Realtor Referrals to Loan Officers: Efficiency or Exploitation?

Panle Jia Barwick Lu Han Jon Kroah Dayin Zhang*

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Abstract

This paper provides to our knowledge the first evidence of realtors' and mortgage loan officers' referral network. Using a unique dataset that traces the entire realtor-mortgage loan officer network in 17 states, we document significant concentration in these networks, with realtors frequently collaborating with a limited number of loan officers. Our analysis shows that homebuyers working with referred loan officers pay higher mortgage rates, with an instrumental variable (IV) approach estimating a premium of 16.5 basis points (or $2,310 in upfront costs). This premium is primarily driven by suboptimal lender selection. The financial burden disproportionately affects vulnerable groups, including Black and Hispanic borrowers, and those with low down payments or high debt-to-income ratios. While referral networks slightly expedite closing times, these benefits are outweighed by the significant financial costs and equity concerns they raise. Our findings highlight the need for greater transparency in referral practices to ensure fairness and efficiency in the mortgage market.

Keywords: realtors, mortgage brokers, network, steering

JEL Classification Codes: L91, R13, R21

*Barwick: Department of Economics, UW-Madison, NBER, and CEPR. pbarwick@wisc.edu. Han: Wisconsin School of Business, UW-Madison, lu.han@wisc.edu. Kroah: Department of Economics, UW-Madison, jkroah@wisc.edu. Zhang: Wisconsin School of Business, UW-Madison, dayin.zhang@wisc.edu.

1 Introduction

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 and securing a mortgage. In the United States, approximately 80% of home transactions involve realtors, contributing to a total transaction volume exceeding $2.5 trillion in 2023. In addition, two-thirds of property purchases are financed through mortgages, which are managed by loan officers.[1] Notably, realtors and mortgage loan officers frequently collaborate to facilitate and streamline the housing transaction process, ensuring a smoother experience for buyers and sellers alike.

Despite the vital roles played by realtors and mortgage loan officers, limited research exists on the informal referral networks between realtors and mortgage loan officers, where realtors recommend specific loan officers to homebuyers. The implications of these networks for homebuyers (mortgage borrowers) remain largely unexplored. These referral networks have the potential to benefit homebuyers by reducing search costs for mortgage loans and streamlining the home purchasing process. However, relying on a limited pool of recommended lenders could also have drawbacks. Homebuyers (mortgage borrowers) may miss opportunities to secure loans with more favorable terms, such as lower interest rates, potentially increasing the overall cost of homeownership.

This paper addresses this research gap by presenting, to our knowledge, the first systematic evidence and quantification of the scope and impact of the realtor-mortgage loan officer referral network. Our analysis is based on a unique dataset we constructed, capturing the "realtor-mortgage loan officer" network across 16 states and the District of Columbia from 2018 to 2021. The dataset provides a comprehensive record of property transactions facilitated by realtors, including detailed property attributes. Crucially, it also documents the mortgage lenders and specific loan officers associated with properties purchased through mortgages. In addition, it includes key financial details – such as interest rates, loan origination costs, and borrower characteristics – for all initiated mortgage loans. This rich dataset enables an in-depth analysis of the referral network and its implications for homebuyers (mortgage borrowers).

We begin by documenting the prevalence of referral networks between realtors and loan officers. Our data reveal that 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 ratio ($CR4$) for each realtor. Our findings indicate that 30% of realtors have a $CR4$ above the high-concentration threshold of 0.7, and 86% exceed the medium-concentration threshold of 0.4. These realtors facilitated 23% (81%) of mortgage-financed home purchases.

Do homebuyers pay higher mortgage rates with realtors who have high loan officer concentration? OLS results suggest they do. Borrowers with top-quintile realtors (by $CR4$) pay 20.4 basis points more than those

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

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 9.9 basis points, and monotonically decreases with the realtor concentration measure.

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 16.5 basis points higher mortgage rates. For an average homebuyer, this translates to an additional \$481.25 in annual interest payments or \$2,310 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 5.3 basis point rate differential between referred and non-referred borrowers. 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 17.4 basis points (\$2,436), while Hispanic borrowers endure an even larger effect of 25.3 basis points (\$3,542). Financially constrained borrowers, such as those with down payments under 5% or DTI ratios above 45%, experience referral effects of 21.4 basis points (\$2,996) and 22 basis points (\$3,080), 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 delays in closing the home purchase. Our findings support this explanation: homebuyers who use referred loan officers close their home purchases 0.47 days faster, compared to the baseline of 41.4 days to close. This suggests that the efficiency offered by referred loan officers may play a significant role in their appeal, particularly in time-sensitive transactions.

Our paper is related to two strands of literature. It is 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.

Our paper is also related to 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 performances. All existing papers, with the exception of Jorgensen (2024), studies realtors separately from mortgage brokers. Jorgensen (2024) focuses on the 100 vertical integration of realtors and mortgage brokers and show 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 networks 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.

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 pre-approved 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.

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, 20221. 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.[2] 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 380 counties from 16 states and the District of Columbia. 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.

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 CoreLogic 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.

Fannie Mae, Freddie Mac, Ginnie Mae Loan Performance Data In additional analyses, we incorporate FICO score information of the borrowers from three prominent public institutions: Fannie Mae, Freddie Mac and Ginnie Mae. These three entities jointly guarantee more than 70% of the mortgages in the U.S. and make origination and performance data (e.g. credit scores) for securitized mortgages available to the public. We merge the loan performance data with the HMDA data (2018-2021) using the overlapping mortgage

[2] Surprisingly, 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.

characteristics.

