of the Data Sample

Note: This figure illustrates the counties covered in our data sample, with different colors representing the dominant MLS in each county. In total, our sample includes 559 counties across 17 states—Arizona, Delaware, Illinois, Iowa, Maryland, Michigan, Minnesota, Mississippi, Missouri, Nevada, New Jersey, Ohio, Oklahoma, Pennsylvania, Rhode Island, Texas, Virginia—and the District of Columbia. These areas collectively represent 34% of the U.S. population.



Figure 2: Distribution of Loan Officer Concentration of Realtors

Note: This figure plots the distributions of loan officer concentration measures (*CR*4 in panel (a), *HHI* in panel (b)) of realtors in our data sample.



Figure 3: Loan Officer Concentration and Lender Concentration by Market Size

(a) By the Size of Purchase Mortgages

Note: These figures depict the relationship between average within-realtor loan officer concentration (measured by CR4) and lender concentration (CR4) with market size. Panel (a) sorts markets (county-year) based on the number of purchase mortgages in our sample, while Panel (b) sorts markets (county-year) according to the number of lenders from HMDA. Both figures present binned scatter plots (100 bins) of maket-level concentration measures alongside their respective linear fit lines. The red scatter points and lines represent the average within-realtor loan officer CR4. When calculating within-realtor concentration, we restrict the analysis to realtors with a minimum of 10 transactions.



Figure 4: Mortgage Interest Rate By Loan Officer/Lender Concentration

(a) Interest Rates By Within-Realtor Loan Officer CR4

Note: This figure presents the relationship between interest rate spreads and lender concentration across different concentration quintiles. The y-axis represents the mortgage interest rate spread, defined as the deviation from the benchmark rate offered on prime mortgage loans of a comparable type. In Panel (a), concentration is measured by the within-realtor CR4 of loan officers. The black lines (both dotted and solid) represent estimates from the core sample, incorporating a sequential addition of controls, following the specifications in Table 2. The red line represents results from the GSE-matched sample, which includes FICO score bin fixed effects as additional controls to account for borrower creditworthiness. In Panel (b), concentration is measured by the market-wide lender CR4.

Tables

	F	Full	High Co	ncentration	Medium Concentration		Low Concentration	
			(CR4)	$1 \ge 0.7$	(<i>CR</i> 4 ∈	[0.4,0.7))	(<i>CR</i> 4	< 0.4)
	((1)		(2)		(3)	((4)
	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
Realtor	120	5,598	35	5,330	7	1,575	19	,693
CR4 of Matched Loan Officers	0.59	(0.18)	0.82	(0.09)	0.55	(0.08)	0.32	(0.06)
HHI of Matched Loan Officers	1892	(1395)	3523	(1526)	1440	(560)	606	(186)
Completed Home Phurchases	33.62	(82.28)	24.47	(25.32)	34.26	(37.37)	47.73	(192.20)
Matched Loan Officers	17.88	(25.61)	8.43	(5.07)	18.46	(14.39)	32.73	(55.09)
Top 4 Matched Loan Officers	280	280,245),391	16	60,709	39	,145
Mortgage Broker	0.06	(0.24)	0.08	(0.26)	0.06	(0.23)	0.05	(0.22)
Bank In-house Loan Officer	0.26	(0.44)	0.25	(0.43)	0.27	(0.44)	0.29	(0.45)
Hired by Top 4 Lenders in Market	0.18	(0.36)	0.16	(0.34)	0.18	(0.36)	0.19	(0.37)
Homebuyers	1,531,875		34	0,394	88	35,581	305	5,900
Referral	0.18	(0.39)	0.82	(0.39)	0.00	(0.00)	0.00	(0.00)
Likely Referral	0.32	(0.47)	0.00	(0.00)	0.56	(0.50)	0.00	(0.00)
Interest Rate Spread (%)	0.45	(0.64)	0.56	(0.68)	0.43	(0.63)	0.36	(0.60)
APR Spread (%)	0.54	(0.68)	0.67	(0.73)	0.53	(0.67)	0.44	(0.64)
Days to Close	40.94	(23.80)	40.92	(23.75)	40.81	(23.68)	41.33	(24.20)
Loan Amount (\$K)	287.88	(164.35)	274.37	(144.39)	287.94	(162.37)	302.74	(187.95)
County Median Income	76.77	(19.81)	77.60	(20.55)	76.82	(19.91)	75.72	(18.60)
Income Ratio	1.46	(8.59)	1.24	(2.64)	1.48	(9.99)	1.66	(8.55)
Minority	0.33	(0.47)	0.44	(0.50)	0.31	(0.46)	0.27	(0.45)
-Black	0.10	(0.30)	0.12	(0.33)	0.09	(0.29)	0.09	(0.28)
-Hispanic	0.15	(0.35)	0.23	(0.42)	0.13	(0.34)	0.10	(0.30)
-Asian	0.06	(0.24)	0.08	(0.27)	0.06	(0.24)	0.06	(0.24)
LTV (%)	89.38	(12.13)	90.88	(11.26)	89.17	(12.20)	88.35	(12.71)
DTI (%)	35.23	(11.35)	36.73	(10.90)	34.99	(11.38)	34.25	(11.58)
FICO Score*	739.24	(55.05)	739.31	(55.09)	739.25	(55.03)	739.14	(55.05)
Close Price (\$K)	331.45	(212.85)	308.67	(180.58)	332.10	(209.86)	354.90	(248.92)
Sqft	2117	(5091)	1989	(989)	2124	(6632)	2237	(1223)
Bedrooms	3.41	(0.84)	3.38	(0.82)	3.40	(0.84)	3.46	(0.86)
Bathrooms	2.51	(1.15)	2.37	(1.12)	2.51	(1.14)	2.67	(1.17)
House Age	41.08	(29.30)	42.63	(28.84)	41.26	(29.46)	38.86	(29.21)

