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Do Networks Matter in Real Estate? Real Estate Agent Performance Through Network Analysis

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ABSTRACT

DO NETWORKS MATTER IN REAL ESTATE? REAL ESTATE AGENT PERFORMANCE THROUGH NETWORK ANALYSIS

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The role of real estate agents as intermediaries in property transactions is well-established. However, the extent to which their positioning within professional networks influences transaction outcomes remains to be discovered. Drawing inspiration from network theory, this dissertation explores the relationship between real estate agent networks and performance metrics. Using a comprehensive dataset of Tarrant County, Texas, MLS transactions spanning 2002-2022, I test how agent network size and position relate to the property sale price and time on the market (TOM). The analyses suggest that network positioning could be pivotal in determining transactional outcomes. This study promises to fill a gap in the real estate and finance literature by focusing on the often-overlooked dimension of agent networks, with implications for industry and academia.

DEDICATION

To my dad, Vardan Khachatryan, who lives on in my heart.

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Finally, praise and glory to God.

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CHAPTER 1: INTRODUCTION

Introduction

The residential real estate market is one of the largest asset classes in the US economy, profoundly shaping urban landscapes and serving as a significant investment avenue for individuals and families. In the residential real estate market, agents play a pivotal intermediary role, facilitating home buyers and sellers. While the prevailing notion suggests that their expertise, extensive network, and localized market knowledge add substantial value to the transactions, the extent of their actual contribution remains a subject of inquiry. For homebuyers, real estate agents are often portrayed as indispensable guides, providing personalized assistance, evaluating their needs, and presenting suitable property options. Similarly, for home sellers, agents are deemed strategic partners, orchestrating marketing efforts, conducting property evaluations, and facilitating negotiations to optimize the selling process.

However, a comprehensive assessment of the actual impact and necessity of real estate agents in the overall efficiency and fluidity of the residential real estate market warrants further investigation. In the US residential real estate market, recent statistics underscore the paramount significance of comprehending the role of real estate agents. According to the National Association of Realtors® (NAR), as of 2023, approximately 93%[1] home sales involved real estate agents' services to navigate the transaction process. Indeed, technology has significantly transformed the real estate industry, and the rise of iBuying and proptech has made property transactions more efficient and convenient. However, the human touch and personal connection provided by real estate agents remain highly valued by home buyers, particularly millennials.

[1] National Association of Realtors® 2023 Profile of Home Buyers and Sellers https://cdn.nar.realtor/sites/default/files/documents/2023-profile-of-home-buyers-and-sellers-highlights-11-13-2023.pdf

The National Association of Realtors' generational survey[2] highlights millennials, who constituted the largest group of home buyers in 2019, were the most likely to leverage both the Internet and the expertise of real estate agents during their home-buying journey. This shows that despite the wealth of online resources available, millennials still appreciate a professional's assistance in navigating the complex process of purchasing a property.

Several reasons could explain why buyers, including millennials, continue to value real estate agents:

1. Expertise and guidance: Real estate agents have in-depth knowledge of the local market, trends, and regulations. They can provide valuable insights and advice to help buyers and sellers choose the best school district or the “correct” listing price.
2. Personalized service: Agents can tailor their services to meet individual needs, preferences, and budget constraints. They take the time to understand the buyer's requirements and show them relevant properties accordingly. They can also help with financing inquiries. On the selling side, agents can help find any services, including general contractors, to fix the properties, staging, and more.
3. Negotiation skills: Experienced agents excel at negotiating with sellers to secure the best possible deal for their clients, ensuring they get the most value for their investment. Negotiation skills are essential for buyer agents to find the balance between bargaining the sale price and other terms and maintaining a competitive edge over other bidders.
4. Paperwork and legalities: Home-buying involves substantial paperwork and legal documentation. Agents can handle these aspects efficiently, reducing the parties' burden.

[2] National Association of Realtors® 2019 Home Buyer and Seller Generational Trends https://www.nar.realtor/sites/default/files/documents/2019-home-buyers-and-sellers-generational-trends-report-08-16-2019.pdf

5. Building trust: Establishing trust is essential in any significant financial transaction. A real estate agent is a reliable partner who boosts the buyer and seller's confidence and security.
6. Emotional support: Buying a home can be an emotional experience. Real estate agents can offer support and reassurance, helping buyers and sellers navigate uncertainties.
7. Access to off-market listings: Not all properties for sale are publicly listed. Historically, real estate agents often had access to off-market listings, so-called “pocket listings,” giving their clients exclusive opportunities. In 2020, the NAR’s MLS Clear Cooperation Policy made registering REALTOR® listings on MLS compulsory within one business day. This policy is designed to eliminate “pocket listings.”
8. Connections: Well-connected real estate agents have access to a network of other agents, industry professionals, and resources, providing valuable insights into the local market. This network enables them to be aware of new homes coming onto the market before they are officially listed. This "off-market" knowledge can be a significant advantage for buyers, as they can get a head start on the competition and make an offer on a desirable property before it becomes widely known to other potential buyers. For the sellers, pocket listings can potentially decrease the commission rate they have to pay to buyers’ agents if their agent represents both sides or cuts a deal with the other agent. With their network, a well-connected agent can gauge the level of competition for a particular property. By talking to buying agents in the area, they can determine if other buyers are also interested in the house. This information can help the buyers make the right offer and position themselves favorably in negotiations. A well-connected real estate agent improves the negotiation process for both parties. Their strong relationships with other agents can facilitate gathering essential details to create an appealing offer that suits both parties' needs. Their expertise

in buying and selling properties ensures a smoother and more successful negotiation experience. For example, if the sellers prioritize a quick closing date or a particular financing method, an agent can gather these details to include in the offer. While the broad agent network comprises other agents and professionals like lenders, inspectors, contractors, and investors, I focus on the network they create with other agents through prior transactions.

Information asymmetry is a crucial factor when discussing real estate markets and the role of the agents. The intuition is that agents possess information unavailable to the sellers and buyers unless they work with an agent. Often, agents specialize in a geographic area and are well-informed about the particulars of local markets (see Hayunga & Fang, 2023). It is difficult for uniformed or non-local buyers to evaluate market options. Likewise, for a seller with prior experience, deciding a house's listing price can take time and effort. Agents are expected to have expert knowledge relevant to the current market situation. However, agency problems between agents and their clients remain a concern.

The dynamics of social networks have garnered significant attention across various fields, including sociology, economics, and information science. Despite this interest, exploring social networks within real estate transactions still needs to be developed. This dissertation addresses this gap by examining the networks of real estate agents and their impact on transaction outcomes.

The importance of studying networks cannot be overstated, especially for such a network-centered industry as real estate. In this study, I construct a network of agents using historical transaction data from Tarrant County, Texas, from October 2002 till March 2022. By studying the different characteristics of agent networks, including network size, agent position, and influence, I aim to explain the role professional networks play in the performance outcomes of agents and what that means for the sellers and buyers working with those agents. I use the sale price and time-on-the-market (TOM) as performance indicators. The research questions I pose include:

1. How does listing and selling agent network size relate to the sale price and TOM?
2. How does listing and selling agents' position as intermediaries in the network relate to the sale price and TOM?
3. How does listing and selling agents' influence, as measured by the influence of their immediate network, relate to the sale price and TOM?

This research contributes to the field by providing a deeper understanding of the role of social networks in real estate transactions. The findings can inform strategies for agents to optimize their network-building activities and improve performance. The study can also help sellers and buyers decide how to choose an agent. Moreover, considering the recent lawsuit against large brokerages in the U.S., this and future studies of agent networks can help policymakers develop regulations preventing large players in the market from colluding to boost their profits at the expense of their clients.

The study builds upon the Efficient Market Hypothesis (EMH), agency theory, social capital theory, and organizational theory of social networks, collectively providing a basis for analyzing the interplay between network dynamics and transaction outcomes, which I describe in Chapter 2.

The study focuses on real estate transactions within a single county in Texas over twenty years. Limitations include potential biases due to data availability, the relatively simple approach used for network construction, the need for more information regarding the contractual relationships between buyers and selling agents, and the exclusion of specific network effects not captured in the dataset. The concluding chapter provides a more detailed discussion of the study's limitations.

I construct an agent network for a one-year (or three-year) window before the transaction date. Listing and selling agents that have completed transactions within that window comprise the network nodes, and the transactions between them serve as the network edges (or ties). The three metrics I use to describe each agent in the network are degree centrality, betweenness centrality, and eigenvector centrality. The degree centrality, or the agent network size, shows how many unique connections each agent has made in the network window. The betweenness centrality, or agent bridging power, shows each agent's relative position as an intermediary in the network. The eigenvector centrality, or agent influence, shows the impact of each agent's immediate network. It is a relative measure of the quality of agents' connections. I use a Three-Stage Least Squares (3SLS) regression to simultaneously model the relationship between each network metric with the sale price and TOM.

Chapter 2 reviews the relevant literature on agents' role in the real estate markets and social networks. Chapter 3 explains the social network analysis metrics and the development of hypotheses. Chapter 4 describes the data and methodology. Chapter 5 discusses the findings and additional tests performed. Chapter 6 provides the conclusions, research limitations, and future work.

CHAPTER 2: LITERATURE REVIEW

Introduction

The multidisciplinary nature of this study necessitates a comprehensive literature review that spans several fields, including real estate, finance, and sociology (with an emphasis on social network analysis). The study's primary research question is to establish whether and how a real estate agent's position within the network affects the transaction outcomes. To analyze this question, we delve into the nature of real estate markets, the role of real estate agents in the transaction process, and how finance and real estate literature have used network analysis techniques to evaluate similar questions.

In this literature review, I first introduce different works addressing the market efficiency hypothesis in real estate research. This is a fundamental question in finance and real estate literature. Hence, the body of research directly or indirectly addressing this question is significant. To keep the discussion within manageable limits, I focus on articles that discuss market efficiency from the lens of real estate agent participation in the market as intermediaries and include relatively recent articles since the structure of the residential real estate market has changed dramatically after the introduction of the Internet and various online platforms.

Agents are instrumental in the real estate markets as, often irrational, human factors create additional frictions unique to this field. As we will see, agents are often related to information asymmetries and agency problems partly because of the unique compensation structure prevalent in the US, at least until the moment of writing this dissertation. Even though I do not directly address the nuances arising from the standard 6% commission structure, usually paid by the seller to the listing and selling agents, I acknowledge that it is an integral part of the market mechanism.

The reasons why I do not include agent commission in the analysis are discussed in the Methodology and Models section.

After presenting the large picture of literature findings on real estate market efficiency through information asymmetries and agency problems, I further summarize the literature on the role of real estate agents. Agent characteristics, such as gender, experience, brokerage affiliation, specialization, inventory size, and location, are some of the factors discussed in the literature as researchers seek to measure the value added by the agents.

Often, the studies focus on listing or selling agents separately, failing to capture both sides simultaneously. Another vital feature of brokerage studies is that the available data varies significantly depending on the geography. There can be significant differences in the information multiple listing services (MLS) collect about the agents involved, property, and deal characteristics. This makes it unattainable to replicate and generalize the findings of many articles. MLS data is also proprietary, meaning it cannot be shared with third parties without permission. Therefore, it becomes crucial to investigate similar research questions using data from different geographies and try to capture the uniqueness of the local market.

The literature on social network analysis is multifaceted. It originated in sociology but was quickly adopted as a tool in various disciplines, including finance and accounting. While the theory behind social networks is generalizable in many areas, the mechanisms are unique for each. For example, social network analysis of friendship networks in sociology, sports teams in sports science, and professional networks in finance likely answer the same general question of whether connections matter but do it with different mechanisms and motivations. As we will see, the finance literature on social networks is rapidly growing. The most popular theme is the executive (directors, board members, CEOs) connections within and among firms and their relationship to phenomena such as executive compensation, firm performance, and M&A patterns. A few articles also use network analysis to study mutual fund flows, herding behaviors, and more.

On the other hand, the real estate literature has only a few articles that directly or indirectly use network analysis, which I discuss in the section below. This dissertation is one of the first studies with distinct data, models, and methodology to study agent professional networks and their relationship to transaction outcomes for single-family properties. Prior works related to agent networks find that listing agents prioritize the social capital they build with other agents over sellers' best interests, especially in the early years of their careers (Smith et al., 2019, Shen and Sun, 2023). However, these studies use modified variables to capture agent network size and focus on listing agents only. This study, however, models agent network size and position directly and simultaneously for listing and selling agents. Therefore, it allows for capturing and quantifying of the effect of agent network size and position on one's performance.

I also present a brief synthesis of real estate studies that examine TOM and sale price. The literature highlights potential endogeneity issues between sale price and TOM as they influence each other simultaneously. Setting a higher sale price may result in a longer TOM, and a house that stays on the market for a long time might eventually sell for a lower price as sellers become more willing to accept lower offers. In the section for sale price and TOM, I will discuss the solutions in the literature to mitigate the effect of endogeneity.

To summarize, in the following literature review, I will present the main theories behind real estate market efficiency that may help us explain agent behavior, discuss the origins of social network analysis, present a synopsis of research conducted in finance and real estate that use social network analysis, discuss how this work differs from a few other studies looking into agent networks and present how literature addresses sale price and TOM endogeneity.

Market Efficiency: A Real Estate Perspective

The real estate market, particularly single-family detached properties, represents one of the largest asset classes in the United States, with an estimated value reaching a record $37.4 trillion, according to CoreLogic (2023). This immense value raises questions about market efficiency that are often discussed concerning stock markets. Unlike the stock market, where price formation is often perceived as a black box due to its complexity and the influence of numerous automated trading systems, the real estate market is significantly influenced by the actions of real estate agents. Agents play a critical role in determining house list prices, which can lead to varying degrees of market (in)efficiencies. This subsection of the literature review will explore the efficiency of real estate markets by examining the information asymmetries and agency problems associated with agents. By recognizing these paradigms, we can better understand how agent characteristics, including networks, relate to transaction outcomes.

A series of publications discusses whether real estate markets are efficient in the finance and real estate literature. According to the efficient market hypothesis, prices reflect all available information (Fama et al., 1969). However, real estate markets, especially residential ones, are characterized by significant information frictions. Information about properties, market conditions, location characteristics, and prospects is not instantaneously and equally available to all market participants. This information asymmetry creates disparities in knowledge, preventing prices from adjusting to news promptly and accurately. The localized nature of real estate markets and the heterogeneity of properties exacerbate these frictions. The findings in the literature are mixed. Earlier studies do not find agent characteristics related to better transaction outcomes, suggesting that the information flow in the MLS market is efficient (Donald et al., 1996; Jud & Winkler, 1994). However, more recent studies find support for information asymmetries and agency problems. Technological advancements have reduced frictions, but real estate transactions still present obstacles to achieving the efficiency observed in more liquid and homogeneous stock markets.

Information Asymmetries and Agency Problems in Real Estate. The literature has identified information asymmetry in real estate markets. For example, Garmaise and Moskowitz (2004) examine the quality of more than 10,000 commercial real estate property tax assessment ratios. They argue that higher dispersion in these ratios signifies a higher potential for asymmetric information exploitation, rendering public assessments less reliable and informative. They find that buyers acquire local properties to reduce information asymmetries, and uninformed buyers prefer properties with long income histories. Moreover, they show that when information asymmetries are high, informed brokers are more likely to trade with other informed brokers, indicative of market segmentation.

Garmaise and Moskowitz (2004) posit that commercial real estate brokers have several reasons for restraining some information from buyers. One of those reasons they mention is that brokers are frequent sellers or buyers for themselves. This creates competition between brokers and non-brokers. Next, the higher the sales price, the higher the broker commission. This is an issue widely discussed in real estate literature. Finally, buyer broker commissions usually are the subagents of the seller's broker and are paid by the seller. Hence, the buyer's broker has a fiduciary duty to the seller. Garmaise and Moskowitz (2004) conclude that their findings robustly attest to the significant influence of asymmetric information on commercial real estate market dynamics.

Another study discussing information asymmetry is Lambson et al. (2004). They examine the impact of information asymmetries in the real estate market by analyzing nearly 3,000 apartment transactions, half involving out-of-state buyers. They extend Turnbull and Sirmans's

(1993) real estate search model to the less-than-perfect apartment market. The research models the conditions under which out-of-state buyers would pay more. They posit that if out-of-town buyers incur higher search costs, hold upwardly biased price beliefs, or face time constraints, they are more likely to pay a premium, suggesting that information asymmetries and transaction characteristics significantly influence real estate pricing dynamics.

In a later work, Holmes and Xie (2018) revisit information asymmetries associated with out-of-state buyers and sellers, this time in the housing market. The authors find that property and transaction characteristics explain out-of-state buyers' price premiums for the Indiana housing market. For out-of-state sellers, the considerable price discount of 21.2% is attributable to various transaction characteristics, motivations, agent characteristics, and market conditions.

Rutherford et al. (2005) discuss a classic case of agency problem between home sellers and their agents and find a 4.5% premium for agent-owned houses with no significant difference for the duration. Despite many articles discussing how commission-based compensation exacerbates principal-agent conflict, this compensation model remains prevalent in the US residential real estate market (The effect of the class action lawsuit against NAR and several large brokerages on the market has yet to be observable).

The study by Levitt and Syverson (2008) reignites a new wave of research into information asymmetry and agency problems in real estate housing markets. While Rutherford et al. (2005) focus on agent effort, Levitt and Syverson (2008) discuss the asymmetric information side of the problem. They suggest that agents have informational advantages over their clients, resulting in lower than optimal sale prices unless the property is agent-owned. Levitt and Syverson (2008) find that homes owned by real estate agents sold for approximately 3.7% more and remained on the market for an additional 9.5 days, compared to homes sold for clients, even after controlling for observable characteristics.

To check whether the main findings by Levitt and Syverson (2008) are generalizable to all types of agents and their clients, Xie (2018) takes a sample of all residential properties listed for Johnson County, Indiana. The unique structure of the data allows the study to differentiate between the four types of clients: individual clients, lender clients, corporate, and government clients. They find that non-individual client listings drive non-agent-owned home price discounts. The discount for individual client sales is substantially lower (only 1.5% less than agent-owned properties) with no significant difference in the selling time. Moreover, these discounts are more significant when agents are inexperienced, whereas the number of listings measures experience in the prior year. By offering a nuanced view of the agency problem, Xie (2018) contributes to a deeper understanding of real estate transactions and the potential for market distortions when agents possess an informational advantage over their clients.

Lopez (2021) utilizes a dataset covering nearly 122,000 single-family residences and condominiums sold in Greater Las Vegas to examine the price premiums obtained by sellers who are either real estate license holders or personally affiliated with license holders (e.g., through family relationships). Licensed agent sellers and their affiliates achieve approximately 1.6% higher prices than non-agent sellers, using market timing strategies to buy low and sell high. These findings, yet again, underscore the presence of information asymmetries in real estate markets and their impact on transaction outcomes.