3 Realtor-Loan Officer Referral Network

3.1 Stylized Facts

To motivate our analysis, we first compare the relationship between loan officer market structure and market size at the market level versus at the individual realtor level. Textbook entry models predict that as the market size grows, the equilibrium number of competitors rises, causing market concentration to decline. Thus, at the market level, we would expect loan officer market concentration to decline as market size increases. Within a single realtor's loan officer network, we would expect the same pattern if the realtor did not steer homebuyers towards specific lenders: the network would become less concentrated as the "market size" (the number of transactions handled by the realtor) declined. However, if realtors steer homebuyers towards specific lenders, then lender networks may remain highly concentrated even for large market sizes.

Realtors' Lender Networks and Transaction Volume In Figure 2, we analyze whether realtors tend to use few lenders relative to their transaction volume or the size of the lender choice set in their market. We plot the number of unique lenders a realtor works with on the vertical axis against the number of transactions a realtor handles in each market on the horizontal axis. We also plot the maximum number of lenders each realtor could possibly work with in each market, which we assume is the minimum of the number of active lenders in the market and the number of transactions the realtor handles in the market. We present binned scatterplots for clarity. The figure shows that buyer agents tend to work with a few lenders, relative to the maximum number they could work with, regardless of how many transactions an agent handles in a given market.

Market-Level Versus Realtor-Level Lender Concentration In each geographic market, we compute loan officer $CR4$ and HHI based on the total number of purchase mortgage transactions across all years (2018–2021). Then, we compute $CR4$ and HHI within each realtor in the market (i.e., treating the realtor as a "market").

We then construct a market-level measure of average within-agent lender concentration by taking a weighted average of the agent-level concentration statistics, weighting each agent by her transaction volume. For this step, we drop buyer agents that have fewer than 10 transactions in the market across all years. To illustrate, suppose a market had two lenders and two realtors; Lender 1 has 100 transactions with Realtor 1, and Lender 2 has 100 transactions with Realtor 2. The market-level HHI is 5,000, since the lenders split the market. However, each realtor works exclusively with one lender, so the HHI within each lender is 10,000, and the average realtor-level HHI in the market is 10,000. If instead realtors worked with lenders in proportion to the lenders' aggregate market shares, then there would be no discrepancy between market-level and agent-level HHI.

Figure 3 plots these concentration measures against market size (estimated as the total number of transactions in the market). In these graphs, a "lender" refers to an individual loan officer. The graphs show two important patterns. First, market-level concentration is generally quite low, while average agent-level concentration is much higher: for example, market HHI ranges from 5 to 1,763, while average agent-level HHI ranges from 62 to 8,347 across markets. (For comparison, the 2023 Merger Guidelines consider markets "highly concentrated" if HHI exceeds 1,800.[3]) Similarly, the market-level 4-firm concentration ratio ($CR4$) ranges from 1% to 74%, while average agent-level CR4 ranges from 9% to 100%. Thus, on average, individual buyer agents work with a small subset of lenders in the market. Second, while market-level concentration declines with market size, average agent-level concentration *increases* with market size. In other words, even in large markets, the average buyer agent tends to work with a limited set of borrowers.

3.2 Prevalence of Referral Networks

Figure 4 presents the distribution of loan officer concentration measures for the 92,343 realtors in our sample. Panel (a) focuses on the $CR4$, revealing significant concentration within referral networks. Specifically, 30% of realtors have a $CR4$ exceeding 0.7, meeting the high-concentration threshold, while 86% surpass the medium-concentration threshold of 0.4. These concentrated networks have a notable influence on the housing market: realtors with a high $CR4$ facilitated 23% of all mortgage-financed home purchases, and those with a medium $CR4$ accounted for 81%. These results highlight the prevalence of concentrated referral practices and their potential effects on lender competition and borrower outcomes, underscoring the importance of further scrutiny of these networks.

Panel (b) examines the alternative concentration measure, HHI, and similarly reveals a high prevalence of concentration within referral networks. Specifically, 41% of realtors have an HHI exceeding 1800, meeting the high-concentration threshold, while 75% surpass the medium-concentration threshold of 1000. These findings align closely with the results from $CR4$, further emphasizing the significant concentration levels within realtor-loan officer referral networks.

4 Implication of the Referral Network

To test the implications 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:

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

[3] https://www.justice.gov/d9/2023-12/2023%20Merger%20Guidelines.pdf

Where mortgage i is associated with a loan officer l and realtor (buyer agent) r. $CR4_r$ measures the level of concentration of realtor r's loan officer network. The coefficients of interest, β, capture the differences in outcomes (Y_{it}) between more-concentrated realtors and the omitted group of realtors (the bottom quintile in terms of $CR4$ in our baseline specifications). For outcomes (Y_{it}), we examine the interest rate spread relative to the benchmark rate offered on prime mortgage loans of comparable types. The control variables (X_{it}) 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.

4.1 Mortgage Interest Rates By Loan Officer Concentration of Realtors

Table 1 presents estimates of Equation (1) for interest rates. Column (1) show the raw differences of the interest rate spreads across realtors with different degrees of loan officer concentration. Borrowers working with top-quintile realtors (by $CR4$) pay significantly higher mortgage interest rates, averaging 20.4 basis points more than those working with bottom-quintile realtors. Moreover, the rate differentials decrease monotonically as the concentration of loan officer networks declines, suggesting a clear relationship between realtor concentration and borrower costs.