Table 1: Summary Statistics

Note: This table presents the summary statistics of the home purchase data used in this study. Column (1) reports statistics for the full sample, while Columns (2)–(4) provide summary statistics for home purchases facilitated by realtors with high, medium, and low loan officer concentration, respectively. The upper panel summarizes the characteristics of realtors, the middle panel reports statistics for the top four ranked loan officers within each realtor's matched loan officers, and the lower panel provides summary statistics for home buyers.

*The FICO score is only available in the GSE sample, where the mortgage has a matched record in the performance data of Ginnie Mae, Fannie Mae, or Freddie Mac.

Tables

	Interest Rate Spread (off Prime Rate, in %)									
						GSE Sample				
Control Var.	No Control (1)	+Market FE (2)	+Borrower Ctrl (3)	+DTI (4)	+LTV (5)	+FICO (6)				
Realtor CR4 Quintile 5	0.244***	0.182***	0.168***	0.154***	0.119***	0.120***				
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)				
Realtor CR4 Quintile 4	0.147***	0.105***	0.097***	0.090***	0.066***	0.068***				
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)				
Realtor CR4 Quintile 3	0.092***	0.065***	0.061***	0.057***	0.040***	0.040***				
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)				
Realtor CR4 Quintile 2	0.043***	0.033***	0.032***	0.031***	0.021***	0.025***				
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)				
Observations	1,434,079	1,431,577	1,431,577	1,431,577	1,431,577	572,303				
R-squared	0.016	0.162	0.180	0.232	0.311	0.324				
Dep. Var. Mean	0.45	0.45	0.45	0.45	0.45	0.46				
Year-Month*County FE		Y	Y	Y	Y	Y				
log[Loan Amount]		Y	Y	Y	Y	Y				
Age Bin FE			Y	Y	Y	Y				
Income Ratio Pencentile FE			Y	Y	Y	Y				
Joint Application			Ŷ	Ŷ	Ŷ	Ŷ				
Conforming FE			Ŷ	Ŷ	Ŷ	Ŷ				
DTI bin FE			-	Ŷ	Ŷ	Ŷ				
LTV bin FE				-	Ŷ	Ŷ				
FICO bin FE					-	Ŷ				

Fable 2: Mortgage	Interest Rate St	preads By	Realtor CR4	Quintiles
00				-

Note: This table reports the differences of mortgage interest rate spreads across realtor concentration quintiles. The concentration is measured by within realtor *CR*4 of the loan officer mortgage shares. The dependent variable is the mortgage interest rate spread off the benchmark rate offered on prime mortgage loans of a comparable type. The income ratio is defined as the reported income over the county median income of the same year. Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