Information asymmetries in the real estate market can also arise when agents and sellers decide to restrain some information from the public. Bian et al. (2021) theorize that the optimal level of information disclosure depends on the degree of heterogeneity among homes. They argue that disclosing less information for properties with many subjective characteristics could be strategic. This approach could avoid alienating potential buyers with specific tastes or preferences, particularly when these attributes cannot be easily or fully captured through conventional listing details. The findings support the hypothesis that less information disclosure is associated with positive returns for a significant subset of properties. The study reveals that when selling their properties, real estate agents tend to disclose less information compared to when they are selling on behalf of clients, especially for high-end properties with more taste-specific attributes.

Hayunga and Munneke (2021) revisit the agency problem between the agents and the clients by contrasting agent-owned property transactions with client-owned ones. Unlike Levitt and Syverson (2008), and Xie (2018), they control the simultaneity between sale prices and duration. The study also examines transactions where agents buy properties and finds that agents negotiate lower prices when they are the buyers of the properties. Like Xie (2018), the study differentiates between different types of buyers and sellers. It finds that agents and companies hold the most bargaining power, followed by individuals, governments, and estates.

As we see, the discussion of information asymmetry and the agency problem is often intertwined. One of the earliest works on the principal-agent problem is Arnold (1992). The paper demonstrates how different agent pay systems affect agent performance, suggesting that the most optimal pay structure for both the principal seller and the agent is the fixed-percentage commission. However, their model is rather simplified. Clauretie and Daneshvary (2008) use an empirical model to assess agent behavior and motivation. They highlight the importance of accounting for the listing contract estimation date when testing the effects on duration. After accounting for the expiration time of the contract and solving simultaneously for the sale price and the time-on-the-market (TOM), they find that the agents are likely to influence the seller to lower the price instead of increasing their efforts to sell.

Contrary to Williams (1998), which suggested an absence of the agency problem due to the independence of an agent's optimal search effort and reservation price from the commission rate, Li et al. (2022) reintroduce the agency problem. Their model shows that commission rates affect the effort level and reservation price, thus highlighting a misalignment of interests between brokers and their clients. Li et al. (2022) propose the "diffused effort" hypothesis, stating that agents with multiple contemporaneous market listings may utilize those listings to find a potential buyer.

The agency problem is exacerbated when the same agent represents both sides of the transaction. However, this depends on the parties involved. Johnson et al. (2015) use propensity score matching to evaluate the effect of dual agency on price distortions. They find that dual agency is associated with high premiums for agent-owned properties but has no significant impact on individual and corporate-owned properties. Angjellari-Dajci et al. (2015) find a considerable price discount when a dual agency (on the level of the brokerage firm) is present. However, they do not control for owner type. Also, Kadiyali et al. (2014) do not find price distortions from dual agencies and advise against laws prohibiting it. In this study, I control for dual agency when both agents work for the same brokerage firm, i.e., the in-house transactions. Since my model includes both agents' network measures, these measures automatically control for dual agency where the same agent represents both sides.

In a discussion of agency problems, Daneshvary and Clauretie (2013) tap into examining transaction outcomes when the sellers change agents. The analysis of 4,336 single-family properties in Nevada suggests that agent change after the listing contract expiration date leads to significant price cuts and an approximately three-month increase in TOM.

Hence, the literature on information asymmetries and agency problems in real estate markets suggests that markets, particularly housing markets, are likely inefficient. The heterogeneity of properties, little regulation over agent due diligence, and the conflict of interests between agents and their clients – all suggest the presence of information friction.

In summary, the extensive literature on information asymmetries and agency problems in real estate markets reveals that these markets, particularly housing markets, are likely inefficient. The reviewed studies underscore significant information frictions due to the unique characteristics of real estate transactions, including the heterogeneity of properties, the localized nature of markets, and the pivotal role of agents. Findings indicate that agent behaviors, such as withholding information or prioritizing personal interests, can lead to market segmentation and price distortions. Despite technological advancements to reduce these frictions, challenges persist in achieving efficiency in more liquid and homogeneous markets like the stock market. The presence of principal-agent conflicts further complicates market dynamics.

Agent network is one aspect often overlooked in the literature. This study aims to show that agent networks create channels for information flow and contagion effects that influence the overall market. The subsequent sections will delve deeper into different agent characteristics that are shown to be related to agent performance in the literature.

The Role of Real Estate Agents

The role of real estate agents in influencing transaction outcomes has been a focal point of research, especially considering their impact on sales price and time-on-market (TOM). This subsection describes how various agent characteristics, such as experience, designation, and gender, affect the efficiency of real estate transactions. By examining studies that assess agent performance and characteristics, this review aims to provide a comprehensive understanding of the agent's role in real estate markets. The implications of these findings are significant for both theoretical models and practical applications, highlighting the importance of studying previously overlooked metrics of agent networks as distinct characteristics. In such a relationship-intense profession as a real estate brokerage, network size and quality can be paramount in how agents perform, and clients perceive agent performance.

Real Estate Agent Characteristics and Performance. One of the main questions is whether sellers benefit from working with agents as it adds extra costs for the seller. Allen et al. (2015) reaffirm that working with agents adds value for the sellers by achieving higher sales prices, but they find no relation between agent efforts and probability of sale and time-on-market.

However, are all agents equal, or are there some who consistently outperform others? Turnbull and Waller (2018) use MLS data to discuss the critical role that real estate agents play in housing transactions. They classify the agents by their performance, which is measured by the number of listings agents have in the market. They test whether agents with extensive listing inventories consistently perform better than other agents. The authors measure agent performance based on “productivity.” If an agent is top-producing, the authors expect her to deliver better-than-average deal terms for the clients. They also argue that the higher the number of listings by an agent, the less effort she can allocate per client. Yet, the large market presence can signal the “superiority” of the listing agent and increase the selling price or decrease the selling time. The authors conclude that only the top agents can deliver such good performance. As the number of listings increases, the performance of most agents deteriorates due to diminishing efforts per transaction. If we look at this finding through the lenses of social network analysis, we can test the "importance" or "superiority" of the agents in the market they serve. Turnbull and Waller (2018) argue that listing agents' top 5% (by market inventory) have higher sales performance. However, the results do not hold for the top 5% (by units sold) of selling agents.

Prior research has also examined whether transaction outcomes differ for MLS-listed transactions by REALTOR® vs. non-REALTOR® agents. To have a REALTOR® designation, an agent must be a member of the National Association of Realtors (NAR), which comes with certain benefits, such as access to local MLS data or more visibility in the market. Also, REALTORS® must abide by the NAR's Code of Ethics. After analyzing a sample of over 100,000 completed deals in Texas counties, Huang and Rutherford (2007) find that having a REALTOR® designation helps the agents achieve significantly higher selling prices. Although not tested, it is also possible that REALTORS® enjoy the benefits of other REALTOR® networks. Perhaps an implicit check of such a hypothesis can be a topic of a different study. Real estate agents should represent buyers' or sellers' best interests and try to form strong ties with them for future referrals. Hence, agents with a large customer base will have a higher potential for future sales. One of the earliest works is Yinger (1981), who develops a theoretical model about the role of agents ("brokers") in the market with the presence of MLS. The model suggests that with experience and through advertising, agents gain market power, and MLS boosts the competition among the agents. However, this is a theoretical model without an empirical test. For this research, the model is relevant in predicting that agents with more extensive networks and higher prestige will have greater market power.

Since this study, the market has evolved a lot. The MLS has become a standard for real estate markets. MLS is the primary tool real estate professionals use to serve their clients' needs. Initially, it had little to no competition. However, with the birth of other online platforms like

Zillow, Realtor, Redfin, Opendoor, and others, the information previously available only through MLS to the agents is now partially available through these platforms directly to everyone. Although buyers and sellers can now see the most available properties in the market, the transaction and property details (e.g., seller's disclosure) are still available only through MLS. To obtain that information, buyers and sellers must work with an agent. However, not all transactions get registered on MLS. Some studies find that deals that do not involve agents (hence, MLS) or have agents but are not listed on MLS have significantly different transaction outcomes (e.g., Hendel et al., 2009). Such studies are essential as they help us understand the information environment in the real estate markets.

More recent studies have also looked at how agent gender is related to their performance. Pham et al. (2022) find that agents impact transaction outcomes, with male agents perceived to have greater bargaining power, leading to different price outcomes than female agents. Also, female agents tend to achieve higher prices and shorter TOM for their listings, which is attributed more to client selection rather than superior skills. Similarly, Seagraves and Gallimore (2013) highlight that clients' choice of agents significantly influences outcomes based on agent gender. Interestingly, the study uses listing (and buying) agents listing and buying volumes (the number of transactions in one year) in their model. Since these measures are somewhat related to the network size measure I use, it is important to note that they find a significant negative (positive) relationship between price and the listing (buying) volume for the listing agent. For the buying agent, they find a significant negative relationship regardless of the type of transaction. With only one year of transactions, the Seagraves and Gallimore (2013) sample size is significantly smaller than that of this present study.

One of the main functions of an agent is to facilitate the seller's decision-making process regarding a pricing strategy that will lead to the highest market price. However, this requires the agent to have such skills and be ready for a longer time on the market. Hong (2022) finds that listing agents influence the listing price (increasing the interest in the house) by suggesting low prices to facilitate easier and faster sales. When compared to agent-owned and withdrawn listings, client-owned listing prices are lower, resulting in lower price premiums. The studies discussed are examples of real estate agent's role in the market. The literature has looked at different characteristics of agents, such as experience, brokerage affiliation, and even gender, to establish the difference they make when comparing transaction outcomes. I propose that agent network size and position are other characteristics that can significantly impact agent performance. All these characteristics have yet to be explored in the literature.

In conclusion, this comprehensive literature review on market efficiency, information asymmetries, agency problems, and the role of agents provides a multifaceted perspective on the essence of real estate markets. From the foundational theories of market efficiency that deal with the unique challenges of real estate's localized and heterogeneous nature to the evolving understanding of information asymmetries and agency problems that highlight the complex interactions between agents and their clients, this review has discussed the various dimensions of brokerage in the real estate market.

Social Networks in Finance and Real Estate

The effect of networking has been analyzed in various business disciplines, including accounting, marketing, management, and finance. Integrating social network analysis into finance and real estate offers a novel tool for studying the dynamics of these sectors. In finance, the proliferation of studies exploring the impact of professional networks on firm behaviors, such as tax avoidance strategies, investment decisions, and merger and acquisition activities, underscores the critical role that social ties play in shaping organizational outcomes. Bianchi et al. (2023) recent study presents a remarkable synthesis of network analysis-related work published in accounting and finance. These articles highlight how networks can facilitate information flow, foster trust, and ultimately influence firm performance and strategy, from examining board connections to analyzing CEO network centrality.

Similarly, the emergence of social network analysis within real estate research, although more recent, marks a significant shift toward recognizing the significance of agent networks in transaction outcomes. The focus has extended from merely agent listing quantification to understanding how agents' embeddedness within professional networks can affect pricing, selling time, and overall market efficiency. Exploring social networks in finance and real estate enhances our understanding of these fields and opens new avenues for research. It allows researchers to reevaluate the traditional theories of market efficiency and agency problems, suggesting that professional networks comprise a part of complex systems.

In the following subsections, I will introduce the literature on social networks in finance and real estate. This will allow readers to consider the versatility and flexibility of social network analysis as a tool, see the same tool used in various contexts, and familiarize themselves with the measures commonly used in the literature. I will also present the goals and mechanisms social networks employ. In discussing related literature in real estate, I will also present some gaps and limitations that the current study aims to address.

Networks in Finance. Compared to other disciplines like information sciences and sociology, most finance articles involving social network analysis use less advanced methodologies and more superficial data structures. Nevertheless, the insights these articles provide significantly contribute to a better understanding of the role of relationships in finance. As mentioned, social network analysis has found a place in different areas of financial research, including CEO, director, and board connections in M&As, venture capital, asset pricing, and more. Manager networks are discussed extensively in M&A research. Renneboog and Zhao (2014) study the directors' networks in the U.K. takeovers data. They argue that bidder companies are likelier to choose targets with whom they have connections. Moreover, the more connections the directors have, the higher the acquisition probability. Large director networks seem to save time spent on deal negotiations. One possible explanation for these findings is the trust formed between the networking directors.

Brown and Drake (2014) examine board connections with low-tax firms and find that firms with more ties to low-tax firms show more extensive tax avoidance, mainly when those connections belong to the executive directors. Some possible explanations the authors propose are the information-sharing channel and the diffusion of new ideas through these networks. Another important aspect the article touches upon is greater trust between connected firms that share a joint local auditor. Indeed, a study by Bottazzi et al. (2016) on venture capital (VC) shows that investors are more likely to invest if their level of trust is high, and high levels of trust are negatively associated with success. The authors reason it by saying that the higher the level of investors' trust, the riskier projects they accept, decreasing the likelihood of success. Even though the authors do not study social networks, they list social networks as one of the possible channels of forming trust. Agents who have previously worked together might have a higher level of mutual trust and information-sharing potential than agents who have not transacted before. This study can help us understand whether the excessive trust towards central, "prestigious," established agents can hurt the clients. A paper that closely relates to this research in terms of methodology is a highly cited

Hochberg et al. (2007) paper. It finds that VC firms with better networks experience significantly improved fund performance, measured by successful exits (IPOs or sales). Better-networked VCs also enhance the survival rates of their portfolio companies through subsequent funding rounds and successful exits. The study uses graph theory-based centrality measures to assess a VC's network position, including degree centrality (number of ties), closeness centrality (proximity to others), and betweenness centrality (ability to act as an intermediary). These metrics highlight how a VC's network size, frequency of syndication invitations, and access to well-connected VCs contribute to better performance, underscoring the value of strategic networking in the VC industry. I use the degree centrality and the betweenness centrality but not the closeness centrality. Although it is an informative measure, it requires a connected network. This means there should be no isolated nodes or groups of nodes in the overall network; that is not true for the agent networks dataset I use.

El-Khatib et al. (2015) examine CEO centrality and merger performance measured by CARs. The authors bring up two opposing findings from prior literature. Some authors find the takeover premium is lower when the target and acquirer have a common director (greater value for the acquirer). In contrast, others find that shareholders of both parties suffer losses when there are target-acquirer ties. El-Khatib et al. (2015) argue that the directionality of the network is an essential factor that, if neglected, can lead to misleading conclusions. They use the BoardEx database to obtain four measures of CEO work through standard education and work experience (including board seats): closeness, degree, betweenness, and eigenvector. The analysis shows that the bidding CEOs with higher centrality, on average, deliver poorer returns to their shareholders. The motivation for such behavior comes from the disproportionately high total compensation high-centrality CEOs receive after the deal completion, regardless of acquisition returns. Although the roles of a CEO and a real estate agent are different, these findings suggest that higher network centrality of agents might not necessarily serve the best interests of the principals, whether those are firm stakeholders or property buyers and sellers. Social ties have also been studied in the context of investment analysis.

Cai et al. (2016) find that social ties increase the trading costs for a firm’s shareholders as the flow of information through social networks affects the financial markets. This information-sharing relationship can be observed even in the context of international trade. Cohen et al. (2017) argue that firms trade more with countries whose residents live near their headquarters. Firms are also more likely to acquire targets and do more trade (import and export) in those countries where they have connections.

Social networks are also used in asset pricing studies. Pool et al. (2015) study the U.S. mutual funds market and the ties fund managers have with each other. They use the LexisNexis Public Records database to identify the residence proximities of fund managers. They apply an interesting algorithm that measures the “social distance” of two managers based on the density of the city they live in to decide whether those managers can be considered “neighbors.” They find that mutual fund managers who are socially connected share value-relevant information regarding their holdings and trades. Prior literature suggests that manager ties can significantly impact a company's performance (Egginton & McCumber, 2019; Rossi et al., 2018; Chuluun, 2015).

Besides the CEOs and board networks, research also shows that firm networks (customers, suppliers, competitors) can drive the industry merger waves (Ahern & Harford, 2014). Corporate boards present another setting for social network analysis. Studies of board interlocks (having a joint board member between companies) date back to the 1970s and are still popular among researchers. Amin et al. (2020) find that board connectedness nurtures a firm's corporate social responsibility performance: the more connections the board members have, the more informed they are. This informational advantage allows the board to give better advice to benefit the company's CSR activities. Board interlocks were shown to have a significant association with the M&A performance abroad. Kopoboru et al. (2020) study acquisitions in Spain, board members' connections, and political background. They suggest that having an ex-politician member on the board cuts the deal time and increases the probability of the deal being more significant (by scale and shares acquired). More details on the history of board interlocks can be found in Borgatti and Foster (2003) and Bianchi et al. (2023).

An interested reader should see Bianchi et al. (2023), who conducted a systematic review of articles published in top accounting and finance journals that used social network analysis as far back as 2002. They identify 75 articles from 5 finance journals. They follow Borgatti and Foster (2003) and classify these articles based on their explanatory goals and mechanisms into four paradigms: structural capital, resource access, contagion, and environmental shaping. This categorization is crucial for this study. I explain the importance of the network paradigm in Chapter 3.

Networks in Real Estate. While social network analysis has picked up in the finance literature, it is new to the real estate literature. I could identify only a handful of articles discussing networks in real estate. The closest topic to networks common in the literature is debating the number of agent listings. Table 1 presents the research questions, findings, methodologies, and datasets of select papers relevant to this study. Some of the most relevant papers are also discussed below.

The number of listings or the size of agents' inventory, although not the same, is similar to the degree centrality measure. Many also use the number of listings as a measure of agent experience (including, Hughes, 1995; Johnson et at., 2015; Xie, 2018, Beck et al., 2022). What is different from study to study is the time frame for the measure – some use annual data, some aggregate it across the sample period, and some measure only the number of concurrent listings.

For example, Bian et al. (2015) examine the impact of real estate agents' listing inventory on the selling price and duration. The authors propose a theoretical model that suggests a principal-agent problem arises when agents accumulate listings, potentially diluting their effort per listing and negatively affecting sales performance. The study finds that an increase in the number of listings an agent holds is negatively associated with both selling price and time on the market. The difference between agents listing inventory and the agent network size measure I use is that network size shows the number of past transactions. In contrast, the inventory count is a concurrent measure with agents' performance. Unless we assume that a large network size is a precondition to having a large inventory, our results might or might not be similar to Bian et al. (2015) findings.