To ensure robustness, we progressively add controls across to the regressions, accounting for various factors that could influence interest rates. These include aggregate market trends, borrower characteristics such as income, age, and loan attributes such as loan-to-value (LTV) ratios and debt-to-income (DTI) ratios. By the time we reach our baseline specification in column (5), we find that transactions involving top-quintile agents still result in interest rates that are 9.9 basis points higher than those involving bottom-quintile agents.

For the average loan amount in our sample ($293,318.8), this 9.9 basis point differential translates into a substantial financial burden for borrowers. Specifically, it means an additional $290 in annual interest payments. Alternatively, to achieve the same lower interest rate as borrowers working with bottom-quintile realtors, homebuyers would need to pay $1,386 in upfront fees, calculated using a point-based rate reduction factor 4.8 estimated in Bhutta et al. (2019). These findings underscore the financial implications of working with highly concentrated realtor referral networks and suggest that such networks may come at a notable cost to borrowers.

[4] Applicant 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 group FICO scores into bins of approximately 40 points and include FE for these bins. Agency FE control for whether the agency is Ginnie Mae (GNMA), Freddie Mac (FHLMC), or Fannie Mae (FNMA). We define LTV ratio bins as 0-20, 20-40, 40-60, 60-80, 80-100, or 100+.

4.2 OLS Regressions

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

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

A $CR4_r \geq 0.7$ 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 lenders 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:

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

Table 2 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 8 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-4 loan officers in cases where the realtor has medium loan officer concentration. This more targeted approach increases the estimated referral effect to 10.4 basis points, underscoring the impact of referral networks on borrower costs.

4.2.1 Suboptimal Choice of Lenders or Other Factors

In Table 2, Column (3) 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.

4.2.2 Mortgage Origination Costs

Columns (5)-(8) focus on the APR spread, which accounts for both the mortgage rate and origination costs. The results indicate a referral effect that is 0.7–0.9 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.

In columns 1-4, we add controls successively until reaching our baseline specification in column 4. Relative to the bottom quintile of agents, interest rates are 1.7 basis points higher for transactions handled by the top quintile of agents. For a $400,000 loan, this amounts to $68 more in interest payments annually. Column 5 explores whether this difference is driven by specific lenders. Specifically, we interact the CR4 quintile dummies with dummies for whether the lender is one of the agent's top two lenders (ranked by the number of transactions within each agent). Comparing columns 4 and 5, we see that the interest rate differences are driven almost entirely by the top (#1) lender within the top quintile of agents. Finally, as a robustness check, we control for whether the lender is a top lender in the given market and year (ranked across all buyer agents) in column 6. Our estimates do not change qualitatively between columns 5 and 6.

To explore the level at which lender referrals operate, Table **??** repeats the analysis above using buyer agent *office*-level measures of lender network concentration. In contrast to Table **??**, columns 4 and 5 finds that interest rates are 1.1-1.7 basis points lower for the 3rd quintile of offices, relative to the bottom quintile. Comparing columns 4 and 5, this does not appear to be driven by whether a borrower uses an office's top lender. Interestingly, offices in the top quintile are associated with lower interest rates (-1 basis point), but within this quintile, using an office's top two lenders is associated with higher interest rates (+1.9 to +2.4 basis points).

4.3 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., $CR4$) 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:

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

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

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

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 $CR4$, 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:

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

X_{jm} is a vector of lender-market-specific characteristics. We include dummies for whether lender j is a bank, a fintech firm[5], 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.

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

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

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

IV Results Table 3 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, 16.5 basis points higher mortgage rates compared to borrowers outside such networks. For an average homebuyer in our sample, this translates to an additional $481.25 in annual interest payments, based on the average loan size of $293,318.8. Alternatively, borrowers would need to pay approximately $2,310 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 5.3 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.

Columns (3) and (4) analyze the APR spread, which incorporates both the interest rate and origination costs, and reveal an additional 1.4 basis points effect ($296) 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.

4.4 Heterogeneous Effects

Table 4 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 17.4 basis points, translating into an additional $2,436 in upfront costs. Hispanic borrowers face an even greater impact, with a referral effect of 25.3 basis points, amounting to $3,542 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 21.4 basis points, resulting in $2,996 in added costs. Similarly, borrowers with debt-to-income (DTI) ratios above 45%, indicative of lower income, face a referral effect of 22 basis points, translating to $3,080 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.

4.5 Evidence on Days to Close

In the mortgage market, borrowing is not only costly but also risky. Some borrowers may find it particularly challenging in getting a mortgage and would benefit from their realtors' referral network.

Table 5 presents the IV estimates for days to close for home purchases, which is defined as the days between purchase contract date and closing date. Column (2) shows that, conditional on successful closing, homebuyers who use referred loan officers complete their home purchases 0.47 days faster on average compared to the baseline of 41.4 days to close. This finding highlights a potential efficiency benefit of referral networks, as they may streamline the mortgage processing and closing timeline. Realtor-referred loan officers might expedite the process due to established working relationships and familiarity with the specific needs of referred clients. These relationships could help minimize delays by ensuring smoother communication, quicker document processing, or prioritization of referred borrowers. Additionally, referred loan officers may have a better understanding of the local market dynamics and lender practices, enabling them to navigate potential bottlenecks more effectively.

Column (4) and (6) reveal that the probability of a home purchase taking more than 30 days to close decreases by 3.3 percentage points from a baseline of 75%. This suggests that referral networks can help expedite the closing process for transactions that would otherwise experience moderate delays. However, the analysis also shows that the probability of taking more than 45 days to close does not change significantly.