	Interest Rate Spread (off Prime Rate, in %)						APR Spread (off Prime Rate, in %)			
					Sample					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Referral ($CR4 \ge 0.7$, Top 4 Loan Officer) Likely Referral ($CR4 \in [0.4, 0.7)$, Top 4 Loan Officer)	0.093*** (0.001)	0.034*** (0.001)	0.121*** (0.001) 0.068*** (0.001)	0.032*** (0.001) -0.004*** (0.001)	0.118*** (0.002) 0.065*** (0.002)	0.032*** (0.002) -0.005** (0.002)	0.101*** (0.001)	0.037*** (0.001)	0.133*** (0.001) 0.075*** (0.001)	0.036*** (0.001) -0.003*** (0.001)
Observations R-squared Dep. Var. Mean Year-Month*County FE Year-Month*County*Lender FE log[Loan Amount] Age Bin FE Income Ratio Pencentile FE Joint Application Conforming FE DTI bin FE	1,431,577 0.311 0.45 Y · Y Y Y Y Y Y Y	1,213,636 0.565 0.44 Y Y Y Y Y Y Y Y Y	1,431,577 0.313 0.45 Y · Y Y Y Y Y Y Y	1,213,636 0.565 0.44 Y Y Y Y Y Y Y Y Y	572,303 0.325 0.46 Y Y Y Y Y Y Y Y	439,147 0.588 0.46 Y Y Y Y Y Y Y Y Y	1,460,951 0.328 0.54 Y Y Y Y Y Y Y Y Y	1,239,966 0.581 0.54 · Y Y Y Y Y Y Y Y Y	1,460,951 0.331 0.54 Y Y Y Y Y Y Y Y	1,239,966 0.581 0.54 · Y Y Y Y Y Y Y Y Y
FICO bin FE	Ŷ	Ŷ	Ŷ	Ŷ	Y Y	Y Y	Ŷ	Ŷ	Ŷ	Ŷ

 Table 3: Effect of Referral on Purchase Mortgage Costs (OLS)

Note: This table reports the OLS regression estimates of realtor-loan officer referral network effect on mortgage costs. The concentration is measured by within realtor *CR*4 of the loan officer mortgage shares. The mortgage costs are measured by both mortgage interest rate spreads and APR spreads, both off the benchmark rate offered on prime mortgage loans of a comparable type. *Referral* equals 1 if the homebuyer's realtor *CR*4 is above 0.7, and she works with a top 4 loan officer of the realtor. *Likely Referral* equals 1 if the homebuyer's realtor *CR*4 above 0.4 but below 0.7, and she works with a top 4 loan officer of the realtor. The income ratio is defined as the reported income over the county median income of the same year. Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

		Interest Ra (off Prime)	ate Spread Rate, in %)		APR Spread (off Prime Rate, in %)		
			GSE S	Sample			
	IV	IV	IV	IV	IV	IV	
	(1)	(2)	(3)	(4)	(5)	(6)	
Referral	0.197***	0.063***	0.195***	0.066***	0.214***	0.068***	
(<i>CR</i> 4 \geq 0.7, Top 4 Loan Officer)	(0.004)	(0.005)	(0.006)	(0.008)	(0.004)	(0.005)	
Observations	1,047,751	865,997	417,785	307,305	1,069,261	884,936	
R-squared	0.064	0.062	0.066	0.064	0.074	0.073	
Dep. Var. Mean	0.45	0.45	0.46	0.46	0.54	0.54	
Year-Month*County FE	Y		Y		Y		
Year-Month*County*Lender FE		Y		Y		Y	
Age Bin FE	Y	Y	Y	Y	Y	Y	
Income Ratio Pencentile FE	Y	Y	Y	Y	Y	Y	
Joint Application	Y	Y	Y	Y	Y	Y	
Conforming FE	Y	Y	Y	Y	Y	Y	
DTI bin FE	Y	Y	Y	Y	Y	Y	
LTV bin FE	Y	Y	Y	Y	Y	Y	
FICO bin FE			Y	Y			
FS: Cragg-Donald Wald F	154033	97308	61034	32797	157912	100014	
FS: Kleibergen-Paap rk F	164786	99239	64904	32822	169274	102256	
FS: Anderson-Rubin p-val	0	0	0	0	0	0	