Gilbukh and Goldsmith-Pinkham (2023) derive an agent experience measure from agent transactions in the past calendar year (number of listings sold, number of listings unsold, and number of closed transactions as a buyer agent). By examining an extensive dataset of 8.5 million listings from 60 different MLS platforms from 2001 to 2014, they find that listings handled by inexperienced agents have a lower probability of selling, especially during housing market downturns. Again, the study's main measure of experience includes all client contracts an agent had within a year, including withdrawn or canceled transactions. An interesting statistic they present is that 30% of all agents had no prior transaction history, and most listing agents had no more than 12 clients in the past year. This means that inexperienced or rookie agents have a considerable presence in the market and can drive the overall sample results. One of the characteristics of agent networks – agent network size (the degree centrality), is related to the experience measure this study uses, with three main differences. First, degree centrality captures only the completed transactions since, to form a tie, there must be a selling and a buying agent. Second, it captures the transactions between agents who have not worked together in the past year (or three years). Third, instead of taking a calendar year approach, I construct the network by going back 365 calendar days (or three times 365 calendar days) from the day of the current transaction. However, none of the studies discussed so far use the exact measure I use, nor do they have the same research question and models.

Perhaps Shen and Sun's 2023 working paper is the closest study to this research. With a dataset of approximately 36,000 transactions in Atlanta, Georgia, from 2010 to 2017, they construct a network of listing and selling agents with at least one transaction in the preceding three-year period. Their analysis concentrates exclusively on the listing agents. After obtaining the degree centrality of agents, they construct a measure of agent connectedness as a ratio of agent direct ties divided by agent experience. They measure agent experience as the number of all past transactions during the past three years. This measure of agent experience is flawed as it puts a time limit on the count. While agents might lose their connectedness with other agents through time and inactivity, the expertise they built from the first day of starting a career should accumulate without being reset. Because they limit agent experience and connectedness to the past three years, their degree centrality and experience measure have a correlation coefficient of 0.99, which is not the case in the present sample. They find a positive relationship between the sale price and agent connectedness with no effect on the time on the market, especially among agents with diversified networks. The authors do not use the direct measure of agent connectedness – the degree centrality, because of the high correlation with the agent experience. Although they construct a network for listing and selling agents, they focus on only listing agents. In the most recent version available, they also do not look at any other measure of network centrality but the degree. They choose to model the sale price and TOM separately, using an OLS for the price and a hazard model for the TOM.

Also, Smith et al. (2019) construct a degree centrality measure of agent networks for Atlanta MLS but did not use it directly in their analysis. Their emphasis falls on the social capital agents form through cooperation. They find that when two agents who have previously transacted represent the two sides of a home sale, the property sells for a lower price. The study suggests that agents might forgo short-term gains from a single transaction to nurture a network of cooperating agents – create social capital – that could yield more transactions and higher total income over time. Moreover, agents specializing in listings are associated with lower sales prices. Their focus again is on listing agents only.

Beck et al. (2022) examine the specialization of agents in listing versus buying roles. They identify significant differences in the market outcomes based on agents' roles, with listing agents' recent activity having a more pronounced effect on reducing sales prices and TOM than buying agents. They find that properties listed by agents in the most active quintile of their sample sell for 8% less and are on the market for 14 fewer days than by less active agents. Interestingly, these findings contradict Xie (2018), who finds that the more experienced agents, where the experience is measured as the number of homes the agent sold in the past year, are less likely to sell at a discount. Also, Salter et al. (2010) conclude that agents specializing in listing properties can more easily price properties closer to their expected market value.

The first study I could identify that discusses the role of professional networks while using network analyses is Xie (2019). Using data from a Midwestern city during 2008-2010, the research applies the Jackson-Rogers model to analyze the patterns of network formation. The study finds that 35%- 55% of trades are not random—agents conduct network-based searches to find buyers.

Hence, experience gives agents access to a more extensive professional network to succeed in this highly competitive industry.

In a later study, Scofield and Xie (2023) conduct similar research, this time for commercial real estate markets. They find that commercial real estate searches are not random but through agent networks. On a firm level, the authors find that well-connected brokerages tend to trade with less connected ones, increasing their network size and maintaining market power.

One study that looks at the real estate investments market rather than property markets and networks is Cashman et al. (2018). They use the BoardEx database to construct the professional network of REIT directors, focusing on connections within the industry and the firm outcomes. They analyze three network metrics: director degree centrality, closeness centrality, and betweenness centrality. The study finds that more connected REITs are associated with greater deal-making activities, proxied by the line of credit available for new investments, the probability of UPREIT structure, and the level of development activities. Another interesting finding is that increased connectedness also correlates with a higher cost of equity, indicating higher risk to the firm. On the one hand, networks provide valuable connections that enhance deal-making capabilities and profitability by facilitating information flow and access to capital. On the other hand, the benefits of such networks are counterbalanced by increased firm risk and higher equity capital costs, which do not translate into higher market valuations.

In a pioneering paper, Bailey et al. (2016) explore the influence of social networks on individuals' perceptions of the housing market and their subsequent investment decisions. Using a unique dataset of anonymized Facebook social network information of about 520,000 Los Angeles residents with housing transaction data and survey responses, they offer insights into how the network impacts the choices of individuals when making housing decisions. Individuals whose friends have experienced a substantial increase in house prices are more likely to invest in properties. The paper suggests that the observed effects are primarily driven by changes in housing market expectations mediated through social interactions rather than direct financial benefits or shared economic shocks among social network members. On a scale, this behavior can affect overall house prices and trading volumes in the country.

Real estate agents have also become a subject of analysis regarding their position in social media networks. Cifci and Tidwell (2024) investigate the impact of the number of LinkedIn followers on commercial real estate agents' performance. Agents with larger more extensive professional networks on LinkedIn tend to transact more properties and achieve higher transaction prices than their peers with fewer LinkedIn connections or agents not utilizing this platform. The findings contribute to understanding network theory and bargaining power in real estate, demonstrating that more extensive networks provide agents with superior information and negotiation leverage, enhancing their ability to secure better transaction terms.

In conclusion, exploring social networks, especially in the context of real estate agents' performance, introduces a modern lens through which market efficiency and agency dynamics can be re-evaluated. The insights gathered from a wide array of studies underscore the persistent presence of information frictions, the critical impact of agent characteristics and networks, and the nuanced effects these elements have on transaction outcomes. As the real estate market continues to evolve with technological advancements and changing market practices, the themes discussed in this review offer a robust framework for understanding the interplay between market efficiency, agency problems, and the power of networks, paving the way for future research to build upon these foundational insights.

Time on the Market and Price Endogeneity

The two measures I use to measure agent performance are time on the market (TOM) and realized sales price. From a practical point of view, TOM and prices are dependent. This section presents why TOM is essential and the literature's views regarding TOM and price endogeneity.

TOM is critical in housing market studies because it influences transaction prices. It reflects market liquidity, seller motivations, and the effectiveness of marketing strategies. Understanding TOM helps analyze market dynamics and predict future price movements. TOM serves as a signal for market conditions. Short-averaged TOM can indicate a seller's market, while long-averaged TOM might suggest a buyer's market. To optimize sale outcomes, sellers and agents might adjust their pricing strategies based on expected TOM. Extended TOM can stigmatize a property, leading buyers to suspect issues with the property and affecting its desirability and price, as discussed in Jud et al. (1996), Daneshvary and Clauretie (2013), Hayunga and Pace (2019), and others.

However, the theoretical models and empirical findings about TOM and sales price relationships do not always align. Studying TOM helps reconcile discrepancies between theoretical models and empirical findings, providing a clearer understanding of housing market behaviors.

Moreover, TOM might be an even more critical performance metric for listing agents than price. One can argue that any property will sell faster than less skilled agents in the hands of the most skilled agents. I expect that agent network size and position have a detrimental positive effect on TOM.

In a seminal paper, Jud et al. (1996) explore the relationship between TOM and expected prices using a search theory model. They show how TOM and the degree of above-market pricing are determined simultaneously. The paper presents several interesting conclusions. One is that it supports efficient market hypotheses since the analysis does not show a significant difference between heterogeneous agents or brokerage firms. They also find list prices and the atypicality of homes as key variables in determining the TOM. It is important to note that this study was conducted in the early 90s and covered only 2,285 sales, involving 111 brokerages and 600 real estate agents. Thus, I expect these results to not hold in this evolving market with many more market participants.

Another paper highlighting the importance of TOM and prices, including list price, is Anglin et al. (2003). They argue that TOM depends on the list price as it sends a signal to the market about seller motivation. They say that the withdrawn properties—those taken off the market without selling—can influence the research results about TOM, artificially decreasing the average TOM. Hence, they conclude that listing price accuracy is vital to faster sales. They call the listing price accuracy the degree of overpricing (DOP) and measure it as the percentage difference between the list price and the expected list price. However, in their sample, a surprising 45% of all listings are withdrawn listings. In my raw sample, only 5.6% are withdrawn listings (including canceled and expired listings). Therefore, I do not expect the average TOM for this study sample to be significantly biased because of the withdrawn transactions.

Often, real estate literature focuses on the transaction outcomes, such as the sale price, rather than the list price, to measure agent performance. In the context of efficient markets, the list price is not as informative as the sale price. Four commonly used methodologies in the literature for analyzing the sale price and TOM. The first one is OLS, which is known to suffer from biased estimates when endogeneity is present. The second one is hazard models, particularly with Weibull distribution, which also does not address endogeneity and self-selection fully but deals better with the non-linearity of TOM data. The 2SLS estimates one equation at a time without considering the correlations between the error terms of the models. Therefore, more and more studies follow

Turnbull and Dombrow (2006) and use 3SLS to compute the sale price and the TOM simultaneously and more efficiently. The advantage of 3SLS over 2SLS is that the variance-covariance matrices produced by 3SLS will be, at worst, equal to those made by 2SLS.

Hayunga and Pace (2019) address why empirical studies have found varied positive, negative, or insignificant relationships between TOM and prices when using OLS or 2SLS. They argue that the genuine relationship between price and TOM should be positive, as stigmatization will apply to only a fraction of properties on the market. According to this study, many studies find a negative relationship between the two because of weak instrumental variables used in 2SLS. They deem it necessary to account for the structural quality, atypicality, severe overpricing, and other variables often unavailable in the data. In a later study, Fang and Hayunga (2024) use a 3SLS approach to address the endogeneity between the sale price and TOM and find a positive, significant relationship between them. Other studies that use 3SLS include Turnbull and Waller (2018), Pham et al. (2022), and Bian et al. (2015) – which do not report the relationship between TOM and price in their truncated tables, focusing only on the main variables of interest. Bikmetova et al. (2023) find a negative relationship between the sale price and TOM, while Bian et al. (2017), and Waller and Jubran (2012) find a positive relationship between the sale price and TOM.

Hence, the literature generally agrees that there is endogeneity between sale price and TOM. Although the true relationship between the two remains a subject of further inquiry, the 3SLS simultaneous equations model seems to address the concern of endogeneity best. Therefore, after thoroughly investigating methods used in the literature, I decided to use 3SLS as the primary method for my analysis.

Conclusions

This comprehensive literature review covers various aspects of real estate markets, focusing on market efficiency, the role of real estate agents, the application of social network analysis in finance and real estate, and the interplay between TOM and sales prices.

Examining market efficiency in real estate markets underscores the unique challenges of information asymmetries and agency problems; unlike the more liquid stock markets with homogeneous assets, real estate markets are characterized by significant frictions due to the heterogeneity of properties and localized market knowledge. I offer a new lens to examine market efficiency – the agents' network. Real estate agents are pivotal in these markets, influencing transaction outcomes through their actions and network positions. The literature indicates that agents often prioritize their social capital over the best interests of their clients, particularly in the early stages of their careers.

Social network analysis has become an essential tool in finance, revealing how professional networks impact firm behavior, investment decisions, and market outcomes. Though relatively new, applying network analysis to real estate offers valuable insights into agent roles and performance. A few studies have been identified using network analysis to examine agent performance. This study is the first to thoroughly analyze agent network size and look beyond the overall position within the network for both buying and listing agents.

CHAPTER 3: SOCIAL NETWORKS ANALYSIS AND HYPOTHESES DEVELOPMENT

Introduction

In this chapter, I delve into the social network paradigm, a critical framework in social science research that emphasizes the importance of relationships and interactions among social entities. By exploring social network analysis's definition, evolution, and theoretical foundations, I aim to understand how network structures and mechanisms influence organizational outcomes. This chapter also highlights the relevance of these concepts in the study of real estate agent networks, demonstrating the practical applications of social network theories in this research.

Social sciences have studied networks for decades. Social network analysis has its roots in sociology and anthropology. Early contributions from scholars like Radcliffe-Brown and Moreno laid the groundwork for later advancements in network analysis. Radcliffe-Brown's focus on social structures and Moreno's development of sociometry were pivotal. In their review article, Borgatti et al. (2009) begin with a historical account from the fall of 1932, highlighting an epidemic of runaways at the Hudson School for Girls in upstate New York. They describe how Jacob Moreno, a psychiatrist, attributed the high rate of runaways not to individual factors but to the girls' positions of the runaways within an underlying social network. Moreno and his collaborator mapped the social network at Hudson using 'sociometry,' which revealed that the girls' positions within the social network significantly influenced their decisions to run away.

The formalization of social network analysis in the 1970s and 1980s marked a significant advancement in the field. Researchers used matrix algebra and graph theory to quantify and analyze social structures. This period saw the development of critical concepts like centrality, density, and structural holes, which provided tools for systematically studying the impact of network structures on social and organizational behavior.

As discussed in the literature review chapter, little work has been done in real estate literature incorporating social network analysis. This chapter introduces the reader to social networks and explains how select network theories can be applied to the network of real estate agents.

The Social Network Paradigm

The social network paradigm is a foundational approach in social science that focuses on the relationships and interactions among social entities, known as nodes. These entities can range from individuals and groups to organizations and nations. The connections between these nodes, called ties, represent various relationships, such as friendships, professional links, or information flows. The network paradigm shifted the focus from individual attributes to the patterns and structures formed by these relationships, offering a more dynamic understanding of social phenomena.

The social network paradigm offers a comprehensive framework for analyzing social structures by focusing on the relationships and interactions among social entities. This approach contrasts with traditional methods that emphasize individual attributes, shifting the focus to the connections and patterns that emerge within networks. By examining these relationships, social scientists can better understand the underlying mechanisms that drive social behavior and outcomes.

A social network is a system of interconnected social entities, individuals, organizations, or any defined social unit. These entities, often called nodes, are linked by various relationships or ties, including friendships, professional connections, club memberships, or transactional relationships. The structure of these networks, including the arrangement and nature of relations, plays a critical role in shaping the behavior and outcomes of the entities involved.

In organizational research, social network structures and mechanisms are critical for understanding how organizations function and succeed. Various explanatory goals and mechanisms have been offered to explain the roles of network structures. Figure 1 is a modified table representation of the 2-by-2 matrix proposed by Borgatti and Foster (2003).

The structural capital approach focuses on how an actor's position within the broader network affects their access to information and resources, thus impacting performance. It emphasizes the benefits or constraints of one's network position rather than direct ties, such as influencing firm performance and board interlocks among firms. For example, an actor's centrality within the network can significantly affect their access to critical information and resources.

In the context of real estate agents, the structural capital approach highlights the importance of studying agents' positions within the network. Metrics such as eigenvalue centrality and betweenness centrality can help understand how an agent's network position affects their performance. Agents occupying central positions in the network may have better access to market information and client referrals, enhancing their performance and success.

Regarding social access to resources, the emphasis is on direct access to quality resources. This approach merges social capital theory with resource dependency theory, emphasizing the quality of resources an actor can access through their immediate connections. It highlights how organizations and individuals manage their embeddedness in networks to access critical resources, manage dependencies, and foster cooperation. However, this access can also lead to adverse outcomes, such as compromised independence among directors or auditors (see Bianchi et al., 2023). For real estate agents, the degree and eigenvector centralities approximate the resources available through the direct ties they form from past transactions with other agents. Agents with numerous high-quality connections may have greater access to valuable resources, such as exclusive property listings or potential buyers, which can significantly impact their business success.

The contagion paradigm explains how behaviors, practices, or strategies spread through direct connections within a network. It draws from organizational learning and institutional isomorphism theories, suggesting that organizations adopt practices observed in their network to improve legitimacy or performance. Studies often focus on spreading practices like earnings management or corporate governance through mechanisms like board interlocks. The contagion paradigm and the social access to resources paradigm belong to the connectionist explanatory mechanism. This means that networks connect objects (people, companies, events, etc.) and facilitate the flow of information and resources between the connected entities.

In real estate networks, the contagion paradigm can help understand how new marketing strategies, technologies, or business practices spread among agents. Agents connected to influential peers or firms may be more likely to adopt successful practices, leading to a higher level of homogeneity in business strategies and practices across the network.

The environmental shaping approach examines how the structural environment of actors influences their behavior, leading to convergence in practices among those embedded in similar contexts. This approach suggests that the networked environment itself, rather than the direct ties or positions, shapes organizational actions. Theories of organizational learning and herding are often applied to explain phenomena like peer effects in corporate disclosures (see Bianchi et al. (2023) for more details).

This approach can illuminate how market conditions and environmental factors influence real estate agents' behavior. Agents operating in similar market conditions or regulatory environments may adopt similar business practices due to shared external pressures. Understanding these environmental influences can help agents adapt their strategies to meet market trends and regulatory changes.

These paradigms provide a structured way to understand networks' diverse roles in finance and real estate, suggesting avenues for future research to build on their theoretical foundations. Each offers a lens to examine how network structures and relationships impact entity behaviors and outcomes, highlighting the multifaceted influence of networks in the business domain.

Social Network Construction and Analysis Measures

In this subsection, I explain how I construct a real estate agent network and what measures I use to quantify the size and relative position of the agents in the overall network. While there is slight variation in the definition of a social network, the construction details, such as directionality and time windows, are essential and can vary largely depending on the research questions and complexity. I chose approaches that are simple to understand and computationally feasible within this research. I acknowledge that more advanced techniques, such as temporal or dynamic networks, could benefit a deeper understanding of agent relationships and their evolution through time, but leave it for separate research.

Network Construction. A network can be presented as a graph, with its entire topology described by the adjacency matrix. $A = (\alpha_{ij})$, where $\alpha_{ij} = 1$ indicates the presence of a connection between two nodes. Networks can have different topologies depending on the arrangement of the nodes (alters, actors) and the connections (also called ties or edges) between them. The construction of a network can be tailored to the phenomenon under study, resulting in either directed or undirected networks.

In a directed network, the relationship between nodes A and B may differ from the relationship between B and A. In contrast, in undirected networks, the relationship between A and B is symmetrical, meaning it is the same in both directions.