These findings indicate that while referred loan officers may help reduce the likelihood of moderately extended closing timelines, their impact on avoiding longer, more substantial delays is limited. This suggests that the efficiency gains provided by referral networks might primarily target smoother coordination for typical delays, rather than addressing the systemic factors contributing to significant closing delays. Borrowers may benefit from these modest improvements in timeline efficiency but should weigh them against the potential higher borrowing costs associated with referral networks.

5 Conclusion

This study provides the first systematic evidence of the scope and impact of realtor-mortgage loan officer referral networks on homebuyers, highlighting both their benefits and drawbacks. Our findings reveal significant concentration in these networks, with a substantial proportion of realtors collaborating with a limited number of loan officers. While these referral networks offer efficiency benefits, such as slightly faster closing times, they come at a financial cost to borrowers.

Our analysis shows that homebuyers working with referred loan officers pay higher mortgage rates, with the premium primarily driven by suboptimal lender selection within the local market. Even within the same lender, referred borrowers face higher rates, suggesting that factors beyond lender choice—such as loan officer-specific practices—contribute to the increased costs. The financial burden of these referral effects is not evenly distributed, disproportionately impacting historically disadvantaged groups such as Black and Hispanic borrowers, as well as financially constrained individuals with low down payments or high debt-to-income ratios.

These findings raise important policy and ethical considerations about the transparency and fairness of referral practices in the mortgage market. While referral networks may streamline processes and reduce search costs for some homebuyers, they also exacerbate existing inequities and increase the overall cost of homeownership. Future research and regulatory efforts should focus on improving the transparency of referral practices and empowering borrowers to make more informed decisions, ultimately fostering a more equitable and efficient housing market.

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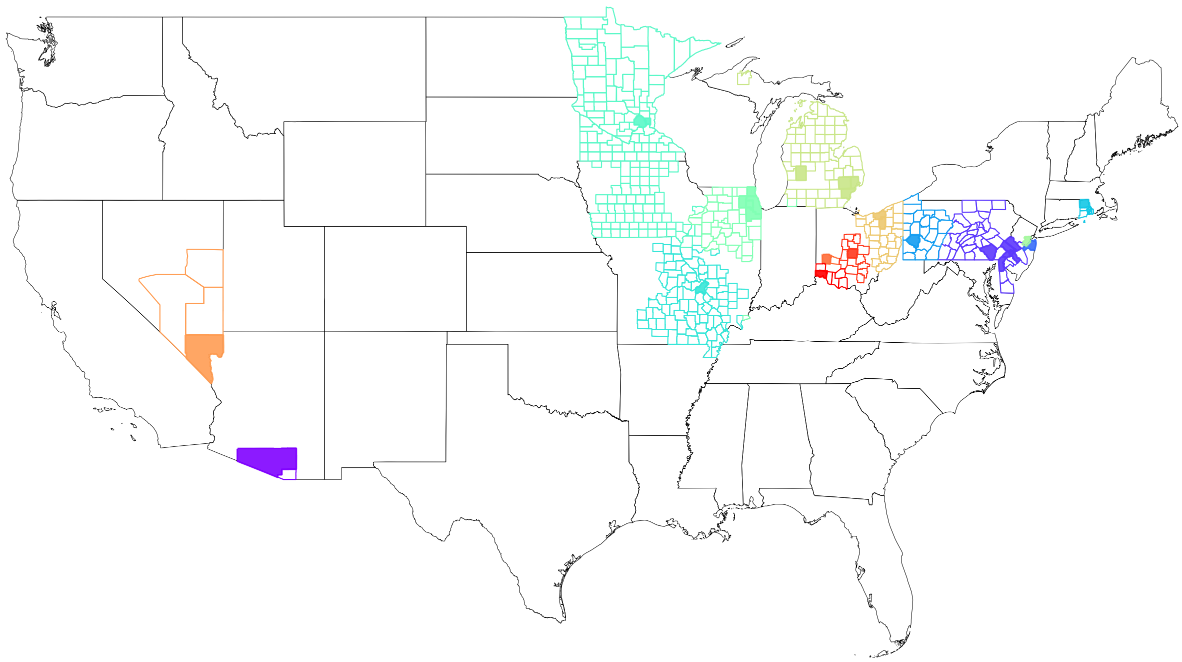
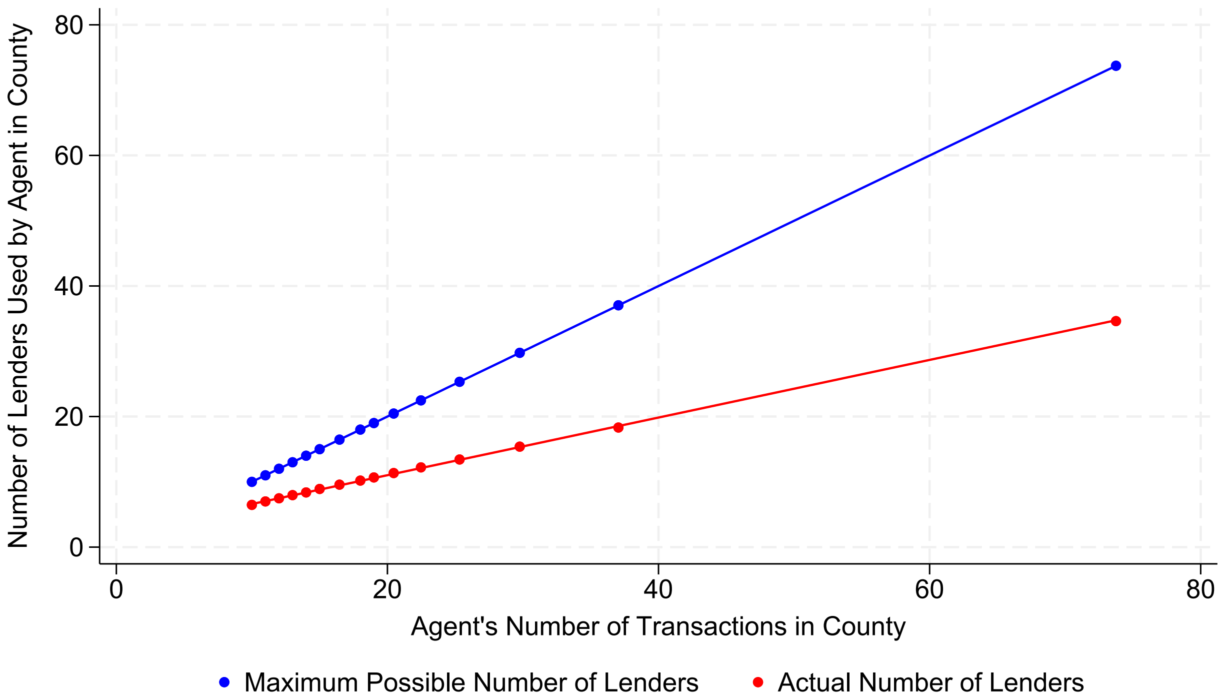
Figures