Table 4: Effect of Referral on Purchase Mortgage Costs (IV: $\widehat{CR4}$)

Note: This table reports the IV regression estimates of realtor-loan officer referral network effect on mortgage costs. The concentration is measure by within realtor *CR*4 of the loan officer mortgage shares. The mortgage costs are measured by both mortgage interest rate spreads and APR spreads, both off the benchmark rate offered on prime mortgage loans of a comparable type. *Referral* equals 1 if the homebuyer's realtor *CR*4 is above 0.7, and she works with a top 4 loan officer of the realtor. It is instrumented with borrower preference adjusted loan officer concentration measure $\widehat{CR4}$. The income ratio is defined as the reported income over the county median income of the same year. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Interest Rate Spread (off Prime Rate , in %)							
	IV	IV	IV	IV				
	(1)	(2)	(3)	(4)				
Referral $(CR4 \ge 0.7, \text{Top 4 Loan Officer})$	0.197*** (0.006)	0.177*** (0.005)	0.127*** (0.005)	0.135*** (0.005)				
Referral*(Age<35)	0.000							
Referral*(DTI>0.45)	(0.000)	0.081^{***}						
Referral*(LTV>0.95)		(0.007)	0.126***					
LTV>0.95			0.349***					
Referral*Black			(0.002)	0.074^{***}				
Referral*Hispanic				0.153***				
Referral*Asian				-0.029**				
Referral*Other				0.086***				
Black				0.181***				
Hispanic				0.170***				
Asian				-0.050***				
Other				(0.003) 0.013** (0.006)				
Observations	1,047,751	1,047,751	1,047,751	1,047,751				
R-squared	0.064	0.064	0.131	0.086				
Dep. Var. Mean	0.45	0.45	0.45	0.45				
Year-Month*County FE	Y	Y	Y	Y				
log[Loan Amount]	Y	Y	Y	Y				
Age Bin FE	Y	Y	Y	Y				
Income Ratio Pencentile FE	Y	Y	Y	Y				
Joint Application	Y	Y	Y	Y				
Conforming FE	Y	Y	Y	Y				
DTI bin FE	Y	Y	Y	Y				
LTV bin FE	Y	Y	Y	Y				
FS: Cragg-Donald Wald F	76503	74181	68603	26966				
FS: Kleibergen-Paap rk F	67178	63763	43618	19423				
FS: Anderson-Rubin p-val	0	0	0	0				

Table 5: Heterogeneous Effect of Referral on Purchase Mortgage Interest Rate Spreads (IV: $\widehat{CR4}$)

Note: This table reports the IV regression estimates of realtor-loan officer referral network effect on mortgage costs across different borrower groups. The concentration is measure by within realtor *CR*4 of the loan officer mortgage shares. The dependent variable is the mortgage interest rate spreads off the benchmark rate offered on prime mortgage loans of a comparable type. *Referral* equals 1 if the homebuyer's realtor *CR*4 is above 0.7, and she works with a top 4 loan officer of the realtor. It and its interactions are instrumented with borrower preference adjusted loan officer concentration measure $\widehat{CR4}$ and interaction terms. The income ratio is defined as the reported income over the county median income of the same year. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Days to	o Close	>30 Day	ys (in %)	>45 Days (in %)		
	IV	IV	IV	IV	IV	IV	
	(1)	(2)	(3)	(4)	(5)	(6)	
Referral	-0.451***	-0.528***	-3.592***	-3.658***	0.004	-0.141	
(<i>CR</i> 4 \geq 0.7, Top 4 Loan Officer)	(0.166)	(0.167)	(0.341)	(0.343)	(0.333)	(0.336)	
Observations	995,912	995,912	995,912	995,912	995,912	995,912	
R-squared	uared 0.000		0.000	0.000	-0.000	0.000	
Dep. Var. Mean	40.31	40.31	72.38	72.38	26.10	26.10	
Year-Month*County FE	Y	Y	Y	Y	Y	Y	
Bedroom FE	Y	Y	Y	Y	Y	Y	
Bathroom FE	Y	Y	Y	Y	Y	Y	
Sqft Bin FE	Y	Y	Y	Y	Y	Y	
House Age FE	Y	Y	Y	Y	Y	Y	
Tract FE	Y	Y	Y	Y	Y	Y	
Age Bin FE		Y		Y		Y	
Income Ratio Pencentile FE		Y		Y		Y	
Joint Application		Y		Y		Y	
Conforming FE		Y		Y		Y	
FS: Cragg-Donald Wald F	143596	141955	143596	141955	143596	141955	
FS: Kleibergen-Paap rk F	150869	149796	150869 149796		150869	149796	
FS: Anderson-Rubin p-val	0.007	0.002	0	0	0.991	0.675	