For this study, I construct an undirected network of listing and selling agents using transaction history data for detached single-family homes. Each transaction between agents represents an undirected edge. For each transaction occurring on a specific day, t_n, I look back to $t_{(n-1-365)}$ and construct a network from all agent transactions within the total sample during that period. Consequently, for each transaction day, I create a new network representing all transactions within the 365 days preceding the current transaction. This way, I capture the prior network agents created. I take a naïve approach and assume that each agent represents himself or herself without help from other agents. In practice, some agents work with sub-agents to facilitate transactions.

In the following section, I will define and discuss the centrality measures I used as explanatory variables in this study to characterize agent position in the network.

Degree Centrality: Agent Direct Network Size. I consider a network of n nodes indexed by $i \in \{1, 2, \ldots n\}$, where the nodes are the agents, and the edges are the completed transactions. Each edge represents a transaction between two agents. The first measure I use is Degree or Degree Centrality. It is a valuable measure for understanding the sizes and dynamics of agent networks in the housing market. It shows the number of direct connections agents develop throughout their careers that may give them access to information about other listings, novice marketing strategies, etc. By examining the number of direct connections an agent has, Degree Centrality can provide insights into the importance of specific agents regarding how many other unique agents she knows. The

Degree Centrality can be used to identify critical agents in the housing market, such as those with high levels of connectivity and network size. The Degree Centrality of a real estate agent can affect their access to information, resources, and social capital, which can be crucial for their success in the market. Real estate agents with a high Degree Centrality, hence network size, are likely to have more significant influence over the flow of information and resources within the market and may be better positioned to identify and capitalize on opportunities. For our analysis, we use the total Degree of an agent calculated as:

$$D_i = \sum_{j=1}^{N} \min(1, \alpha_{ij}), \tag{1}$$

where α_{ij} represents the number of transactions between agent i and j. The $\min(1, \alpha_{ij})$ function ensures that if agents i and j transacted more than once during the 1-year window, the degree will count as only one interaction. This is the main difference between the Degree Centrality measure I use and the commonly used "number of transactions" measure. This measure quantifies the network size, not the agents' experience.

The correlations between the total number of transactions up to the current transaction and the 365-day (3 times 365) Degree Centrality measure I construct are 0.72 and 0.71 (0.79 and 0.82) for listing and selling agents, respectively. I call the Degree Centrality of a listing agent *LA_NetSize* and *SA_NetSize* for a selling agent. Note that for both the calculation of centrality measures and agent experience measures, I use the raw data before applying any filters, except for removing invalid agent identifiers. Table A1 presents the correlations between the main variables.

Betweenness Centrality: Agent Bridging Power. The Betweenness Centrality measures the extent to which a node lies on the shortest paths between other nodes in the network. For an undirected network, the Betweenness Centrality of a node is calculated as:

$$B_i = \sum_{j \neq k \neq i} \frac{\sigma_{jk}(i)}{\sigma_{jk}}, \tag{2}$$

where $\sigma_{jk}(i)$ is the number of paths that pass through the node i and σ_{jk} is the total number of shortest paths from the node j to node k.

Betweenness Centrality shows how central the agent's position is in the network where the agent knows other agents directly and can serve as a link (a broker or intermediary) between the agents who know this agent but do not know each other. For this study, the directionality should not matter, as it makes no difference whether the agent is predominantly a listing agent or a selling agent. All that matters is the agent's position in the network relative to other agents. The higher the Betweenness Centrality of an agent, the more focal position she has. As discussed in the Social Network Paradigm section, the betweenness centrality can indicate environmental shaping mechanisms. By being an intermediary in the network, agents can control and influence the flow of information and resources between different network participants. An agent with high betweenness centrality, who frequently broker deals between different groups of agents, can shape the market environment by connecting otherwise disparate sub-networks and facilitating transactions that might not occur otherwise. Does this give that agent an advantage when negotiating the price of her deals or cut the time to sell? This is a question I address in this study.

Eigenvector Centrality: Agent Influence. Eigenvector centrality for a network quantifies a node's influence based on the premise that connections to highly influential nodes contribute more to a node's score. The Eigenvector Centrality of a node can be presented as:

$$E(i) = \frac{1}{\gamma} \sum_{j=1}^{n} A_{ij} E(j), \tag{3}$$

where γ is a constant (specifically, the largest eigenvalue of the adjacency matrix A), and A_{ij} represents the elements of the adjacency matrix with $A_{ij} = 1$ if there is an edge between nodes

i and j, and 0 otherwise. Eigenvector Centrality shows how well-connected an agent is to other influential agents. It talks about the quality of agent networks. Eigenvector Centrality measures an agent's access to resources through their connections with other influential agents. It reflects the social capital from being well-connected within a network of essential nodes. An agent with high Eigenvector Centrality, such as a broker connected to top-performing agents, has enhanced access to valuable information, clients, and opportunities through their network. The question is whether these influential agents perform better than the less influential ones and what other motives might they have to sacrifice the client's best interests?

For this study, I measure the unidirectional Eigenvector Centrality of agents. In a directional setting, if an agent is solely a listing agent and has never been a selling agent, then both the Eigenvector and the Betweenness Centralities are zero.

In summary, each of these centrality measures provides insights into agent networks' size, structure, and position and offers valuable perspectives on nodes' relative importance or influence within the network.

Hypotheses Development

The development of theoretical expectations in the context of agent network centrality measures and their impact on real estate transaction outcomes is particularly challenging due to the limited scope of existing research. Only a handful of studies have explored related topics in the current literature, primarily focusing on listing agent degree centrality (Smith et al., 2019; Shen & Sun, 2023). Even within this narrow focus, the methodologies and findings vary significantly. Smith et al. (2019) modify the traditional degree centrality measure to account for repeat transactions between the same agents, revealing that agents might build social capital at the expense of sellers' interests by lowering sale prices during frequent collaborations. Interestingly, this behavior appears to change after a certain threshold of cooperation. The Shen and Sun 2023 working paper reports that more connected agents tend to achieve higher sale prices, though it finds no significant impact on the time spent on the market (TOM). These divergent findings underscore network dynamics' complexity and multifaceted nature in real estate transactions.

The brokerage literature lacks research on other centrality measures, such as eigenvector and betweenness centrality, which further complicates the formulation of directional hypotheses. Without a robust body of literature to draw from, it becomes difficult to predict confidently how these network positions might influence sale price and TOM. This uncertainty necessitates the adoption of undirected hypotheses, which do not presuppose the direction of the relationship between centrality measures and transaction outcomes. Such an approach allows for unbiased data exploration, providing a foundation for future research.

The formulation of hypotheses becomes more difficult for the selling agents. We know that selling agents can influence the sales prices by negotiating better deals for the buyers; however, they have little to do with setting the listing price, which usually serves as a starting point in negotiations. In this data, we cannot observe when the selling agent enters a contractual relationship with the buyers. We cannot observe the date the selling agent becomes aware of the new listing she eventually sells. This might explain why many studies avoid including selling agents in the analysis. Nevertheless, selling agents can influence the selling price and the TOM through negotiation, efficient search, and smooth communication with listing agents after showing the listing to their buyers. A priori, one’s position in the network can strongly impact both the negotiation process and the time it takes to close a transaction successfully. Therefore, I proceed to the following general hypotheses, differentiating between the centrality measure and agent roles.

H1: The sale price and TOM are associated with the listing (selling) agent's degree centrality (network size).

From the sale price perspective, the listing agent's network size implications can be multifaceted. On the one hand, a more extensive network size might elevate the sale price, potentially due to the agent's renowned reputation or access to a broader buyer pool (Xie, 2019). They might also use their connections to market properties to reach a large pool of potential buyers in shorter TOM. Alternatively, an extensive network could lower prices if agents prioritize maintaining relationships with other agents over maximizing sale prices (similar to Smith et al. (2019) findings). Agents with large networks can be more interested in selling their inventory faster to decrease the turnaround time and focus on acquiring new clients. It is also possible that well-connected, more experienced agents will handle transactions faster. Although we do not observe it in this study, it is essential to note that the most connected agents usually have a team helping them with transactional procedures. Benefield et al. (2019) note that larger brokerage firms are more likely to have resources to invest in innovations, such as virtual tours, which in turn are associated with shorter TOM. Given that the most connected agents[3] are likely to work for the largest brokerages, the agent network size hypothesis is more probable to have an inverse relationship with TOM.

For selling agents, an extensive network might put upward pressure on the sale price. This could arise as agents try to build and maintain social capital with fellow agents (Smith et al., 2019), possibly leading to more favorable deals or quicker transactions at the expense of achieving the lowest sale price. For selling agents not trying to build social capital, the sale price should be either

[3] This claim does not indicate that the least connected agents are less likely to work for large brokerages. However, brokerage firms are a source of professional network themselves, that can be studied on its own.

lower as they have a large pool of listings to choose from or insignificant. With a more extensive network, selling agents might lead the transactions more smoothly, resulting in shorter TOM, or they might be overwhelmed with other transactions and less efficient in closing a deal.

While agent network size is important, it does not fully describe one's position regarding brokerage position and influence. Therefore, I broadly describe and analyze agent networks, adding agent influence and bridging power characteristics, measured by eigenvector centrality and betweenness centrality, respectively. This will allow us to evaluate the quantity of connections and their qualities.

Betweenness centrality shows how central an agent's position is in the network where the agent knows other agents directly and can serve as a bridge, broker, or intermediary for different agents. It characterizes the relative position of the agents in the network and their reach.

Agents with higher betweenness centrality are positioned as critical intermediaries in the network, potentially granting them access to a broader and more diverse range of information and resources. This unique position allows them to identify better opportunities, connect sellers with a broader and possibly more competitive pool of buyers, and leverage their central role to negotiate higher sale prices. Therefore, one can expect that agents who act as significant connectors in their networks can achieve higher sale prices for their listings due to their enhanced market insight and negotiation leverage.

H2: Listing (selling) agent betweenness centrality (bridging power) is positively (negatively) associated with the sale price and TOM.

The impact of betweenness centrality on TOM could be nuanced. High betweenness centrality might lead to quicker sales because these agents can efficiently bridge buyers and sellers, reducing search times and facilitating faster transactions. Their role as central connectors allows them to disseminate information rapidly between the network parts that otherwise would not be connected (or would be further connected), reaching potential buyers more effectively than their less centrally positioned peers. Consequently, properties listed by agents with high betweenness centrality could experience shorter TOMs due to these agents' ability to tap into and mobilize their extensive networks for quicker sales. However, like the case with eigenvector centrality discussed below, if agents leverage their central position to wait for the best offer to maximize the sale price, this could potentially lengthen TOM. The primary expectation, though, would lean towards reducing TOM due to more efficient market matching and information dissemination capabilities.

Eigenvector centrality shows how well-connected agents are to other central or influential agents. It reflects how many connections an agent has and the quality of those connections. This is where the relationship between the bargaining parties becomes more interesting, especially if both are highly influential. Note that agents with high eigenvector centrality are connected to other influential agents. However, whether these connections will help the agents negotiate more favorable deals for their respective clients is unclear. In commercial brokerage Scofield and Xie (2023) find that better-connected agents trade with less-connected ones, increasing their market power. Therefore, if one party is much more influential than the other, it might intimidate the weaker side to bargain. The hypothesis is as follows:

H3: Listing (selling) agent eigenvector centrality (influence) is positively (negatively) associated with the sale price and negatively with TOM.

All else equal, I expect listing (selling) agents with higher eigenvector centrality to achieve higher (lower) sale prices for the properties they represent. This could be due to several factors, such as their ability to leverage their network to access better market information, more effective marketing through their connections, or their perceived expertise, prestige, and reliability, which allows them to negotiate better deals. Essentially, the better an agent's position in the network, the more likely they will secure higher sale prices due to their enhanced access to resources, information, and influential contacts within the real estate market. For the selling agent, I assume that he/she represents the buyer's best interest. Therefore, their performance improves as the sales price decreases.

The relationship between an agent's influence on a network and TOM is expected to be negative due to their ability to market listings through their networks effectively, access more potential buyers, and quickly match sellers with the right buyers, similar to agent bridging power. However, suppose the most influential agents are more confident in securing a better price. In that case, they might be willing to keep a property on the market longer (or suggest looking more to the buyers in the case of the selling agents) to achieve this, potentially leading to a longer TOM. However, the primary expectation would lean towards a more efficient market matching process due to better connections, potentially reducing TOM on average.

Understanding these relationships can help identify what makes an agent successful beyond traditional measures like experience or marketing spending. This is crucial for agents looking to improve their performance, brokerages aiming to recruit high-performing agents, and sellers choosing an agent to represent their property. Moreover, the hypotheses suggest that the composition of an agent's network (in terms of size, quality, and position) can impact a brokerage's performance. This knowledge can inform brokerage strategies for recruiting agents, structuring their networks, and leveraging their collective social capital to improve overall performance. Insights from these hypotheses could also influence policy and regulation related to real estate practices, especially concerning ethics, transparency, and competition. Suppose network centrality significantly impacts market outcomes like sale prices and TOM. In that case, regulators might consider ensuring fair practices and preventing network-based monopolies or oligopolies that could disadvantage less-connected agents or smaller brokerages.

CHAPTER 4: DATA AND METHODOLOGY

This chapter provides a comprehensive overview of the data sources, sample preparation, and analytical methods utilized in this study. The primary data for this research is sourced from the North Texas Multiple Listing Service (MLS), covering an extensive period from October 2002 to March 2022. The chapter is divided into two main sections: Data and Sample and Methodology and Models. The Data and Sample section outlines data collection and cleaning procedures, including constructing a worldwide network of agents and preparing data for regression analysis. The Methodology and Models section details the statistical techniques and models employed to test the study's hypotheses, focusing on variables describing agent characteristics adopted from prior literature. This chapter aims to provide a clear and detailed account of the processes involved in preparing the data and the methodological framework, ensuring the robustness and reliability of the study's findings.

Data and Sample

The data for this study is collected from the North Texas Multiple Listing Service (MLS). I collect comprehensive data with all listed properties from October 2002 to March 2022. The raw dataset goes through two data-cleaning stages. In the first stage, I obtain the data for network construction, and in the second stage, I clean the data for regression analysis. I will describe both stages below.

To create the global network of agents, I use all closed transactions before applying any filters to the sample. I eliminate the observations with missing or invalid agent license IDs, non-MLS agents, and transactions where the same agent represents both the buyer and the seller (self-loops). This allows me to capture the network of agents as holistically as possible. During the sample period, there are 70,645 agents and 469,483 closed transactions. Interestingly, throughout the sample period, there are 8,303 agents representing exclusively sellers and 31,698 agents representing exclusively buyers. This means that almost 45% of the agents in the raw dataset have not closed a transaction as a listing agent versus only 12% as a selling agent. I will discuss the details of network construction in the next section. Figure 2 shows the number of existing agents per year from 2003 till 2021 – the full years we observe, the number of new agents per year, and the number of agents leaving the profession yearly. Since we observe a limited sample, we should use caution in the first and last years. Figure 3 shows the number of agents exclusively listing versus selling (buying) agents during a calendar year.

In the second stage, I prepare the data for the regression analysis. I exclude the transactions where either agent is a known iBuyer and the new constructions following Bikmetova et al. (2023). I also delete the observations with apparent data entry errors, like negative values for lot size and listings with apparent list price entry errors. The list of the filters applied to the raw data is presented in Table B1. The final sample has 210,279 non-missing observations, covering the period from October 2003 to March 2022. I eliminate the first year of the sample when analyzing the models for one-year-window networks and the first three years of data when analyzing three-year-window networks. The first years of data carry noisy information as we do not observe the prior data to describe the network sufficiently. For example, to construct a t-365-day network for July 2003, we do not have the data before October 2002. Therefore, I require at least one year (three years) of data to construct a network. Table 2 describes and defines the variables used in the study. I will discuss some variables in more detail in the next section. Table 3 shows the summary statistics of the variables used in the model.

I use the annual consumer price index (rent or primary residence in Dallas-Fort Worth-Arlington, TX) from the U.S. Bureau of Labor Statistics and express all sale prices in the base year of 2010.

This subsection has detailed the comprehensive dataset collected from the North Texas MLS and the cleaning processes applied to ensure the data's accuracy and relevance. Eliminating incomplete or invalid data points and carefully preparing for network construction and regression analysis lay a solid foundation for the study. The final dataset, spanning nearly two decades, is robust and well-suited for exploring the dynamics of agent networks and their impacts on market outcomes.

Methodology and Models

In this subsection, I present the models I use to test the hypotheses and discuss the set of control variables included in them. The aim is to provide a clear understanding of the methodological framework that underpins the analysis.

To assess whether the agent network metrics are related to agent performance, measured by the sale price and TOM, I use 3SLS. As discussed earlier, widely used hedonic models suffer from biased OLS coefficients when the price and time-on-market are estimated separately. This endogeneity problem is well-documented in the literature (Benefield et al., 2020; Aroul & Hansz, 2014; Hayunga & Munneke, 2021; Seagraves & Gallimore, 2013; Yavas & Yang, 1995; Anglin et al., 2003, see for examples).

To address the endogeneity problem between Sale Price and TOM, I follow Turnbull and Dombrow (2006) and use a system of simultaneous equations.

$$P = f(TOM, D, N, A, X, Z) + \varepsilon, \tag{4}$$

$$TOM = f(P, C, N, A, X, Z) + \upsilon, \tag{5}$$

where:

P is the natural logarithm of house Sale Prices,

TOM is the natural logarithm of the number of days a house remained on the market,

D and C are the listing density and competition, respectively, calculated in Turnbull and Dombrow (2006), tracking houses within 2 miles of distance and no more than 20% difference in living area,

N is one of the following agent network normalized metrics: degree centrality, betweenness centrality, or eigenvector centrality,

A is a matrix of agent-pair specific control variables, such as the experience, specialization, and listings inventory,

X is a matrix of house and deal characteristics,

Z is a matrix of months and years for time and postal codes.

The network metrics are normalized to facilitate comparison across different periods and smooth the variables' distribution so they better fit into the regression models. Normalization makes the centrality measures independent of the absolute size of the network. It also allows us to identify the relative importance of the node in the network more efficiently, and it prevents extreme values from dominating the analysis. The normalization formulas used for each centrality variable are presented in Appendix C. Details on network construction for calculating centrality metrics are discussed in the Social Network Construction and Analysis Measures subsection above.

I apply the natural logarithm transformation for each continuous variable, except the centrality measures, to handle skewed distributions, reduce the impact of the outliers, stabilize the variances, improve linearity, and interpret coefficients as percentage changes. For more details, please see Table 2 with variable descriptions.

While the control variables for house and deal characteristics are standard in the literature, the control variables for agent characteristics require further discussion. In the Literature Review section, I presented how studies address agent experience, agent active listing inventory, and agent specialization. These variables are relevant and available in the current study. Agent experience is often measured in two ways: the total number of transactions and the agent's tenure.