Figure 1: Geographic Coverage of the Data Sample



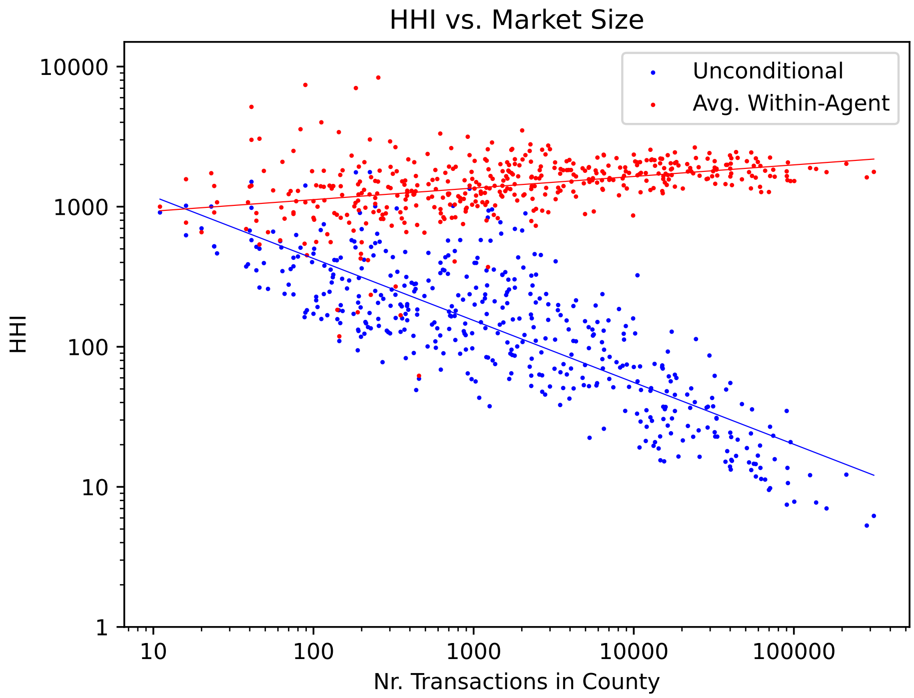
Note: This figure plots the counties that our data sample covers.

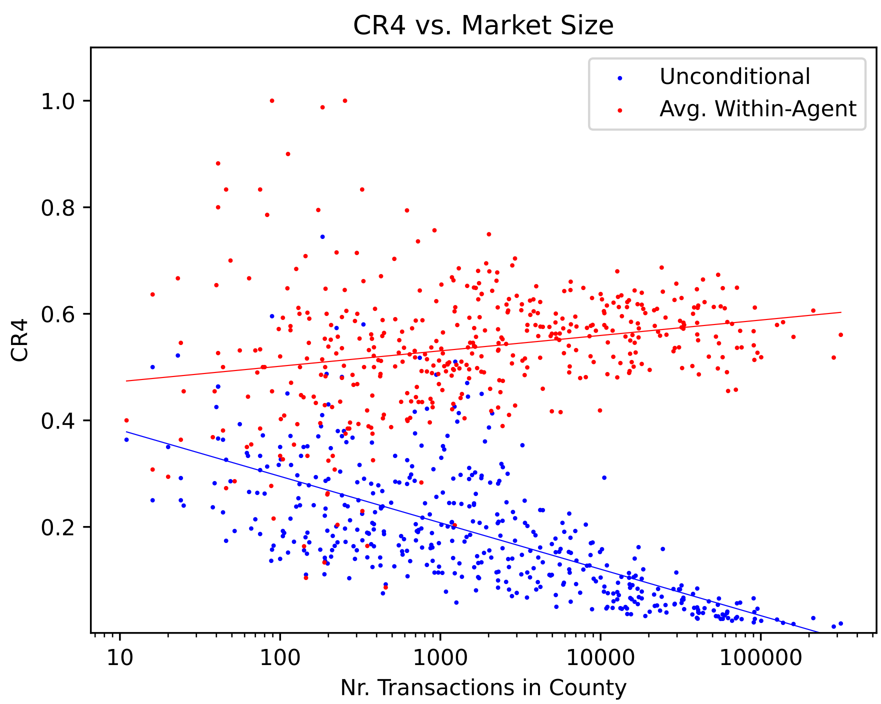
Figure 2: Lender Network Size vs. Transaction Volume for Buyer Agents x Counties



Notes: This figure presents binned scatter plots of the number of lenders a realtor (buyer agent) works with (or could potentially work with) against the number of transactions handled by the realtor, within a given market (county). We limit to realtor-county pairs with at least 10 transactions across all years. The "maximum possible number of lenders" for a realtor in a given county is defined as the minimum of (i) the number of transactions handled by the realtor in the given county; and (ii) the number of lenders active in the given county.