Table 6: Effect of Referral on Days to Close (IV: $\widehat{CR4}$)

Note: This table reports the IV regression estimates of realtor-loan officer referral network effect on home purchase close time. The concentration is measure by within realtor *CR*4 of the loan officer mortgage shares. The dependent variables are the days between purchase contract accepted and purchase close, and the share of days above 30 (45) days. *Referral* equals 1 if the homebuyer's realtor *CR*4 is above 0.7, and she works with a top 4 loan officer of the realtor. It is instrumented with borrower preference adjusted loan officer concentration measure $\widehat{CR4}$. The income ratio is defined as the reported income over the county median income of the same year. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Interest Rate Spread (off Prime Rate, in %)									
	Full Sample		High-Qualit	y Borrowers					
		FICO>780	FICO>780 DTI≤0.36	FICO>780 LTV≤0.8	FICO>780 LTV≤0.8 DTI≤0.36				
	(1)	(2)	(3)	(4)	(5)				
Referral	0.201*** (0.009)	0.191*** (0.012)	0.184*** (0.019)	0.122*** (0.027)	0.163*** (0.039)				
Referral*(FICO>780)	-0.018 (0.014)								
Referral*(FICO<700)	0.001 (0.015)								
(FICO>780)	-0.007** (0.003)								
(FICO<700)	0.021*** (0.003)								
Observations	417,785	121,408	52,926	30,738	17,203				
R-squared	0.066	0.067	0.048	0.026	0.018				
Dep. Var. Mean	0.46	0.42	0.28	0.08	0.05				
Year-Month*County FE	Y	Y	Y	Y	Y				
log[Loan Amount]	Y	Y	Y	Y	Y				
Age Bin FE	Y	Y	Y	Y	Y				
Income Ratio Pencentile FE	Y	Y	Y	Y	Y				
Joint Application	Y	Y	Y	Y	Y				
Conforming FE	Y	Y	Y	Y	Y				
DTI bin FE	Y	Y		Y					
LTV bin FE	Y	Y							
FS: Cragg-Donald Wald F	20341	17237	6416	2883	1396				
FS: Kleibergen-Paap rk F	21396	18467	6362	2823	1306				
FS: Anderson-Rubin p-val	0	0	0	4.95e-06	3.71e-05				

							_	_
Table 7: Effect of	of Referral for	Borrowers with	Little Mortgage	Denial	Concerns	(IV:	CR	4)

Note: This table reports the IV regression estimates of realtor-loan officer referral network effect on mortgage costs for highquality borrowers. The concentration is measure by within realtor *CR*4 of the loan officer mortgage shares. The dependent variable is the mortgage interest rate spreads off the benchmark rate offered on prime mortgage loans of a comparable type. *Referral* equals 1 if the homebuyer's realtor *CR*4 is above 0.7, and she works with a top 4 loan officer of the realtor. It and its interactions are instrumented with borrower preference adjusted loan officer concentration measure $\widehat{CR4}$ and interaction terms. The income ratio is defined as the reported income over the county median income of the same year. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Tables

	Interest Rate Spread (off Prime Rate, in %)								
						GSE Sample			
Control Var.	No Control	+Market FE	+Borrower Ctrl	+DTI	+LTV	+FICO			
	(1)	(2)	(3)	(4)	(5)	(6)			
Realtor HHI Quintile 5	0.165***	0.123***	0.113***	0.103***	0.078***	0.079***			
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)			
Realtor HHI Quintile 4	0.115***	0.086***	0.080***	0.075***	0.056***	0.055***			
-	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)			
Realtor HHI Quintile 3	0.081***	0.061***	0.057***	0.053***	0.039***	0.039***			
-	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)			
Realtor HHI Quintile 2	0.047***	0.036***	0.034***	0.032***	0.022***	0.024***			
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)			
Observations	1,434,079	1,431,577	1,431,577	1,431,577	1,431,577	572,303			
R-squared	0.008	0.158	0.177	0.229	0.310	0.322			
Dep. Var. Mean	0.45	0.45	0.45	0.45	0.45	0.46			
Year-Month*County FE		Y	Y	Y	Y	Y			
log[Loan Amount]		Y	Y	Y	Y	Y			
Age Bin FE			Y	Y	Y	Y			
Income Ratio Pencentile FE			Y	Y	Y	Y			
Joint Application			Y	Y	Y	Y			
Conforming FE			Y	Y	Y	Y			
DTI bin FE				Y	Y	Y			
LTV bin FE					Y	Y			
FICO bin FE						Y			