The total number of transactions can be highly correlated with the degree centrality (network size) measure depending on how a network is constructed. Shen and Sun (2023) find a high correlation of 0.99 between the degree centrality measure they use and the total number of transactions in their sample. As discussed, such a high correlation can be due to constructing the network after applying all the data cleaning filters, hence artificially increasing the correlation between the variables, as well as due to the network construction window and step they choose. They construct the network from t-1 to t-3 without much detail regarding the step. On the contrary, I build the network t-365 days before the current transaction[4]. Moreover, when counting the experience as the number of total transactions, I take the transactions from the first time an agent appears in the dataset instead of resetting the experience in every period. The intuition behind this is that personal interactions - connections with other agents - might lose their strength with time. At the same time, the experience gained from completing a transaction should remain and accumulate throughout their career. As listed in Table A1, the correlation between the network size variable and total transactions is 0.58 for the transformed variables. Between the raw variables, the correlation reaches 0.73. Nevertheless, to fully address the concern of a high correlation

[4] As a robustness test, I also construct the network for three years (365 days times 3) prior to current transaction.

between agent experience measured by the total number of transactions and the network variables, I use two other measures of agent experience.

The first measure, - agent experience in months, is straightforward and commonly used in the literature (e.g., Seagraves & Gallimore, 2013; Huang & Rutherford, 2007). The second measure is the number of total transactions before the current transaction divided by the number of months since the first appearance in the sample. This measure is not used in the literature I cover in the study but is mentioned in Fang and Hayunga (2024) as an indicator to filter out agents who potentially use the help of other agents since such a high frequency of monthly transactions is not feasible for an agent without a team. By including this variable, I control agent productivity (experience) and the potential presence of a team working for the agent.

I use an indicator variable for agent specialization if an agent serves as an exclusively listing or an exclusively selling agent throughout the dataset. To avoid misclassifications, I create this variable before cleaning the data for the regression analysis. Surprisingly, the percentage of selling agents is almost four times higher than the percentage of exclusively listing agents, indicating that many agents prefer representing buyers. Perhaps this is associated with less responsibility that buyers' agents usually have than sellers' agents. One such responsibility would be helping the seller determine the property's listing price and any efforts to market the property. The literature more commonly uses the ratio of listing vs selling transactions as a measure of specialization (e.g., Seagraves & Gallimore, 2013; Salter et al., 2010). However, by using an indicator variable for specialization, I tighten the meaning of specialization to exclusively listing or selling agents.

Another control variable I use, based on the literature, is the number of concurrent listing inventories for each agent. Bian et al. (2015) find that the high number of listing inventory dilutes agent efforts per client, significantly affecting the TOM. Therefore, I include the measure of listing inventory as a proxy for capturing the effort dilution effect. Li et al. (2022) show that agents with large inventory sizes, hence diffused effort, are motivated to ask for higher prices and increase marketing resources to increase the clientele network size. In an empirical analysis, Turnbull and Waller (2018) find that agents with at least 2% of total market listings generate positive shopping externalities from their large market share and that there is no significant performance premium among top-selling agents.

Following Smith et al. (2019), I include indicator variables for in-house transactions, such as transactions where both agents work for the same brokerage and whether the agents have previously transacted with each other. Smith et al. (2019) find that agents who have previously worked together tend to achieve lower sales prices, calling this "building social capital." In-house transactions are associated with slightly higher sales prices. Therefore, I keep these two variables in the models throughout the analysis.

Finally, following Hayunga and Pace's (2019) discussion of the importance of omitted variables in price and TOM simultaneous equations, I include two control variables in the models – indicators for house atypicality and an indicator for listing price reductions, as described in Table 2.

The rest of the model's variables account for property or deal-specific heterogeneities, such as square footage and age, as well as occupancy type and financing. To account for seasonality and economic changes, I use monthly and annual fixed effects and postal code fixed effects for location-specific differences.

In this subsection, I discussed the methodological framework and statistical models employed in this study. Applying normalization techniques and carefully considering agent characteristics and market dynamics further strengthens the analysis. This methodological approach provides a solid foundation for the subsequent analysis and discussion of findings in the following chapters.

In this chapter, I have outlined the detailed processes involved in data collection, cleaning, and preparation from the North Texas MLS and the methodological approaches employed to analyze the data. The comprehensive dataset allows for a robust examination of agent networks and their impact on agent performance metrics. The study ensures accurate and reliable results by utilizing a system of simultaneous equations and addressing endogeneity issues. The various control variables and normalization techniques applied further enhance the validity of the findings. The methodology and models discussed in this chapter form the foundation for the subsequent analysis and results, providing critical insights into the dynamics of real estate agent networks and their influence on market outcomes.

CHAPTER 5: EMPIRICAL ANALYSIS AND ROBUSTNESS

Main Results

First, I conduct mean comparison tests to determine whether agent performance, measured by sale prices and Time on Market (TOM), is related to the agent network size. I divide the listing and selling agent network sizes into above- and below-the-mean groups and check if the average sale prices and/or TOM significantly differ between the groups. The results are reported in Table 4.

This preliminary analysis shows that, before controlling for other factors, listing (selling) agents with an above-mean network size have, on average, $17,395 ($9,216) higher sale prices and only 1.94 (0.65) days shorter TOM. The mean comparison of agent bridging power shows similar results for listing agents. However, for selling agents, the difference in average sale prices is negligible, and the difference in TOM is not statistically significant. When comparing by average agent influence, the means for sale price (TOM) comparison remains positive (negative) and significant for listing agents. However, for selling agents, the difference in average sale price is insignificant ($231), and the difference in average TOM is less than one day.

These results suggest that agent network size and position are critical for listing agents, particularly in achieving higher sale prices. This simple test suggests that any difference in TOM is relatively small for either agent. Network size seems to be the most crucial metric for selling agents, although the sign of the effect contradicts the assumption that selling agents prioritize buyers' interests. It suggests that selling agents are more interested in obtaining higher percentage commissions from more expensive deals rather than negotiating lower prices. All these results are based only on mean comparison and cannot serve as solid arguments supporting my hypotheses. Therefore, I proceed with regression models by adding controls for different agent characteristics.

For each of the three network centrality measures, I construct four models. The first model includes only the measure of network centrality and the standard set of control variables used throughout. In the second model, I add agent experience controls, i.e., agent experience in months and agent average monthly transactions. In the third model, I add indicator variables for agent specialization, and in the fourth model, I add each agent's concurrent listing inventory size. Below, I report the results from the four regression models for each of the three centrality measures.

Table 5 presents the simultaneous regression results for agent network size, where the dependent variables are the natural log-transformed sale price and TOM. Sale prices increase as agents expand their network size while TOM decreases. A one standard deviation increase in the listing agent's normalized degree centrality is associated with a 0.08-0.3 percentage point increase in the sale price. TOM decreases by 2.6-10.71 percentage points, holding all other covariate means constant. For the selling agent, a one standard deviation increase in the normalized degree centrality is associated with a 0.39-0.43 percentage point increase in the sale price and a 6.05-6.15 percentage point decrease in TOM.

The agent's average monthly experience has a significant negative association with the sale price and a positive association with the TOM. In contrast, the experience measured in months (length of experience) has the opposite effect on the sale price and TOM. This suggests that agents consistently in demand might sacrifice price and be less interested in fast turnover than those in less demand. Agent specialization seems to have a negative association with sale prices. Although I use a stricter definition of specialization by limiting it to exclusivity, the findings are like Beck et al.'s (2022).

In Model 4, I include agent concurrent listing inventory to account for shopping externalities from diffused effort. The listing agents' active listings inventory, all else equal, seems not to affect sale prices but significantly increases TOM, suggesting that agents might allocate less effort per listing when they have a large inventory. For selling agents, their listing inventory has a positive association with the sale price and a negative one with TOM, suggesting that selling agents might use their inventory of listings to maximize their commission and find properties faster.

Prior literature has found that in-house transactions are not always based on the buyers' best interest and can be driven by the incentives offered to agents (Han & Hong, 2016). The results also indicate higher sale prices with shorter time for in-house transactions, like Smith et al. (2019). However, I find no evidence of "building social capital" between agents who have transacted previously, as the coefficient on the *Previous* is positive and significant. Smith et al. (2019) argue that agents who have worked together before sell houses at a discount to enhance the value of the social capital they have built together. I find this explanation more intuitive than the social capital theory. Agent commissions depend upon sale prices. Agents who have transacted before might try to maximize their commission, especially since the selling agent is paid from the listing agent's share.

Overall, the analysis indicates that a more extensive agent network enables agents to sell houses at a premium and more quickly, all else equal. Although buyers may not directly benefit financially from this, the reduction in TOM suggests potential advantages. Specifically, working with an agent who has an extensive network could help buyers find their desired property faster, even though the property search time itself is not directly observed in this analysis.

I note that negative, significant coefficients on the constant of TOM models and negative R-squared values are not unusual for 3SLS regressions (e.g., Bian et al., 2017). Although I report the R-squared values, a reader should interpret them cautiously, as the R-squared of 3SLS is regarded as meaningless and should not be compared with the R-squared of OLS estimation.[5]

In Table 6 and Table 7, I report the results of 3SLS estimations for agent bridging power (betweenness centrality) and agent influence (eigenvector centrality), respectively. Agent bridging power shows how often an agent is positioned on the shortest path to connect other agents. It indicates that this agent is the most probable common contact for unrelated agents. For agents, having high bridging power can mean serving as a messenger, spreading information quickly, and receiving information from other agents. He or she can also become a channel for spreading innovation between other, otherwise directly unrelated agents. Table 6 shows that before controlling for agent experience, inventory size, and specialization, listing agent bridging power is insignificant for both sale price and TOM and is highly significant for the selling agent. As I introduce controls for agent characteristics, they also become significant for the listing agent. The significance level for the selling agent drops when listing inventory size is introduced. To my knowledge, this is the first study to look at agent network position metrics. Without prior research, deciding what other agent characteristics might be driving the results is arbitrary. However, the importance of the agent characteristics I include in the full model has already been shown in the prior literature. Therefore, despite the irregular pattern of significance for those variables, I believe that simply excluding the insignificant ones from the model might introduce a severe concern for omitted variables. Excluding agent listing inventory size significantly lowers the Bayesian information criterion (BIC), indicating a better fit for Model 3.

Table 6, Model 3 shows that the normalized betweenness centrality of agents is associated with higher sale prices and shorter TOM. A one standard deviation increase in the normalized

[5] https://www.stata.com/manuals/rreg3.pdf

betweenness centrality is related to a 0.12 and 0.3 percentage point increase in the sale price and a 3.4 and 5.1 percentage point decrease in TOM for listing and selling agents, respectively. The economic significance, especially for sale price, seems very small; however, it is difficult to quantify the normalized betweenness centrality. This is a vast network, and I have not applied any network dichotomization techniques in this analysis. In future research, one can try to limit the network's diameter to see whether these results hold and estimate a more realistic effect size.

Agent influence, or eigenvector centrality, shows agents' relative importance in one’s network. Table 7 reports the results of eigenvector centrality. In contrast to the bridging power, in Model 1, agent influence is significant for the listing agents but not the selling agents. More interestingly, if the coefficients on the sale price (TOM) are positive (negative) for network size and agent bridging power, the results for agent influence suggest the opposite. Listing agents with an influential network are associated with lower sale prices and longer TOM. The same result applies to selling agents when controlling for other agent characteristics. BIC suggests the best fit for Model 3. A one standard deviation increase in agent influence is associated with a 0.25 percentage point decrease in the sale price, a 6.5 percentage point increase in TOM for listing agents, a 0.21 percentage point decrease in the sale price, and a 6.9 percentage point increase in TOM for selling agents.

As discussed in the Hypotheses Development subsection, these results might indicate that the most influential agents are willing to hold properties longer to achieve better deals. However, this conjecture holds only for selling agents, assuming they are interested in lowering the price for the buyers. The negative relationship between listing agent influence and sale price requires further investigation. If the results do indeed hold in practice, this can mean that sellers should avoid "famous" agents with big names, as those might have secured their titles and now do not put enough effort into individual transactions.

Market Cycles

The price discovery process in real estate markets is quite different. Unlike financial markets, in real estate markets, buyers and sellers participate in the price formation directly and frequently and can negotiate the price. Cheng et al. (2020) examine real estate market sellers, grouping them into constrained and unconstrained. Unlike the constrained sellers, the unconstrained sellers are willing to wait until they get their desired asking price. Hence, the transaction prices are "noisy" and depend on the state of the market and seller motivation. Like Marcato and Nanda (2022), I argue that market participants' behaviors change depending on the economic cycle. I expect agent behaviors to change depending on cold vs. hot markets.

While I cannot observe seller motivation in this dataset, I can analyze the different subperiods to see if agent behavior changes depending on the market state. Table 8, Table 9, and 10 Table 10 present the market cycle analysis. I use subperiod cutoff years based on Private Residential Fixed Investments annual data. In Table A2, I present the mean and median CPI-adjusted sale price and TOM per calendar year and for each subperiod. As we can see, the Tarrant County residential housing market shows a steady price increase, except during the financial crisis, which first increased till 2011, then decreased the trend for the TOM. This trend is somewhat different from the national trend I used to decide the cutoff periods.

Marcato and Nanda (2022) find evidence that real estate investors respond asymmetrically to the shifts in bargaining power as supply and demand shift. In the sellers' market, the chances that a property gets bids are higher. At the same time, during economic prosperity, the overall market activity increases, including a large inflow of new agents and an increase in the number of transactions. Therefore, I expect agent network position metrics to have different levels of importance depending on the market cycle.

When market activity is high, agent network size is likely highly significant. Agents with more connections can leverage their network to match buyers with properties quickly, negotiate favorable terms, and expedite transactions.

Market activity slows during contraction periods, and there are fewer transactions. Agent network size might be less critical since the volume of available buyers and properties diminishes. However, agents with a high degree centrality can still benefit from their extensive networks by identifying scarce opportunities, maintaining market visibility, and staying informed. I expect the speed of information flow within the network to be less critical in cold markets. Thus, the degree centrality may remain valuable, but its impact on the sale price and TOM might be less pronounced than in expansion periods.

Table 8 shows that the size of the agent network for both listing and selling agents became insignificant during 2005-2010. For listing agents, it is the most significant in the early years of 2003-2004, which can be due to the higher importance of personal contacts as real estate marketing tools were less advanced and less significant from 2011 to 2019. The network size is insignificant for buying agents until 2010, after which it becomes significant. Interestingly, during the COVID-19 pandemic, the network size lost its significance on the sale price and TOM for the listing agents but remained highly significant for selling agents. These differences in the patterns between listing and selling agents can indicate that listing agents give less priority to personal contacts for advertising as technology advances. In contrast, personal connections become more critical for selling agents in identifying better deals.

Table 9 shows the results for agent bridging power in different market cycles. Agent's position as an intermediary in the network indicates their ability to control information and resource flow between other agents. In optimistic markets, agents with high betweenness centrality can play pivotal roles in facilitating transactions, bridging gaps between buyers and sellers, and streamlining processes. Their intermediary position allows them to connect disparate network segments, enhancing market efficiency. Consequently, these agents can achieve higher sale prices and reduced TOM by efficiently matching buyers with suitable properties and navigating complex negotiations.

Unlike network size, listing agent bridging power is significant and positive before and during the downturn until 2011. Surprisingly, it was insignificant for both agents from 2011 to 2019. During the observable pandemic period, it has a significant negative association with price and positive with TOM for listing agents and the exact opposite effect for selling agents. The pandemic had a profound impact on the real estate markets. The market experienced a considerable inflow of capital, often cash. At the same time, personal interactions with agents and in-person showings became less critical due to the fear of contracting the virus and social distancing rules. It is possible that our model does not capture all the changes impacting the prices and TOM during the pandemic. Therefore, I will leave a more detailed analysis of network dynamics during the pandemic for future research, especially since my sample ends in March 2022. For the robustness of the results, I also define the pandemic start year as 2019 instead of 2020. The results remain qualitatively unchanged.

A careful reader might also notice that the selling agent bridging power coefficients are highly significant in the sample period. However, in the market cycle analysis, selling agent bridging power loses its significance in all periods except after 2019. This can mean several things.

First, the full sample aggregates the diverse effects of different market conditions, smoothing out short-term volatility and highlighting consistent trends. The varying market conditions can obscure the influence of betweenness centrality, making it less consistently significant. It could also be due to a reduced sample size. While reduced sample size can be a concern for shorter periods, the number of observations between 2011-2019 is large enough to give us sufficient statistical power. Therefore, the primary analysis's selling agent bridging power results should undergo additional tests. Also, as reported in Table A2 we do not see distinct market cycles in price fluctuations in Tarrant County for our sample, except during the financial crisis of 2007-2009.

Finally, Table 10 shows the regression results for agent influence and performance during different market cycles. During 2003-2004, listing agents with higher eigenvector centrality significantly influenced higher sale prices and reduced TOM. This suggests that well-connected listing agents leveraged their networks effectively to achieve better prices and quicker sales. However, buying agents' influence on price and TOM was insignificant, indicating that their network centrality did not substantially impact performance during this time.

During the housing bubble and subsequent crash, listing agents with high eigenvector centrality were associated with lower sale prices and increased TOM. This could be due to the market's speculative nature and eventual crash, where even well-connected listing agents struggled to secure high prices and quick sales. Conversely, buying agents with higher centrality significantly influenced lower prices and much longer TOM, indicating that their network positions allowed them to negotiate better deals for buyers, albeit with more time required to close transactions.

In the recovery phase, listing agents with higher eigenvector centrality continued to be associated with lower sale prices and longer TOM. This suggests that despite the market's recovery, the influence of listing agents' networks did not translate into higher prices or quicker sales. For buying agents, higher centrality was still associated with securing lower prices, reflecting their continued negotiation leverage. The positive relationship with TOM indicates that these transactions took longer, possibly due to cautious buyer behavior post-crisis. It is also possible that well-connected agents feel extremely secure about their jobs and put minimal effort into executing deals for their clients.

During COVID-19, the trend for listing agents persisted, with high eigenvector centrality correlating with lower sale prices and longer TOM. The pandemic-induced uncertainty and market disruptions likely intensified challenges for listing agents, even those with strong networks. The relationship between eigenvector centrality and price/TOM was insignificant for selling agents, suggesting that network influence was less critical for their performance during this unprecedented period.

Hence, market cycle analysis suggests that the importance of the size and the relative position of agent networks change with the market. This analysis underscores the importance of network positions and the adaptability of real estate agents in responding to different market conditions.