Figure 3: Loan Officer Concentration vs. Market Size (Purchase Loans)

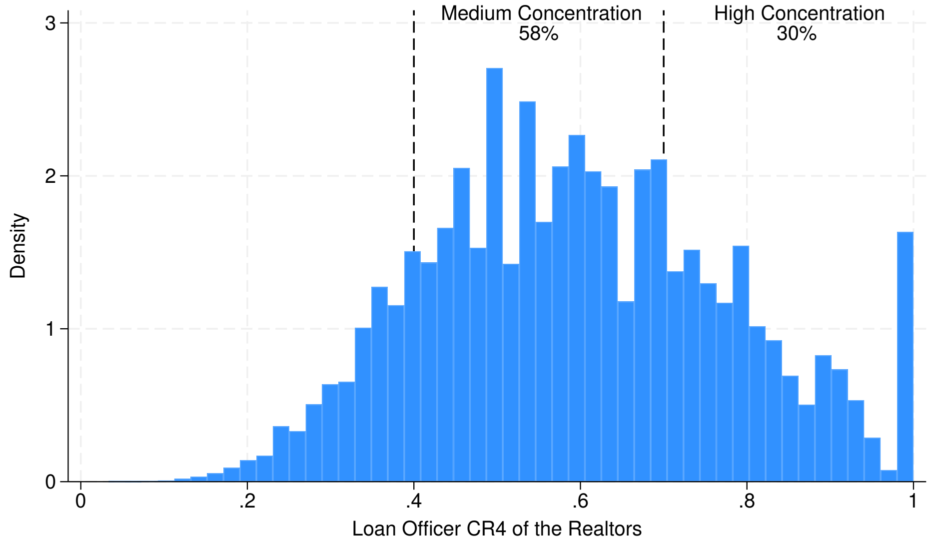




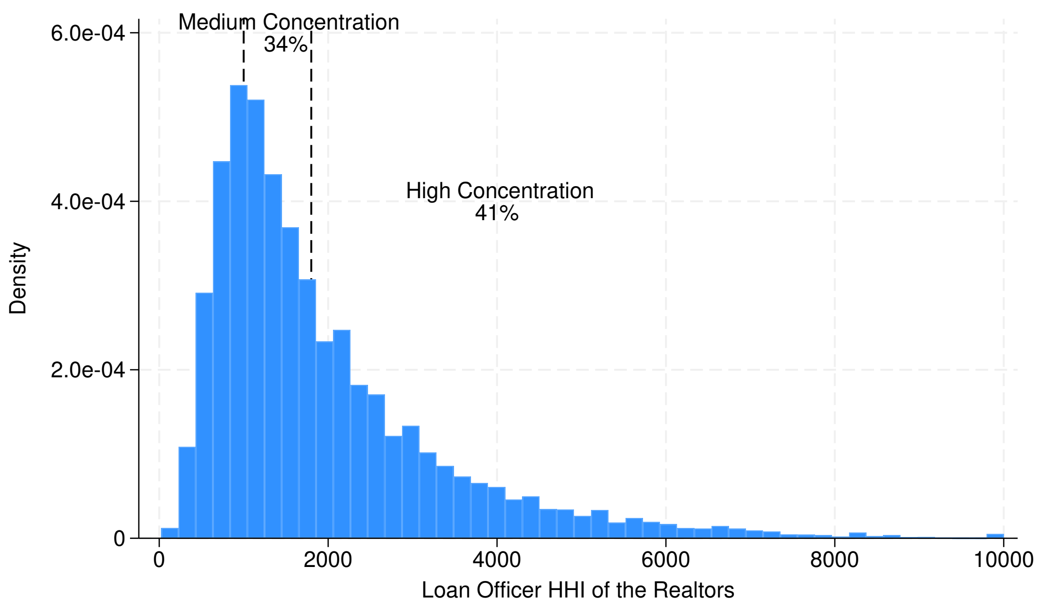
Note: These figures plot average within-buyer agent concentration and market-level concentration against market size (defined as the total number of transactions in the market). We plot two measures of market concentration: the Herfindahl-Hirschman Index (HHI, equal to the sum of lenders' squared market shares) and four-firm concentration ratio (CR4, equal to the sum of the top four lenders' market shares). Market shares are based on the number of purchase mortgage transactions associated with each lender. When computing average within-agent concentration, we limit to buyer agents with at least 10 transactions.

Figure 4: Distribution of Loan Officer Concentration of Realtors

(a) *CR*4



(b) *HHI*



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.