Table A1: Mortgage	Interest Rate S	preads By	Realtor HHI	Quintiles
00				

Note: This table reports the differences of mortgage interest rate spreads across realtor concentration quintiles. The concentration is measured by within realtor *CR*4 of the loan officer mortgage shares. The dependent variable is the mortgage interest rate spread off the benchmark rate offered on prime mortgage loans of a comparable type. The income ratio is defined as the reported income over the county median income of the same year. Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

		Interest Rate Spread (off Prime Rate, in %)						APR Spread (off Prime Rate, in %)		
		GSE Sample								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Referral (<i>HHI</i> \geq 1800, Top 4 Loan Officer) Likely Referral (<i>HHI</i> \in [1000, 1800), Top 4 Loan Officer)	0.087*** (0.001)	0.002** (0.001)	0.087*** (0.001) -	0.002** (0.001) -	0.085*** (0.001) -	0.002 (0.002)	0.096*** (0.001)	0.003*** (0.001)	0.096*** (0.001) -	0.003*** (0.001) -
Observations R-squared Dep. Var. Mean Year-Month*County FE Year-Month*County*Lender FE log[Loan Amount] Age Bin FE Income Ratio Pencentile FE Joint Application Conforming FE DTI bin FE	1,431,577 0.312 0.45 Y Y Y Y Y Y Y	1,213,636 0.565 0.44 Y Y Y Y Y Y Y	1,431,577 0.312 0.45 Y Y Y Y Y Y Y	1,213,636 0.565 0.44 Y Y Y Y Y Y Y	572,303 0.325 0.46 Y Y Y Y Y Y Y Y	439,147 0.588 0.46 Y Y Y Y Y Y Y	1,460,951 0.330 0.54 Y Y Y Y Y Y Y	1,239,966 0.581 0.54 · Y Y Y Y Y Y Y	1,460,951 0.330 0.54 Y Y Y Y Y Y Y	1,239,966 0.581 0.54 · Y Y Y Y Y Y Y Y
LTV bin FE FICO bin FE	Y	Y	Y	Y	Y Y	Y Y	Y	Y	Y	Y

Table A2: Effect of Referral on Purchase Mortgage Costs (OLS with HHI)

Note: This table reports the OLS regression estimates of realtor-loan officer referral network effect on mortgage costs. The concentration is measured by within realtor *HHI* of the loan officer mortgage shares. The mortgage costs are measured by both mortgage interest rate spreads and APR spreads, both off the benchmark rate offered on prime mortgage loans of a comparable type. *Referral* equals 1 if the homebuyer's realtor *HHI* is above 1800, and she works with a top 4 loan officer of the realtor. *Likely Referral* equals 1 if the homebuyer's realtor *CR*4 above 1000 but below 1800, and she works with a top 4 loan officer of the realtor. The income ratio is defined as the reported income over the county median income of the same year. Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

	Interest Rate Spread (off Prime Rate, in %)			APR Spread (off Prime Rate, in %)		
			GSE Sample			
	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Referral	0.224***	0.075***	0.209***	0.081***	0.242***	0.080***
$(HHI \ge 1800, \text{Top 4 Loan Officer})$	(0.006)	(0.009)	(0.009)	(0.015)	(0.006)	(0.009)
Observations	1,047,751	865,997	417,785	307,305	1,069,261	884,936
R-squared	0.053	0.057	0.058	0.058	0.063	0.067
Dep. Var. Mean	0.45	0.45	0.46	0.46	0.54	0.54
Year-Month*County FE	Y		Y		Y	
Year-Month*County*Lender FE		Y		Y		Y
Age Bin FE	Y	Y	Y	Y	Y	Y
Income Ratio Pencentile FE	Y	Y	Y	Y	Y	Y
Joint Application	Y	Y	Y	Y	Y	Y
Conforming FE	Y	Y	Y	Y	Y	Y
DTI bin FE	Y	Y	Y	Y	Y	Y
LTV bin FE	Y	Y	Y	Y	Y	Y
FICO bin FE			Y	Y		
FS: Cragg-Donald Wald F	37946	16356	15229	5074	38593	16751
FS: Kleibergen-Paap rk F	40733	15106	16349	4657	41451	15476
FS: Anderson-Rubin p-val	0	0	0	1.62e-07	0	0