Brokerage Size

Brokerage size can directly and indirectly affect the results of this study. First, agents working for large brokerage firms can have specific attributes that agents working in small brokerages do not, or vice versa. Moreover, large brokerages usually provide agents with more comprehensive resources. Besides these direct effects, working in a brokerage creates a network of colleagues. I address this indirect effect by controlling for in-house transactions throughout the analysis. The large number of brokerages and agents makes using brokerage and agent fixed effects unfeasible. Therefore, I control brokerage size by categorizing each based on the median number of agents below and above for each calendar year. Then, I group listing and selling brokerages into four groups: small-small, small-large, large-small, and large-large. This divides our sample into approximately equal subsamples.

Brokerage size is an essential factor in agent performance. For example, Angjellari-Dajci et al. (2015) find that properties listed by brokerages associated with a national franchise sell for lower prices. Benjamin et al. (2005) find a positive association between brokerage size and the use of technology, with larger firms generating higher revenues but lower net margins. In this subsection, I check if agent network size and position matter more for large vs small brokerages.

Table 11 shows how the size of the agent's network, along with the brokerage size, influences real estate transaction outcomes. For small listing and selling brokerages, the degree centrality of listing agents does not significantly impact the sale price, though it slightly reduces the TOM. Conversely, the selling agents' network size has a significant positive effect on sale prices and a substantial negative impact on TOM. This suggests that in smaller brokerages, selling agents with larger networks are less effective in securing lower prices and more effective in expediting transactions.

In configurations where small listing brokerages interact with large selling brokerages, neither listing nor selling agents' degree centrality significantly impacts the sale prices or TOM. This implies that the network size of agents in this scenario does not play a crucial role in determining transaction outcomes.

When large listing brokerages interact with small selling brokerages, both listing and selling agents' network sizes significantly influence sale prices and TOM. Listing agents with more extensive networks achieve higher sale prices and reduce TOM substantially. Similarly, selling agents with more extensive networks also achieve higher prices and reduce TOM, though to a lesser extent than listing agents. This indicates that listing and selling agents can leverage their extensive networks to enhance transaction efficiency and maximize their gains in such configurations.

In the case of large listing and large selling brokerages, the network size of listing agents significantly impacts both the sale prices and TOM, with more extensive networks leading to higher prices and shorter TOM. However, while their network size reduces TOM for selling agents, it does not significantly affect sale prices. This suggests that in large brokerages, listing agents' networks are more influential in driving transaction outcomes, likely due to large listing brokerages' more significant resources and market presence.

The overall results also suggest that if a seller chooses to work with a large brokerage firm, the client should prefer an agent with an extensive network to maximize the sale price and minimize the TOM. However, the listing agent's network size in small brokerages does not significantly impact their performance. The result is the opposite for the buyers when choosing an agent. When working with large brokerages, the selling agent's network size is less critical, perhaps because brokerage networks compensate for individual agent networks. However, when working with selling agents from small brokerages, buyers should consider the higher price – shorter transaction time trade-off associated with the large network size of the selling agents.

Table 12 shows the results for agent bridging power in the four brokerage size groups. When both agencies are below the median by the number of agents working for them, listing agents' bridging power does not significantly impact the sale prices or TOM. However, the bridging power of selling agents significantly influences the sale price and TOM. This indicates that in small brokerages, selling agents who can act as effective intermediaries are critical for faster sales with some increase in the sale price.

When a small listing brokerage transacts with a large selling brokerage, the listing agent's intermediary power seems to lower the sale price and increase the TOM. This indicates that in such configurations, the bridging power of listing agents might be less effective in negotiating prices with large selling firms. Both listing and selling agents' betweenness centrality significantly influences sale prices and TOM for large listing brokerages interacting with small selling brokerages. Listing agents with higher bridging power achieve higher sale prices and reduce TOM substantially. Similarly, selling agents with higher betweenness centrality agree to higher prices for reduced TOM, indicating that in this configuration, the bridging power of both types of agents is crucial in optimizing transaction outcomes.

In the case of high-volume listing and selling brokerages, the betweenness centrality of listing agents significantly impacts both sale prices and TOM. However, the effect is less pronounced than in other configurations. Listing agents with higher bridging power achieve slightly higher sale prices and moderately reduce TOM. For selling agents, betweenness centrality does not significantly affect sale prices or TOM, suggesting that in large brokerage configurations, the bridging power of selling agents is less critical than listing agents.

The results suggest that listing agents with high bridging power can utilize it in large brokerages, not small ones. If a buyer is interested in quicker transaction processing, then he or she should work with well-positioned agents from small brokerages. The selling agents' bridging power is irrelevant in larger brokerages.

Table 14 presents the results of a 3SLS regression analysis examining the impact of agent influence, as measured by eigenvector centrality, on the sale price and TOM across different configurations of listing and selling brokerage sizes. For small listing and small selling brokerages, higher eigenvector centrality in both listing and selling agents is associated with lower sale prices and longer TOM. This indicates that even influential agents may struggle to secure higher prices and expedite sales in smaller brokerages. The competitive dynamics and limited market reach of smaller brokerages may dilute the benefits of agent influence.

For small listing brokerages working with large selling brokerages, agent influence gives overconfidence and leads to the underperformance of listing agents and an overperformance of selling agents. If the seller decides to work with a large brokerage firm, the better choice would be to select a well-connected agent, as he or she will have higher motivation (perhaps for inter-agency competition) to provide the best deal outcomes for the seller. Unlike the previous two metrics, agent influence is the one metric buyers should concentrate on when selecting their representatives to achieve significantly faster sales and price discounts.

The results show that the size and influence of an agent's network matter differently depending on the brokerage size configurations. For instance, in small listing and small selling brokerages, selling agents with more extensive networks can secure higher sale prices and expedite transactions, while listing agents' network size has less impact. In configurations where small listing brokerages interact with large selling brokerages, agent network size does not significantly affect outcomes, indicating a potential mismatch in resources and strategies.

When large listing brokerages interact with small selling brokerages, both listing and selling agents' network sizes positively influence sale prices and reduce TOM, suggesting that extensive networks are crucial in these settings. Conversely, in high-volume listing and selling brokerages, the network size of listing agents is more influential, leading to higher prices and shorter TOM, while selling agents' network size has a lesser effect.

Agent bridging power, measured by betweenness centrality, also varies in importance based on brokerage size. In small brokerages, selling agents with high bridging power can expedite transactions and slightly increase sale prices, while listing agents' bridging power is less effective. In mixed-size configurations, the bridging power of listing agents may even decrease sale prices and increase TOM. In large brokerage configurations, listing agents with high bridging power achieve better outcomes, while selling agents' bridging power is less critical.

As measured by eigenvector centrality, agent influence shows that in small brokerages, even influential agents may struggle to achieve higher prices and quicker sales. However, well-connected agents can leverage their influence more effectively in large brokerages, particularly in configurations involving large listing brokerages.

Overall, the analysis underscores the importance of considering agent network characteristics and brokerage size when evaluating real estate transaction outcomes. For sellers, working with large brokerages and selecting well-connected agents can maximize sale prices and minimize TOM. Choosing agents with high bridging power in small brokerages can facilitate quicker buyer transactions. These findings provide valuable insights for optimizing agent and brokerage choosing strategies and improving transaction efficiency for sellers and buyers.

Market Segmentation

In this subsection, I check whether agent network size and position are more important in specific market segments. Agent connections may matter more in high-priced markets where the demand is usually lower than in low- or mid-priced markets. On the opposite, agents rely more on their network for lower-priced markets. To minimize the risk of misclassification, I use two approaches to categorize the houses into price segments. First, I split the sample based on each postal code's median CPI-adjusted sale price (e.g., Benefield et al., 2019; Fang & Hayunga, 2024). The median adjusted sale price of the overall sample from October 2003 to March 2022 is

$160,652 and is $200,000 without adjusting the sale price. More details on median prices and TOM are available in Table A2.

Table 14 shows the results of 3SLS regression for agent network size and median sale price. We see that for both agents, the network size is much more critical for below-median-priced houses than for median below-median-priced houses and above-median ones. For the listing agents working with less expensive homes, having an extensive network allows them to sell the houses for a higher price and faster. For more expensive homes, listing agent network size is less critical, and the coefficients flip the signs, indicating that the size is either value-destroying or unimportant. Hence, the main results for the network size are driven by less expensive properties. Interestingly, the coefficients for *InHouse* and *Previous* are very different in magnitude, direction, and significance for the two groups. In-house transactions and transactions where agents have previously collaborated are associated with higher sale prices and lower TOM for above-median-priced properties. On average, more experienced agents sell cheaper houses faster, but not necessarily with a discount. Unlike in the overall sample, the TOM's selling agent network size coefficient is positive for below-median-priced houses. This indicates that perhaps buying agents try to sell more expensive houses before offering the buyers less expensive alternatives.

Table 15 presents the results for agent bridging power. For the listing agent, bridging power helps them sell less expensive properties more efficiently but not more expensive ones. Their intermediary position in the network seems to distract them from achieving the highest possible sale prices and quicker sales in the more expensive price segment. Like the case with network size, selling agents take longer to transact on cheaper properties and tend to maximize their profit from already low commissions.

In Table 16, I report the regression results for agent influence. The main results for agent influence are driven by the higher-priced properties, where agent influence is value-destroying for the sellers as it is associated with significantly lower sale prices and longer TOM. For below-median-priced houses, well-connected listing agents can sell the properties faster without a significant price difference. In the case of selling agents, having an influential network signals overconfidence and poorer performance regardless of the price segment.

If the median sale prices do not provide enough information about the property's price segment, I divided the sample into three, using $100,000 and $500,000 as breakpoints.[6] Table 17 presents the results for the three segments and agent network size. We see a similar pattern in the median sale price analysis. The listing agent network size is associated with higher sale prices and shorter TOM for low- and mid-priced segments. The analysis shows a negative association between the sale price, network size, and none with TOM for high-end properties. This indicates that the agent quantity in the network is not as essential and crucial in the luxury market, at least for the transaction speed, as it is in the non-luxury market. For the selling agents, the quantity of connections matters more in more liquid low-price markets, which helps them earn higher commissions on small sale prices, with a little compromise on the TOM.

As shown in Table 18, listing agent bridging power becomes insignificant in the considered price segments, except for luxury properties worth above $500,000. Selling agents with favorable intermediary positions try to maximize their commissions earned on low-priced houses and are ready to negotiate better prices for their clients in the high-end market.

[6] In untabulated results, I divide the sample into below 5 and above 95 percentiles, and in between. The results are qualitatively similar for almost all of the coefficients of interest, with a few exceptions.

Listing agent influence in low-priced segments helps agents secure higher sale prices in a shorter time, as shown in Table 20. The significant negative (positive) association between agent network influence and price (TOM) is driven by the high-end properties for listing agents and even more so for selling agents. These results suggest that depending on the property price segments, clients should choose their agents carefully, considering the agent's position in the network.

This subsection examines the importance of agent network size and position in different market segments, emphasizing its implications for buyers and sellers. Understanding whether agent connections matter more in high-priced or low-priced markets is crucial for optimizing real estate transactions. Two approaches were used to categorize houses into price segments: the median adjusted sale price for each postal code and dividing the sample into three segments using $100,000 and $500,000 as breakpoints.

The findings reveal that agent network size is critical for below-median-priced houses, allowing listing agents to achieve higher sale prices and faster transactions. Conversely, agent network size appears less beneficial for higher-priced homes, sometimes even detrimental. This suggests that agent networks play a more significant role in less expensive markets. Additionally, in-house transactions and previous collaborations positively impact sale prices and TOM for above-median-priced properties, highlighting the varying effects of agent experience across price segments.

Agent bridging power helps sell less expensive properties more efficiently but is less effective for more expensive homes. Well-connected listing agents can sell below median-priced houses faster without significantly affecting prices, while for selling agents, an extensive network often indicates overconfidence and poorer performance regardless of the price segment unless their immediate network is also an influential one.

The analysis underscores the importance of strategically considering agent network characteristics when choosing an agent. Clients dealing with low- to mid-priced properties should prioritize agents with extensive networks to maximize sale prices and minimize TOM. In contrast, network size and bridging power become less critical for high-end properties, suggesting that other factors might drive transaction efficiency and outcomes in the luxury market.

Mispricing

One of the main functions of a real estate agent is to help her client determine the listing or offer price. Therefore, my next question is how agent network size and position relate to agent performance and mispricing. I use a straightforward measure of mispricing following Shen and Sun (2023) and finding the absolute value of the difference between the sale and listing prices (using their natural logarithms, without CPI adjustment). Then, I either include the measure of mispricing in the models or divide the sample into properties with and without mispricing. The sample has 38,031 observations where the sale price was equal to the asking price and 172,248 observations with an average mispricing of $7,500.

The coefficient on the *Mispricing* remains consistent and significant across all models. Table 20 shows that agent network size remains a strong positive predictor for sale price and a negative one for TOM, regardless of mispricing in the deal. The results in Table 21 suggest that agent bridging power is more critical for listing agents who accurately price the properties and for selling agents who negotiate the sale prices.

Agent influence and mispricing results are reported in Table 22. On average, more significant mispricing is associated with lower sale prices and longer TOM. However, looking at the mispricing subsamples, we see that the coefficient of listing agent influence on sale price is negative but insignificant, suggesting that listing agents who accurately price the properties rely on their influential connections less, all else equal. For selling agents, the coefficient for TOM is positive and significant in both subsamples, yet it takes much longer for influential selling agents to finalize deals in mispriced properties.

This subsection investigates how agent network size and position impact agent performance and property mispricing. The results show that agent network size consistently predicts higher sale prices and shorter TOM, regardless of mispricing. For listing agents, bridging power is essential when properties are accurately priced, while for selling agents, it aids in negotiating sale prices effectively. Mispricing is linked to lower sale prices and longer TOM. Listing agent influence is less critical when properties are accurately priced, whereas influential selling agents face longer TOM in mispriced deals. Overall, the analysis highlights the importance of agent network characteristics in the presence of mispricing.

Other Robustness Checks

Robustness checks are critical in validating the results and providing confidence that the conclusions drawn from the analysis are not artifacts of the specific methodologies or time frames used. This subsection details two additional robustness checks: using three-year network metrics instead of one-year metrics and OLS regressions instead of the 3SLS method for the main results.

The initial analysis utilizes one-year network metrics to capture the dynamics and relationships within the network. While one-year metrics provide a snapshot of network interactions, they may not fully capture the longer-term trends and stability within the network. To address this, three-year network metrics are calculated as an alternative measure. This longer timeframe allows for assessing more stable and persistent network effects, mitigating the potential noise and short-term fluctuations that can affect one-year metrics. By examining the consistency of the results with three-year metrics, we can ensure that the findings are robust to the choice of the window and reflect more enduring network characteristics. The results with 3-year network metrics are reported in Table 23, Table 24, and Table 25.

When using the 3-year window for the agent network size variable and substituting it with 1-year window measures in the regression analysis, we see consistent, slightly different magnitude results for both the listing and selling agents. Interestingly, the sale price and TOM coefficients are slightly slower for listing agents when taking a 3-year window and marginally higher for the selling agents. This implies that when listing a property, agents rely more on relatively recent connections they made, while to find a “perfect” house for the buyers, selling agents rely on a more extensive, more established network that goes beyond one year.

Agent bridging power seems more persistent in the short term, especially when listing properties. As reported in Table 24, although the sign on the sale price and TOM coefficients remain consistent for all models, the significance fades for the 3-year window estimates. I do not observe any significant change in the coefficients' magnitudes for selling agents, meaning that agents with an intermediary position can maintain it much longer in selling properties. Agent influence remains substantial and significant, with little change in the 3-year window estimation. This shows that agents can maintain influential connections and rely on them throughout their careers.

As discussed in the Literature Review, using OLS to estimate the sale price and the TOM introduces endogeneity in the analysis, leading to inconsistent, biased estimates. Despite the theory showing endogeneity between the sale price and TOM, I conducted a Hausman test to check if endogeneity exists in the data. I run an instrumental variable regression for sale price, where the exogenous variable for the TOM is the *Competition* and the rest of the variables without robust standard errors. The Chi-squared statistic for the Hausman test is 904.06 with 27 degrees of freedom, and the p-value is 0.0000. This highly significant result indicates a systematic difference between the 2SLS and OLS coefficients, suggesting the presence of endogeneity in the model. Consequently, the OLS estimates are biased and inconsistent, necessitating other estimation techniques. For an interested reader, I report the OLS regression results for the main four models in Appendix D. The signs of some coefficients on the variables of interest differ from the 3SLS results reported in Table 5, Table 6, and Table 7. The sign between the sale price and TOM is negative – an estimation bias described by Hayunga and Pace (2019).

This section aims to reinforce the credibility of the study's findings by incorporating these additional robustness checks. Using OLS regressions provides a more straightforward benchmark against which to compare the 3SLS results. At the same time, the analysis with three-year network metrics offers insights into the stability and persistence of network effects. Together, these robustness checks enhance the overall confidence in the study's conclusions, demonstrating that the results are not unduly sensitive to the specific methodologies or estimation windows initially employed.

In this chapter, I performed several analyses to investigate the relationship between agent performance and network size and the robustness of my findings. The initial mean comparison tests revealed that agents with more extensive networks achieve higher sale prices and shorter TOM. However, these preliminary results did not control for other variables.

To address potential confounding factors, I conducted a series of regression analyses. My models confirmed that more extensive networks enable agents to sell properties at higher prices and more quickly. I found that agent network size is more critical for listing agents, particularly in achieving higher sale prices, while the impact on TOM was less significant for selling agents.

I also examined the role of agent bridging power and influence within their networks. Bridging power was found to be significant for selling agents, especially in terms of achieving higher sale prices. On the other hand, agent influence, measured by eigenvector centrality, was associated with lower sale prices and longer TOM, suggesting that well-connected agents may hold properties longer to achieve better deals.

Furthermore, I analyzed market cycles and found that the importance of agent network metrics varies with market conditions. For instance, agent network size is more significant in active markets, while bridging power remains crucial in different market segments.

My robustness checks, including the use of three-year network metrics and OLS regressions, reinforced the reliability of my findings. The consistency of results across different methodologies and time frames underscores the robustness of the study's conclusions.

This chapter proves that agent network size and position significantly influence real estate transaction outcomes. These findings highlight the importance of considering agent network characteristics in real estate transactions and offer valuable insights for buyers and sellers when selecting agents.

CHAPTER 6: CONCLUSIONS, LIMITATIONS, AND FUTURE WORK

In this concluding chapter, I will synthesize this study's key findings, aligning them with the original aims and questions posed at the outset. The chapter will also evaluate the significance and contribution of these findings to the field. Additionally, I will discuss the limitations encountered during the study and suggest directions for future research to build upon this work.