Tables

Table 1: Mortgage Interest Rate Spreads By Realtor *CR*4 Quintiles

	Interest Rate Spread (off Prime Rate, in %)				
Control Var.	No Control (1)	+Market FE (2)	+Borrower Ctrl (3)	+DTI (4)	+LTV (5)
Realtor *CR*4 Quintile 5	0.204***	0.155***	0.143***	0.131***	0.099***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Realtor *CR*4 Quintile 4	0.119***	0.086***	0.079***	0.073***	0.052***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Realtor *CR*4 Quintile 3	0.074***	0.053***	0.049***	0.046***	0.031***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Realtor *CR*4 Quintile 2	0.033***	0.025***	0.024***	0.024***	0.015***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Observations	1,118,956	1,117,239	1,117,239	1,117,239	1,117,239
Adjusted R-squared	0.012	0.152	0.169	0.223	0.304
Dep. Var. Mean	0.42	0.42	0.42	0.42	0.42
Year-Month*County FE		Y	Y	Y	Y
log[Loan Amount]		Y	Y	Y	Y
Age Bin FE			Y	Y	Y
Income Ratio Percentile FE			Y	Y	Y
Joint Application			Y	Y	Y
Conforming FE			Y	Y	Y
DTI bin FE				Y	Y
LTV bin FE					Y

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.

Table 2: Effect of Referral on Purchase Mortgage Costs (OLS)

	Interest Rate Spread (off Prime Rate, in %)				APR Spread (off Prime Rate, in %)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Referral	0.080***	0.028***	0.104***	0.024***	0.087***	0.030***	0.113***	0.027***
($CR4 \geq 0.7$, Top 4 Loan Officer)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Likely Referral			0.056***	-0.007***			0.062***	-0.006***
($CR4 \in [0.4, 0.7)$, Top 4 Loan Officer)			(0.001)	(0.001)			(0.001)	(0.001)
Observations	1,117,239	950,041	1,117,239	950,041	1,137,541	968,099	1,137,541	968,099
Adjusted R-squared	0.303	0.471	0.305	0.471	0.320	0.491	0.321	0.491
Dep. Var. Mean	0.42	0.41	0.42	0.41	0.51	0.50	0.51	0.50
Year-Month*County FE	Y	.	Y	.	Y	.	Y	.
Year-Month*County*Lender FE	.	Y	.	Y	.	Y	.	Y
log[Loan Amount]	Y	Y	Y	Y	Y	Y	Y	Y
Age Bin FE	Y	Y	Y	Y	Y	Y	Y	Y
Income Ratio Pencentile FE	Y	Y	Y	Y	Y	Y	Y	Y
Joint Application	Y	Y	Y	Y	Y	Y	Y	Y
Conforming FE	Y	Y	Y	Y	Y	Y	Y	Y
DTI bin FE	Y	Y	Y	Y	Y	Y	Y	Y
LTV bin FE	Y	Y	Y	Y	Y	Y	Y	Y

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 $CR4$ 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 $CR4$ 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 $CR4$ 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.

Table 3: Effect of Referral on Purchase Mortgage Costs (IV: $\widehat{CR4}$)

	Interest Rate Spread (off Prime Rate, in %)		APR Spread (off Prime Rate, in %)	
	IV	IV	IV	IV
	(1)	(2)	(3)	(4)
Referral	0.165***	0.053***	0.179***	0.057***
($CR4$ $\geq$0.7, Top 4 Loan Officer)	(0.004)	(0.005)	(0.004)	(0.005)
Observations	833,430	692,633	848,614	705,911
Adjusted R-squared	0.052	-0.151	0.061	-0.136
Dep. Var. Mean	0.43	0.42	0.51	0.51
Year-Month*County FE	Y	.	Y	.
Year-Month*County*Lender FE	.	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	128388	81635	131343	83654
FS: Kleibergen-Paap rk F	136012	82421	139294	84568
FS: Anderson-Rubin p-val	0	0	0	0

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 $CR4$ 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 $CR4$ 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.

Table 4: Heterogeneous Effect of Referral on Purchase Mortgage Interest Rate Spreads (IV: $\widehat{CR4}$)

	Interest Rate Spread (off Prime Rate , in %)			
	IV	IV	IV	IV
	(1)	(2)	(3)	(4)
Referral	0.168***	0.148***	0.103***	0.111***
($CR4$ $\geq$0.7, Top 4 Loan Officer)	(0.006)	(0.005)	(0.005)	(0.005)
Referral*(Age<35)	-0.007			
	(0.008)			
Referral*(DTI>0.45)		0.072***		
		(0.009)		
Referral*(LTV>0.95)			0.111***	
			(0.008)	
LTV>0.95			0.350***	
			(0.002)	
Referral*Black				0.063***
				(0.015)
Referral*Hispanic				0.142***
				(0.011)
Referral*Asian				0.004
				(0.013)
Referral*Other				0.117***
				(0.036)
Black				0.189***
				(0.004)
Hispanic				0.167***
				(0.004)
Asian				-0.042***
				(0.003)
Other				0.024***
				(0.007)
Observations	833,430	833,430	833,430	833,430
Adjusted R-squared	0.052	0.052	0.125	0.073
Dep. Var. Mean	0.43	0.43	0.43	0.43
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	64086	61868	57977	22709
FS: Kleibergen-Paap rk F	64391	53486	37612	16835
FS: Anderson-Rubin p-val	0	0	0	0

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 $CR4$ 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 $CR4$ 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.