Table A3: Effect of Referral on Purchase Mortgage Costs (IV: \widehat{HHI})

Note: This table reports the IV regression estimates of realtor-loan officer referral network effect on mortgage costs. The concentration is measure by within realtor *HHI* of the loan officer mortgage shares. The mortgage costs are measured by both mortgage interest rate spreads and APR spreads, both off the benchmark rate offered on prime mortgage loans of a comparable type. *Referral* equals 1 if the homebuyer's realtor *HHI* is above 1800, and she works with a top 4 loan officer of the realtor. It is instrumented with borrower preference adjusted loan officer concentration measure \widehat{HHI} . The income ratio is defined as the reported income over the county median income of the same year. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Interest Rate Spread (off Prime Rate , in %)				
	IV (1)	IV (2)	IV (3)	IV (4)	
Referral (<i>HHI</i> ≥1800, Top 4 Loan Officer) Referral*(Age<35)	0.211*** (0.008) 0.031*** (0.011)	0.207*** (0.007)	0.153*** (0.007)	0.142*** (0.007)	
Referral*(DTI>0.45)	(0.011)	0.073^{***}			
Referral*(LTV>0.95)		(0.014)	0.110***		
LTV>0.95			(0.012) 0.308*** (0.007)		
Referral*Black			(0.007)	0.087***	
Referral*Hispanic				(0.021) 0.260^{***} (0.021)	
Referral*Asian				-0.027	
Referral*Other				(0.017) 0.114***	
Black				(0.044) 0.151***	
Hispanic				(0.012) 0.056***	
Asian				(0.013) -0.033*** (0.010)	
Other				-0.035 (0.024)	
Observations	1,047,751	1,047,751	1,047,751	1,047,751	
R-squared	0.053	0.054	0.127	0.079	
Dep. Var. Mean	0.45	0.45	0.45	0.45 X	
log [] oan Amount]	ĭ V	I V	I V	r V	
Age Bin FE	I V	ı V	I V	I V	
Income Ratio Pencentile FE	Ŷ	Ŷ	Ŷ	Ŷ	
Joint Application	Ŷ	Ŷ	Ŷ	Ŷ	
Conforming FE	Y	Y	Y	Y	
DTI bin FE	Y	Y	Y	Y	
LTV bin FE	Y	Y	Y	Y	
FS: Cragg-Donald Wald F	18958	18137	16384	6605	
FS: Kleibergen-Paap rk F	19539	15666	10625	5024	
FS: Anderson-Rubin p-val	0	0	0	0	

Table A4: Heterogeneous Effect of Referral on Purchase Mortgage Interest Rate Spreads (IV: \widehat{HHI})