Conclusions

In this study, I examine whether agent performance is related to the agents' network size and position in an extensive network of real estate agents in Tarrant County, Texas, from 2003 to 2022. Social and professional networks are essential in the economy, whether political ties, ties among corporate board members, mutual fund managers, venture capital, etc. Nevertheless, in a relationship-based industry such as real estate, limited research has been conducted to study the relationship between real estate agents' professional connections with other agents and their performance. To analyze the performance of real estate agents, I used the sale price and TOM – two measures widely used in prior literature as agent performance indicators.

During the past 50 years of various research on real estate market efficiency, real estate agents have been one of the most discussed subjects to support or reject the efficient markets hypothesis (EMH). The role agents play in deal intermediation is a root cause of agency conflicts, the presence of which itself challenges the EMH. This study aims to show if networks are relevant in determining agent performance for either of the two agents usually involved in residential real estate trades. To quantify network effects, I use three distinct measures: agent network size (degree centrality), agent bridging power (betweenness centrality), and agent influence (eigenvector centrality). The network size measures agents' unique connections in a specific time window. In contrast, the other two measures describe the relative position of an agent in the overall network of all the agents observable in the dataset. The results suggest that agent network size plays a significant role in the real estate markets for listing and selling agents. The findings show that agents with more extensive networks sell properties faster and for higher prices.

Agent bridging power—whether an agent serves as a bridge between otherwise unconnected agents—also indicates their better position in the network to negotiate higher prices in a shorter time. While these results are expected for the listing agent, they contradict our assumption that selling agents represent the buyers' best interests. However, one explanation for this is the compensation structure prevalent in the U.S. market during the sample period—both agents typically are paid by the seller. Hence, buyers' agents might be motivated to keep the sale price high and find a matching buyer quickly.

Agent influence, on the other hand, has a negative relationship with the sale price and a positive one with the TOM. The analysis shows that agents related to other influential agents have a value-destroying effect on the sellers in terms of price and duration. In network theory, high eigenvector centrality indicates increased homogeneity and spread of ideas. The literature suggests that having too many listings can diffuse agents' focus on individual properties and negatively affect their performance. Agents with high influence may become overconfident in their ability to generate sales, hence putting less effort into individual deals. Selling agents with high influence are also associated with lower sale prices and longer TOM. These findings suggest that highly central network agents might suffer from diffused efforts.

To confirm the overall validity of the results, I perform additional tests, including dividing the sample period into subsamples following the market cycle and separating the COVID-19 period, breaking down the analysis by brokerage size or property price segments, or mispricing.

Market cycle analysis shows that the importance of agent networks as a factor in predicting their performance changes depending on the state of the market. Overall, agent network size appears less important during uncertain market downturns than growth and expansion. The subsample analysis of agent bridging power suggests that it is more critical for listing agents as it remains significant throughout and less important for the selling agents as the results become insignificant for all the periods except the pandemic years. Agent influence remains consistent throughout the subsamples after 2004 for listing agents. For selling agents, the agent influence becomes insignificant during the pandemic. Hence, the network size and agent position remain essential indicators of agent success in various market cycles.

Further, the results of brokerage size analysis show that the brokerage size interplays with the size and quality of individual agent networks. For listing agents working for brokerages with below the median number of agents employed, network size appears to be less critical than for the listing agents working for large firms. Selling agents' network size remains significant regardless of the brokerage size. Brokerage size also plays a vital role in agent position in the network, although to a lesser extent. In a nutshell, agent bridging power is positively associated with the performance of listing agents from large brokerages, which might be related to their access to information from inside the brokerage. It helps selling agents from smaller brokerages. Agent influence gives us perhaps the most interesting insights from the brokerage size analysis—for the listing agents, the negative (positive) association between agent influence and price (TOM) is likely driven by the smaller brokerages, where the inner competition among the agents is lower. In contrast, listing agent influence in large brokerages helps them secure better deals, especially when working with smaller brokerages. On the other hand, the selling agents' main results hold regardless of the brokerage size. In the Results section, I present a more detailed analysis of the results for three different price segments.

While investigating whether segment differences in property price segments drive the main results, I find that network size is likely more important for lower-priced houses and less critical for higher-end ones. Similarly, agent bridging power helps agents in lower-priced markets, not higher segments. Listing agents with strong influence are likely to secure deals for below-median-priced houses faster with no significant difference in price – the only difference I observe from the main results. Finally, I find no evidence that the main results for agent network size, position, and quality are driven by mispricing.

To ensure the validity of the network variables, I recalculate all the metrics using a three-year window before a transaction date. The main results remain qualitatively similar to those using a one-year window. The main difference between the two seems to be the strength of the relationship between the network variables and agent performance. Network size is stronger in a shorter window, and listing agent bridging power becomes insignificant in the extended period. In contrast, the effect of agent influence is more prominent in three years.

To my knowledge, the uniqueness of this study stems from several factors. First, this study involves a vast network of agents for almost 20 years, which allows us to detect any significant changes in the influence of networks over individual agent performance. Second, unlike prior research, I analyze not only the role of the listing agents but also the role of the selling agents' network. Of course, this comes at some expense to the interpretability of the results, further discussed in the limitations section. Third, I use network construction methods not previously used in the literature. Lastly, besides agent network size (better known as agent connectedness in the literature), I examine the relative position and importance of the connections for individual agents.

Limitations and Future Work

Before discussing future work and extensions to this research, I will address the current study's limitations. These limitations arise from various sources, including data availability, computational constraints, research design and methods, and the inherent nature of networks.

Limitations. First and foremost, the study suffers from a limited theoretical background due to its empirical nature and the scarcity of existing literature. As mentioned earlier, few studies in real estate literature examine agent networks and agent performance. The nature of the real estate brokerage profession provides limited opportunities to draw parallels with social network research in other areas, such as board interlocks or political ties. While this research is grounded in discussions of the Efficient Market Hypothesis (EMH), agency problems, and building social capital in real estate literature, as well as introducing theoretical bases for organizational network analysis, it does not propose theoretical models to frame the empirical research. This is both a limitation for this study and a prospect for future research aiming to model the simultaneous relationships between agents and their clients.

The second limitation and opportunity stem from the vastness of the data and the challenges of constructing a network meaningfully. In this study, I build a new network for every transaction going back one or three years. This approach allows for observing the dynamics in the network for each agent-transaction pair. However, it fails to capture the interdependence between networks from previous transactions. Using two distinct time windows (one year and three years) and comparing the results allows me to address the concern of network dependency somewhat, though not entirely. I recognize that an agent's network formed on the first day of their career will relate to their network. Some details on agent turnover and specialization are provided in Table A3.

Moreover, I do not limit the network construction except by removing invalid observations and canceled deals from the dataset. This approach captures the entire network but creates significant challenges for interpreting the results. Each year, thousands of agents complete tens of thousands of transactions. Including all these transactions in each network—from agents with hundreds of transactions to those with only a few—makes the network very skewed and impacts the magnitude of the regression analysis results. Meaningful interpretation of the results and their economic significance requires limiting the network size, potentially removing outliers from both ends or modifying the metrics to make their conversion to dollar and time terms easier and more meaningful. For example, Shen and Sun (2023) used modified indicator measures of agent connectedness to find significant dollar value differences between connected and less connected agents. Future research could develop research designs and network construction methods that account for the vast size of the network and use techniques to allow for a better interpretation of the results.

One of the distinct elements of this research is that it involves the network of listing and selling agents participating in each transaction. Prior research has predominantly focused on listing agents, and introducing the selling agent into the analysis presents challenges. The literature discussing the role and behavior of buyer's agents is much more limited. It is also debatable whose best interests the selling agent should represent – the seller's, who effectively pays for their services, or the buyer's, whom they represent. Hence, in addition to the agency issues discussed for listing agents, we add a layer of complexity to the selling agents.

Moreover, I do not observe the contract date between the buyer and the selling agent. This introduces several limitations to the study. First, I assume that the Time on Market (TOM) is an equally good measure of the selling agents' performance as it is for the listing agent. While this may not be entirely accurate, it is permissible since the TOM involves the period from when the buyer's offer is accepted until the closing date. During this time, both agents work with their clients on deal terms, document submissions, property inspections, etc. Second, in calculating the selling agents' current listing inventory size, I use the window from the listing date to the contract date. This is likely to introduce some bias in the results. However, the dataset includes no information on the buyer's and selling agents' contracts.

Another technical limitation is that the data is censored at the beginning of the sample period, so I do not observe transactions before the start of the sample. Since our measures of agent experience in months and the total number of transactions are derived from the sample, the estimates for the earlier years are likely to be biased. In the first year, agents with more extended experience will be equated with agents whose start year coincides with the start of the sample period. In later years, this should be less of a concern for the most experienced agents in the dataset.

The data for this study comes from only one county in Texas, which poses a threat to the generalizability of the study. This study's network relationships may differ greatly from networks formed in other counties due to geographic characteristics or local market supply and demand. Future research can extend the study to other geographies and periods to assess the external validity of the results. I employ several variables in this study to capture the potential confounding effects of agent network characteristics. To ensure that agent experience does not influence the results, I include two variables: agent tenure in months (from the sample's start) and agent monthly activity. In untabulated results, I also use the total number of transactions to indicate agent experience and find no substantial differences in the overall results. This helps mitigate concerns that agent experience, rather than network connections, drives the results. Additionally, I include indicator variables for agent specialization. The sample contains many agents who appear exclusively as selling agents throughout the sample period and fewer exclusively listing agents. Incorporating these indicator variables allows me to control for the effect of agent specialization. Agent listing inventory is another variable I include to account for two factors discussed in the prior literature. First, an extensive listing inventory can indicate that an agent's effort per transaction might be diminished. Second, the inventory can serve as a source of potential buyers. By including these variables in the models, I aim to address the internal validity of the results and mitigate concerns about omitted variables. The large number of unique agents and the regression method chosen for the analysis make it impractical to include agent-fixed effects. Therefore, I use these additional agent characteristics to address agent heterogeneity.

Many studies avoid simultaneously analyzing the characteristics of listing and selling agents. Historically, the literature has concentrated on listing agents, with much less research dedicated to understanding selling agents' motives, behaviors, and impact on transaction outcomes. This scarcity in the literature presents a challenge, making analyzing selling agents highly empirical. Additionally, introducing the characteristics of both agents simultaneously can complicate the interpretation of results, making it difficult to isolate the effects of each agent individually.

Future Work. Social networks are an exciting and understudied phenomenon in finance and real estate literature. Network studies have progressed drastically in recent decades, yet interdisciplinary research is still developing. This research is one of the pioneer studies aiming to describe real estate agent networks and tie them to their performance.

In this research, I aim to show that real estate agent networks are an essential indicator of their performance. The metrics I use to describe the networks are widely employed in various research fields, including finance. As discussed earlier, I adopt a straightforward approach by constructing a new network before each transaction, which has advantages and disadvantages. Future research can build upon this study and employ more complex network construction techniques such as Temporal Exponential Random Graph Models (TERGMs). These models are more flexible and allow dynamic networks with complex temporal dependencies. However, they are computationally intensive, especially for large networks with many time points like the one in this study. This complexity was a primary reason for choosing a more straightforward approach in this research.

Instead of using 3SLS regressions to model the relationships between agent networks and performance, future research could use a repeat sales approach to better control for asset heterogeneity. Social network studies offer a plethora of other measures to describe an agent's position within the network. These include clustering coefficients, closeness centralities, core-periphery analysis, and other intriguing metrics that can address various aspects of real estate agent behaviors and performance.

Networks also enable multi-level analysis, opening doors to research in agent-brokerage dynamics, agent-switching behaviors, brokerage recruitment strategies, and more. Future research can also explore how agent networks influence pricing strategies, as described by Beracha and Seiler (2014). This study did not explore co-listing strategies involving many high-performing agents working in teams. The data does not provide a complete picture of agent teams, but with available data, this would be a worthwhile topic for further exploration.

An interesting avenue for future research would be investigating whether agent network size and position contribute to an agent's future success in the market. Questions such as whether agents with more extensive, better-positioned networks are more likely to complete transactions or find new clients and whether there is a difference in the type of clientele served by central versus non-central agents could yield valuable insights.

In summary, this study has made a step forward in linking real estate agent networks to their performance, highlighting the potential of network analysis in this field. While the current research lays the groundwork, there is ample opportunity for future studies to expand on these findings. Future work can provide a deeper understanding of the complex dynamics between real estate agents and their networks by employing more sophisticated network modeling techniques, exploring additional network metrics, and examining new research questions. Such research will advance academic knowledge and offer practical insights for improving agent performance and strategies in the real estate industry.

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Table 1. Table of select studies relevant to this study.

Authors (year) Journal	Main findings	Dataset	Relevance to this study
Fang and Hayunga (2024) Real Estate Economics	Local market knowledge is the most important factor affecting transaction prices, while the time agents have held their licenses and transaction volumes have minimal impact. Agents' expertise levels do not significantly affect time on the market (TOM).	Single-family broker-assisted residential transactions within the DFW Metroplex from September 2003 to March 2013.	Price and List Agent Transaction Volume are negatively significantly related. Price and Sell Agent Transaction Volumes are not related significantly TOM and List Agent Transaction Volume are significantly negatively related. TOM and Sell Agent Transaction Volume are negatively significantly related.
Cifci and Tidwell (2024) Real Estate Economics	As measured by LinkedIn followers, real estate agents with larger professional online social networks transact more properties, achieve higher prices, and have better bargaining power in the commercial real estate market.	Office property transactions in California, New York, and ten other states over three years from 2019q1 to 2021q4. Agent followers are hand-collected from LinkedIn.	The study shows that real estate agent social connections are related to their performance.
Beck and Saadatmand (2023) Business Economics	Agent and firm characteristics significantly impact home sales prices, with the effects being more pronounced in cold markets and for lower-priced homes. The impact is weakest during hot markets, and the effects are largest on the lowest-priced homes, decreasing as home prices increase.	MLS data of Chatham County, Georgia, 2008-2021 dataset containing information on real estate transactions, agent and firm characteristics, market conditions, and housing prices.	Use the number of transactions as a proxy for listing agent activity and brokerage firm size.
Shen and Sun (2023) Working paper	Agents with diversified and extensive network connections achieve better transaction outcomes, such as higher sales prices, without increased time on the market. Network connectedness is particularly crucial for transactions involving unique properties. Experienced agents with diversified connections tend to list and sell houses at higher prices and have a smaller discrepancy between listing and final sales prices.	MLS data of Atlanta, GA, with 40,000 housing transactions between 2010 and 2017.	Construct an undirected network of real estate agents based on the transaction history. Measures the degree centrality of agents and modifies the parameter to capture agent connectedness and diversification. Focuses on listing agents.

Table 1. A table of select studies relevant to this study (Cont.)

Cunningham, Gerardi and Shen (2022) Federal Reserve Bank of Atlanta, Working Paper	An average real estate agent does not justify their commission by securing higher prices; high-performing agents constitute a minority who add significant value to the home-selling process.	CoreLogic MLS Database for three large cities containing real estate transaction listings from January 2000 to December 2019.	Measure the experience of listing and buying agents by the months since an agent's first sale.
Hayunga and Munneke (2021) Real Estate Economics	Real estate agents hold bargaining power relative to individuals, with a slight increase during economic recovery periods. Companies (investors) exhibit the greatest bargaining power, consistently showing an increase in sale prices and a decrease in purchase prices of more than 3% across the economic cycle.	Dallas-Fort Worth Metroplex (DFW) MLS data from 2002 to 2013, data from public tax assessors' files, and Texas Real Estate Commission (TREC) for agent identification.	A 3SLS regression model was used for the sale price log and TOM log.
Smith, Zahirovic-Herbert and Gibler (2020) Journal of Real Estate Research	The study supports social capital theory in explaining agent behavior in real estate transactions. Listing agents achieve 4.09% lower prices when transacting with selling agents they have previously worked with. In the earlier stages of their partnership, the more agents cooperate, the lower the transaction prices.	The Georgia MLS contains sales transactions from January 1997 to September 2014, focusing on single-family detached transactions in five counties.	A measure of listing degree centrality is computed, though not used directly. Social Capital Theory finds support as listing agents negotiate lower prices with buying agents they have worked with previously.
Xie (2019) Real Estate Economics	Real estate agents rely significantly on network-based searches, with 35%-55% of trades made through such searches. As agents gain more career experience, they shift from relying on random to network-based searches. On average, a real estate agent trades with 1 out of every 5-10 agents they meet through random or network-based searches.	MLS data from a major Midwestern city during 2008-2010.	Constructing agent networks through past transactions and evaluating the randomness of the networks at different stages of an agent's career.
Turnbull and Waller (2018) Journal of Housing Economics	Top-tier listing principal brokers with the largest market presence in terms of listings achieve higher prices and faster sales, indicating that shopping externalities may offset the thinning effect of inventory externalities. This effect disappears for top-tier associate brokers. Top-tier selling agents did not consistently obtain higher prices or faster sales for their listing clients, suggesting that the benefits of market presence may not extend to all types of agents. No performance premiums were observed for properties	MLS records for Central Virginia covering single-family houses listed for sale between 1999 and 2009, with 12,899 observations and a focus on properties sold and withdrawn/expired listings.	Identifying agents with a minimum of 2% and 5% of current market listings. Theory discussions of shopping externalities, diffused effort, and marketing productivity effects.

Table 1. A table of select studies relevant to this study (Cont.)

	listed with top-tier selling agents, regardless of their market share in units sold.		
Xie (2018) Real Estate Economics	Homes owned by institutional clients are sold cheaper and faster than agent-owned homes, primarily driven by less and moderately experienced agents. The current commission system works well for individual clients but not for institutional clients, suggesting a need for contract redesign or hiring highly experienced agents. Motivation heterogeneity, with institutional clients being more motivated to sell, is a critical factor in the observed differences in home sale prices and TOM.	MLS data from Indiana, Johnson County, from June 2000 to June 2010.	Use the number of agent transactions in the past year as a proxy for agent experience.
Bailey et al. (2018) Journal of Political Economy	Individuals' housing market decisions are significantly influenced by their friends' house price experiences, leading to changes in their perceptions of property investments and actual investment behavior. Social interactions are crucial in shaping individuals' expectations and decisions in the housing market.	The study's dataset includes anonymized Facebook data, housing transaction data, and survey responses from Facebook users in Los Angeles.	To analyze their housing decisions, use a snapshot of users' social networks and social interactions.
Cashman, Harrison and Whitby (2018) Journal of Real Estate Literature	REIT director connections have a positive correlation with deal-making and accounting profitability metrics. A well-connected director enhances REIT deal-making, resulting in more property developments, increased credit lines, and a greater probability of being structured as a UPREIT. Although there is no direct positive link between FFO and REIT connections, firms with more connections tend to have higher NOI and real estate sales gains.	The data comes from BoardEx and SNL Financial, which track corporate directors and their connectedness within networks, including degree, closeness, and betweenness centrality metrics.	Use director network centrality metrics to assess REIT performance.