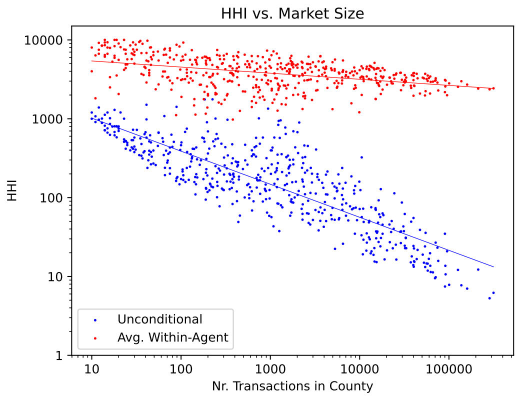
Table 5: Effect of Referral on Days to Close (IV: $\widehat{CR4}$)

	Days to Close		>30 Days (in %)		>45 Days (in %)	
	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Referral	-0.378**	-0.470**	-3.258***	-3.312***	-0.360	-0.521
($CR4 \geq 0.7$, Top 4 Loan Officer)	(0.184)	(0.185)	(0.358)	(0.361)	(0.374)	(0.376)
Observations	791,361	791,361	791,361	791,361	791,361	791,361
Adjusted R-squared	-0.029	-0.029	-0.029	-0.029	-0.029	-0.029
Dep. Var. Mean	41.44	41.44	75.35	75.35	28.91	28.91
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	119660	118285	119660	118285	119660	118285
FS: Kleibergen-Paap rk F	124441	123508	124441	123508	124441	123508
FS: Anderson-Rubin p-val	0.0399	0.0111	0	0	0.336	0.166

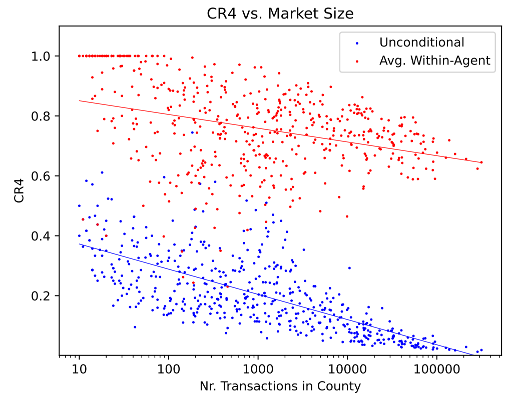
Note: This table reports the IV regression estimates of realtor-loan officer referral network effect on home purchase close time. The concentration is measure by within realtor $CR4$ of the loan officer mortgage shares. The dependent variables are the days between purchase contract accepted and purchase close, and the share of days above 30 (45) days. $Referral$ equals 1 if the homebuyer's realtor $CR4$ 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.

Appendix Figures

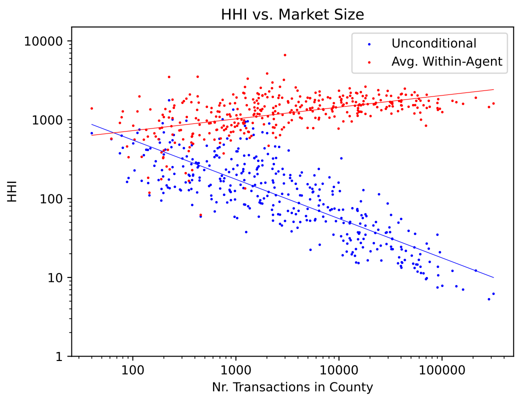
Figure A1: Loan Officer Concentration vs. Market Size (Purchase Loans): Alternative Transaction Count Cutoffs



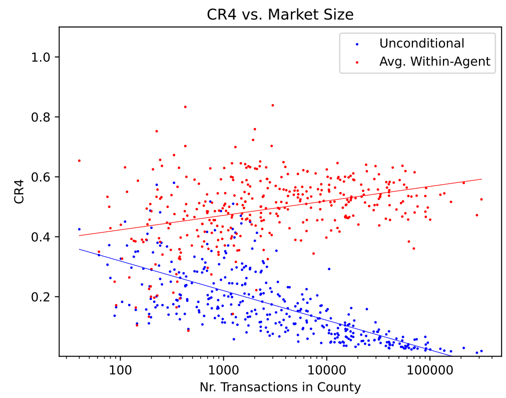
HHI, Agents with 1+ Txns.



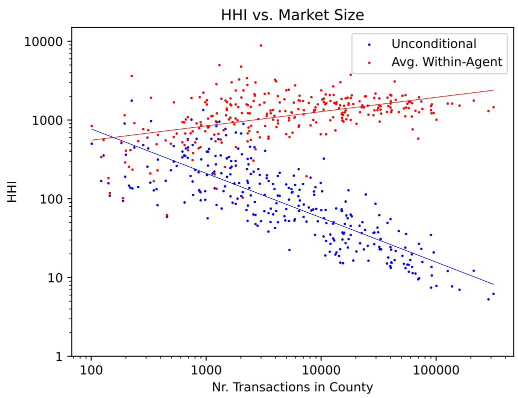
CR4, Agents with 1+ Txns.



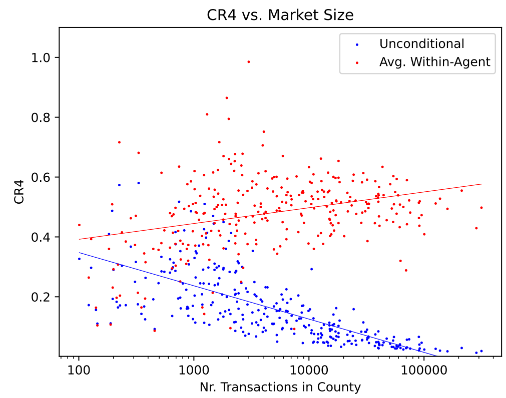
HHI, Agents with 25+ Txns.



CR4, Agents with 25+ Txns.



HHI, Agents with 50+ Txns.



CR4, Agents with 50+ Txns.

Note: These figures plot average within-buyer agent concentration and market-level concentration against market size (defined as the total number of transactions in the market). Each row limits to agents with a different minimum number of transactions.