Note: This table reports the IV regression estimates of realtor-loan officer referral network effect on mortgage costs across different borrower groups. The concentration is measure by within realtor *HHI* of the loan officer mortgage shares. The dependent variable is the mortgage interest rate spreads off the benchmark rate offered on prime mortgage loans of a comparable type. *Referral* equals 1 if the homebuyer's realtor *HHI* is above 1800, and she works with a top 4 loan officer of the realtor. It and its interactions are instrumented with borrower preference adjusted loan officer concentration measure \widehat{HHI} and interaction terms. The income ratio is defined as the reported income over the county median income of the same year. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Days to Close		>30 Day	>30 Days (in %)		>45 Days (in %)	
	IV	IV	IV	IV	IV	IV	
	(1)	(2)	(3)	(4)	(5)	(6)	
Referral	-0.557**	-0.631***	-4.037***	-4.098***	0.310	0.184	
$(HHI \ge 1800, \text{Top 4 Loan Officer})$	(0.231)	(0.233)	(0.461)	(0.466)	(0.454)	(0.458)	
Observations	995,912	995,912	995,912	995,912	995,912	995,912	
R-squared	0.001	0.001	0.002	0.002	-0.000	-0.000	
Dep. Var. Mean	40.31	40.31	72.38	72.38	26.10	26.10	
Year-Month*County FE	Y	Y	Y	Y	Y	Y	
Bedroom FE	Y	Y	Y	Y	Y	Y	
Bathroom FE	Y	Y	Y	Y	Y	Y	
Sqft Bin FE	Y	Y	Y	Y	Y	Y	
House Age FE	Y	Y	Y	Y	Y	Y	
Tract FE	Y	Y	Y	Y	Y	Y	
Age Bin FE		Y		Y		Y	
Income Ratio Pencentile FE		Y		Y		Y	
Joint Application		Y		Y		Y	
Conforming FE		Y		Y		Y	
FS: Cragg-Donald Wald F	36275	35678	36275	35678	36275	35678	
FS: Kleibergen-Paap rk F	39052	38379	39052	38379	39052	38379	
FS: Anderson-Rubin p-val	0.0158	0.00664	0	0	0.495	0.689	

Table A5: Effect of Referral on Days to Close (IV: \widehat{HHI})

Note: This table reports the IV regression estimates of realtor-loan officer referral network effect on home purchase close time. The concentration is measure by within realtor *HHI* of the loan officer mortgage shares. The dependent variables are the days between purchase contract accepted and purchase close, and the share of days above 30 (45) days. *Referral* equals 1 if the homebuyer's realtor *HHI* is above 1800, and she works with a top 4 loan officer of the realtor. It is instrumented with borrower preference adjusted loan officer concentration measure \widehat{HHI} . The income ratio is defined as the reported income over the county median income of the same year. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Interest Rate Spread (off Prime Rate, in %)					
	Full Sample High-Quality Borrowers					
		FICO>780	FICO>780 DTI≤0.36	FICO>780 LTV≤0.8	FICO>780 LTV≤0.8 DTI≤0.36	
	(1)	(2)	(3)	(4)	(5)	
Referral	0.210^{***}	0.222^{***}	0.205^{***}	0.108***	0.119***	
Referral*(FICO>780)	0.002 (0.021)	(0.017)	(0.020)	(0.001)	(0.012)	
Referral*(FICO<700)	-0.002 (0.022)					
(FICO>780)	-0.010 (0.012)					
(FICO<700)	0.024* (0.012)					
Observations	417,785	121,408	52,926	30,738	17,203	
R-squared	0.058	0.056	0.035	0.026	0.023	
Dep. Var. Mean	0.46	0.42	0.28	0.08	0.05	
Year-Month*County FE	Y	Y	Y	Y	Y	
log[Loan Amount]	Y	Y	Y	Y	Y	
Age Bin FE	Y	Y	Y	Y	Y	
Income Ratio Pencentile FE	Y	Y	Y	Y	Y	
Joint Application	Y	Y	Y	Y	Y	
Conforming FE	Y	Y	Y	Y	Y	
DTI bin FE	Y	Y	Y	Y	Y	
LTV bin FE	Y	Y	Y	Y	Y	
FS: Cragg-Donald Wald F	5050	4231	1584	755.6	349.8	
FS: Kleibergen-Paap rk F	4758	4509	1644	768.5	352.6	
FS: Anderson-Rubin p-val	0	0	0	0.000530	0.00566	

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Table A6 ¹	Effect of Referrs	I for Borrowers	with Little Mortgage	Denial Concerns ($1 \vee HHI$
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Note: This table reports the IV regression estimates of realtor-loan officer referral network effect on mortgage costs for highquality borrowers. The concentration is measure by within realtor *HHI* of the loan officer mortgage shares. The dependent variable is the mortgage interest rate spreads off the benchmark rate offered on prime mortgage loans of a comparable type. *Referral* equals 1 if the homebuyer's realtor *HHI* is above 1800, and she works with a top 4 loan officer of the realtor. It and its interactions are instrumented with borrower preference adjusted loan officer concentration measure \widehat{HHI} and interaction terms. The income ratio is defined as the reported income over the county median income of the same year. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.