Table 1. A table of select studies relevant to this study (Cont.)

Palmon and Sopranzetti (2017) Review of Quantitative Finance and Accounting	Sellers who use active brokerages achieve higher selling prices, smaller negotiated discounts from the list prices, and shorter times on the market.	Houston MLS dataset from 1992-1996 for transactions data and housing characteristics data from Harris County Appraisal District.	Examine the relationship between the number of brokerage listings and transaction outcomes.
Angjellari-Dajci, Cebula and Boylan (2015) Journal of Housing Research	Small brokerages provide better results in terms of sale prices for both buyers and sellers.	Northeast Florida Association of Realtors MLS data from Duval County, Florida, covering the period from 2008 through 2013 and includes more than 58,600 single-family homes and condominiums.	Brokerage characteristics considered are the number of listings selling/listing firms had within the last 365 days, broken down into interval ranges.
Bian, Waller, Turnbull and Wentland (2015) Journal of Real Estate Finance and Economics	Greater agent inventory significantly negatively impacts selling prices and liquidity for clients' properties in the housing market. The study highlights the adverse effects of agent incentives to secure additional listing contracts on sales performance and market outcomes. The results suggest that agent inventory diverts selling effort from existing listings, leading to longer time on the market and reduced selling prices.	Virginia MLS from 1999-2009, with 12,388 observations.	The study shows that agent inventory size is related to effort dilution and worse outcomes for sellers. Uses 3SLS for price and TOM.
Waller and Jubran (2012) Journal of Housing Research	Properties listed by more experienced agents have a higher sales price, faster TOM, and higher probability of a successful transaction than those listed by less experienced agents.	A mid-Atlantic MLS data of single-family residential properties sold, withdrawn, or expired between March 1999 and July 2009. The dataset includes 10,065 observations, with 5,947 sold properties and 4,118 properties either withdrawn or expired. The study focuses on the years 2004-2009.	Categorization of agents based on experience, measured by the number of years in the profession.
Salter, Johnson and King (2010) Journal of Real Estate Finance and Economics	Agents specializing in listing properties increase pricing precision for sellers, particularly financially constrained and risk-averse sellers.	MLS data from a Southeastern MSA, with 1,410 final sample size.	Listing specialization as a factor of agent performance.

Table 2. Variables Description

Variable	Description
Sale Price	Natural logarithm of CPI (2010) adjusted sale price.
TOM	Natural logarithm of the sum of the days between the listing contract date and the closing date.
LA_NetSize	Listing agent normalized degree centrality. Degree centrality measures the size of an agent's network, including all transactions with other unique agents within the prior 365 days (or 365 times 3 for 3-year models).
SA_NetSize	Selling agent normalized degree centrality. Degree centrality measures the size of an agent's network, including all transactions with other unique agents within the prior 365 days (or 365 times 3 for 3-year models).
LA_NetSizeLn	Listing agent natural log-transformed degree centrality plus 1. Degree centrality measures the size of an agent's network, including all transactions with other unique agents within the prior 365 days (or 365 times 3 for 3-year models).
SA_NetSizeLn	Selling agent natural log-transformed degree centrality plus 1. Degree centrality measures the size of an agent's network, including all transactions with other unique agents within the prior 365 days (or 365 times 3 for 3-year models).
LA_BPower	Listing agent normalized betweenness centrality shows an agent's bridging power, indicating how often an agent was on the shortest path connecting otherwise unconnected agents within the prior 365 days (or 3 years) relative to others in the network.
SA_BPower	Selling agent normalized betweenness centrality. It shows the bridging power of an agent, indicating how often an agent was on the shortest path connecting otherwise unconnected agents within the prior 365 days (or three years), relative to others in the network.
LA_Influence	Listing agent normalized eigenvector centrality. It shows the bridging power of an agent, indicating how often an agent was on the shortest path connecting otherwise unconnected agents within the prior 365 days (or three years), relative to others in the network.
SA_Influence	Selling agent normalized eigenvector centrality. It shows the bridging power of an agent, indicating how often an agent was on the shortest path connecting otherwise unconnected agents within the prior 365 days (or three years), relative to others in the network.
LA_Experience	Natural logarithm of listing agent’s monthly average experience plus 1. The number of total transactions up to the current transaction is divided by the number of months since the first appearance in the sample. If the number of months is zero, the monthly average experience equals the total number of transactions.
SA_Experience	Natural logarithm of selling agent’s monthly average experience, plus 1. The number of total transactions up to the current transaction is divided by the number of months since the first appearance in the sample. If the number of months is zero, the monthly average experience equals the total number of transactions.

Table 2. Variables Description (Cont.)

Variable	Description
LA_Experience_M	Natural logarithm of listing agent's experience in months, plus 1. The experience is counted from the first month the agent appears in the sample till the current transaction in any role.
SA_Experience_M	Natural logarithm of selling agent's experience in months, plus 1. The experience is counted from the first month the agent appears in the sample till the current transaction in any role.
LA_TotTrans	The total number of transactions the listing agent had in the dataset up until the current observation in any role.
SA_TotTrans	The total number of transactions the selling agent had in the dataset up until the current observation in any role.
LA_Inventory	Listing agent's active listings inventory. Natural logarithm of the number of active listings of the listing agent during the current listing's window plus 1.
SA_Inventory	Selling agent's active listings inventory. Natural logarithm of the number of active listings of the selling agent during the current listing's window plus 1.
ExclList	Dummy variable indicates the exclusive listing agents with the sample.
ExclSell	Dummy variable indicates the exclusive selling agents with the sample.
InHouse	Dummy variable indicating transactions with listing and selling agents from the same brokerage firm.
Previous	The dummy variable indicates if the listing and selling agents have worked together.
Density	The natural log of 1 plus the listing density as described in (Turnbull & Dombrow, 2006)
Competition	The natural log of 1 plus the competition as described in (Turnbull & Dombrow, 2006)
PriceReduced	Dummy variable indicates the reduction in list price from the original list price.
AtypBeds	Dummy variable indicates if the number of bedrooms is more than 4.
AtypBaths	Dummy variable indicates if the number of total bathrooms is more than 3.
AtypFirep	Dummy variable indicates if the number of fireplaces is more than 1.
AtypAge	Dummy variable indicates if the age of the house is more than 65.
AtypGar	Dummy variable indicates if the number of garages is more than 3.
Bathrooms	The natural log of the number of total bathrooms plus 1.
Beds	The natural log of the number of bedrooms plus 1.
SqFt	The natural log of the square footage.
Age	The natural log of 1 plus the age of the house is calculated from the year built and the selling year.
Garages	The natural log of the number of garages plus 1.
Fireplaces	The natural log of the number of fireplaces plus 1.
Photos	The natural log of the number of photos plus 1.
Acres	The natural log of the acres plus 1.

Table 2. Variables Description (Cont.)

Variable	Description
Pool	Dummy variable indicating the presence of a pool.
Owner	Dummy variable indicating property occupied by the owner (base).
Tenant	Dummy variable indicating property occupied by a tenant.
Vacant	Dummy variable indicating a vacant property.
Mandatory	Dummy variable indicating property with mandatory HOA (base).
No_HOA	Dummy variable indicating property with no HOA.
Vol_HOA	Dummy variable indicating property with voluntary HOA.
Cash	Dummy variable indicating cash financing.
Conventional	Dummy variable indicating conventional financing (base).
Government	Dummy variable indicating government financing.
OtherFin	Dummy variable indicating other financing.
LA_BrSize	The dummy variable indicates a brokerage size (BR_SIZE) higher than the year-long median for each listing agent.
SA_BrSize	The dummy variable indicates a brokerage size (BR_SIZE) higher than the year-long median for each buying agent.
Mispricing	The absolute value of the difference between the sale price's natural logarithm and the listing price's natural logarithm.

Table 3. Descriptive Statistics

	Mean	St. Dev.	Median	Min	Max
Sale Price	245,532	190,700	200,000	25,000	6,730,000
Sale Price* ($, adjusted)	199,700	148,151	160,652	17,119	4,451,047
TOM* (days)	75	61	55	1	1,718
LA_NetSize* (count)	21	29	11	0	310
SA_NetSize* (count)	13	22	7	0	306
LA_NetSize_3y* (count)	54	75	29	0	776
SA_NetSize_3y* (count)	33	54	16	0	611
LA_NetSize	0.07	0.10	0.03	0	1
SA_NetSize	0.04	0.07	0.02	0	1
LA_NetSize_3y	0.08	0.11	0.04	0	1
SA_NetSize_3y	0.05	0.07	0.02	0	1
LA_BPower* (count)	126,172	347,943	26,183	0	6,361,741
SA_BPower* (count)	76,902	319,592	11,806	0	8,245,061
LA_BPower_3y* (count)	243,423	675,663	50,069	0	12,700,000
SA_BPower_3y* (count)	131,012	500,670	19,650	0	12,200,000
LA_BPower	0.04	0.08	0.01	0	1
SA_BPower	0.02	0.06	0.00	0	1
LA_BPower_3y	0.03	0.08	0.01	0	1
SA_BPower_3y	0.02	0.05	0.00	0	1
LA_Influence* (not norm.)	0.06	0.10	0.02	0	1
SA_Influence* (not norm.)	0.04	0.07	0.01	0	1
LA_Influence_3y* (not norm.)	0.10	0.13	0.05	0	1
SA_Influence_3y* (not norm.)	0.06	0.10	0.03	0	1
LA_Influence	0.02	0.03	0.01	0	0.32
SA_Influence	0.01	0.02	0.00	0	0.28
LA_Influence_3y	0.02	0.03	0.01	0	0.22
SA_Influence_3y	0.01	0.02	0.01	0	0.21
LA_Experience*	1.24	1.83	0.68	0	37
SA_Experience*	0.71	1.18	0.40	0	44
LA_Inventory*	6.05	12.77	2.00	0	461
SA_Inventory*	1.91	5.68	0.00	0	386
ExclList	0.02	0.15	0	0	1
ExclSell	0.10	0.30	0	0	1
InHouse	0.05	0.22	0	0	1
Previous	0.05	0.21	0	0	1
Density*	19	14	15	0	199
Competition*	714	797	474	0	17,509
PriceReduced	0.31	0.46	0	0	1
Bathrooms*	2.54	0.93	2	0	12
Beds*	3.48	0.70	3	1	9
SqFt*	2,238	937	2,004	392	19,673
Age*	26	20	20	0	137
Garages*	1.96	0.71	2	0	14

Table 3. Descriptive Statistics (Cont.)

	Mean	St. Dev.	Median	Min	Max
Fireplaces*	0.91	0.56	1	0	9
Photos*	18	13	21	0	75
Acres*	0.23	0.22	0	0	2.29
Pool	1.18	0.38	1	1	2
Owner	0.67	0.47	1	0	1
Tenant	0.03	0.17	0	0	1
Vacant	0.30	0.46	0	0	1
Mandatory	0.37	0.48	0	0	1
No_HOA	0.59	0.49	1	0	1
Vol_HOA	0.04	0.20	0	0	1
Cash	0.14	0.35	0	0	1
Conventional	0.56	0.50	1	0	1
Government	0.29	0.45	0	0	1
OtherFin	0.01	0.12	0	0	1
LA_TotTrans*	112	218	38	0	2,249
SA_TotTrans*	54	129	16	0	2,214
LA_Experience_M*	76	58	63	0	516
SA_Experience_M*	63	57	47	0	449
LA_BrSize	78	109	38	1	450
SA_BrSize	71	105	31	1	450

Note. The descriptive statistics for the October 2003 to March 2022 sample period for the cleaned sample used in the analysis are presented. The sample size is 210,279.
*All statistics are presented before any variable transformations.

Table 4. Mean Comparison Tests

	Above	Below	Difference	t-statistics
Panel A:	***Sale Prices* ($) by Mean Network Size**			
LA_NetSize	209,293	191,898	17,395	26.09
SA_NetSize	203,508	194,292	9,216	14.22
	***TOM* (days) by Mean Network Size**			
LA_NetSize	74.27	76.21	-1.94	-7.72
SA_NetSize	75.19	75.84	-0.65	-2.47
Panel B:	***Sale Prices* ($) by Mean Agent Bridging Power**			
LA_BPower	210,651	193,240	17,411	23.36
SA_BPower	201,853	195,834	6,019	8.16
	***TOM* (days) by Mean Agent Bridging Power**			
LA_BPower	74.69	75.91	-1.22	-4.41
SA_BPower	76.12	75.53	0.59	1.96
Panel C:	***Sale Prices* ($) by Mean Agent Influence**			
LA_Influence	205,208	193,572	11,636	18.25
SA_ Influence	196,824	197,055	-231	-0.37
	***TOM* (days) by Mean Agent Influence**			
LA_ Influence	73.78	76.42	-2.64	-10.53
SA_ Influence	75.18	75.83	-0.66	-2.54

Note: This table presents the results of the mean comparison tests for *Sale Price* and *TOM* by agent groups. I create a dummy variable for all agents with the above mean network metric. Panels A and B present the mean comparison t-test with unequal variances for agent network size, Panel B presents the mean comparison t-test with unequal variances for agent bridging power, and Panel C presents the mean comparison t-test with unequal variances for agent influence.

Table 5. 3SLS for Sale Price and TOM with Agent Network Size (Degree centrality)

	(1)		(2)		(3)		(4)	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
LA_NetSize	0.008*	-0.260*	0.027***	-0.763***	0.029***	-0.798***	0.030***	-1.071***
	(0.004)	(0.103)	(0.006)	(0.165)	(0.006)	(0.166)	(0.006)	(0.174)
SA_NetSize	0.055***	-1.522***	0.060***	-1.404***	0.061***	-1.439***	0.035***	-0.864***
	(0.005)	(0.159)	(0.007)	(0.227)	(0.007)	(0.228)	(0.008)	(0.216)
LA_Experience			-0.005***	0.143***	-0.006***	0.151***	-0.005***	0.059
			(0.001)	(0.032)	(0.001)	(0.032)	(0.001)	(0.039)
SA_Experience			-0.006***	0.102*	-0.007***	0.112**	-0.014***	0.266***
			(0.001)	(0.040)	(0.001)	(0.040)	(0.002)	(0.050)
LA_Experience_M			0.001**	-0.025**	0	-0.015	0.001	-0.024*
			(0.000)	(0.009)	(0.000)	(0.009)	(0.000)	(0.009)
SA_Experience_M			0.003***	-0.092***	0.003***	-0.081***	0.003***	-0.071***
			(0.000)	(0.009)	(0.000)	(0.009)	(0.000)	(0.009)
ExclList					-0.009**	0.246**	-0.009**	0.231**
					(0.003)	(0.080)	(0.003)	(0.081)
ExclSell					-0.005***	0.124***	-0.003	0.081*
					(0.001)	(0.037)	(0.001)	(0.037)
LA_Inventory							0.000	0.085***
							(0.001)	(0.018)
SA_Inventory							0.010***	-0.210***
							(0.001)	(0.027)
InHouse	0.006**	-0.165**	0.007***	-0.180**	0.006**	-0.176**	0.006**	-0.170**
	(0.002)	(0.055)	(0.002)	(0.055)	(0.002)	(0.055)	(0.002)	(0.055)
Previous	0.017***	-0.458***	0.016***	-0.433***	0.017***	-0.439***	0.017***	-0.452***
	(0.002)	(0.065)	(0.002)	(0.066)	(0.002)	(0.066)	(0.002)	(0.067)
TOM	0.010***		0.010***		0.010***		0.009***	
	(0.002)		(0.002)		(0.002)		(0.002)	
Sale Price		26.945***		27.109***		27.095***		27.320***
		(1.678)		(1.704)		(1.702)		(1.804)
Density	-0.025***		-0.025***		-0.025***		-0.025***	
	(0.001)		(0.001)		(0.001)		(0.001)	
Competition		0.625***		0.627***		0.627***		0.632***
		(0.030)		(0.031)		(0.031)		(0.033)

Table 5. 3SLS for Sale Price and TOM with Agent Network Size (Degree centrality) (Cont.)

	(1)		*(2)*		*(3)*		*(4)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
PriceReduced	-0.031***	1.103***	-0.031***	1.106***	-0.031***	1.106***	-0.031***	1.121***
	(0.001)	(0.043)	(0.001)	(0.044)	(0.001)	(0.044)	(0.001)	(0.048)
AtypBeds	-0.044***	1.227***	-0.044***	1.232***	-0.044***	1.231***	-0.044***	1.238***
	(0.002)	(0.086)	(0.002)	(0.087)	(0.002)	(0.087)	(0.002)	(0.091)
AtypBaths	0.033***	-0.861***	0.033***	-0.861***	0.033***	-0.860***	0.033***	-0.864***
	(0.002)	(0.077)	(0.002)	(0.078)	(0.002)	(0.078)	(0.002)	(0.080)
AtypFirep	0.056***	-1.451***	0.056***	-1.465***	0.056***	-1.465***	0.056***	-1.479***
	(0.002)	(0.114)	(0.002)	(0.115)	(0.002)	(0.115)	(0.002)	(0.120)
AtypAge	0.097***	-2.603***	0.097***	-2.622***	0.097***	-2.620***	0.097***	-2.635***
	(0.004)	(0.196)	(0.004)	(0.198)	(0.004)	(0.198)	(0.004)	(0.206)
AtypGar	0.087***	-2.274***	0.087***	-2.289***	0.087***	-2.287***	0.087***	-2.312***
	(0.005)	(0.201)	(0.005)	(0.203)	(0.005)	(0.203)	(0.005)	(0.210)
Bathrooms	0.104***	-2.781***	0.105***	-2.813***	0.105***	-2.812***	0.105***	-2.847***
	(0.004)	(0.207)	(0.004)	(0.210)	(0.004)	(0.210)	(0.004)	(0.220)
Beds	-0.104***	2.694***	-0.103***	2.696***	-0.103***	2.694***	-0.103***	2.704***
	(0.005)	(0.231)	(0.005)	(0.233)	(0.005)	(0.233)	(0.005)	(0.241)
SqFt	0.662***	-17.868***	0.662***	-17.960***	0.662***	-17.951***	0.661***	-18.076***
	(0.003)	(1.130)	(0.003)	(1.147)	(0.003)	(1.146)	(0.003)	(1.211)
Age	-0.085***	2.282***	-0.085***	2.300***	-0.085***	2.299***	-0.085***	2.319***
	(0.001)	(0.143)	(0.001)	(0.145)	(0.001)	(0.145)	(0.001)	(0.154)
Garages	0.107***	-2.935***	0.107***	-2.943***	0.107***	-2.941***	0.107***	-2.964***
	(0.002)	(0.185)	(0.002)	(0.187)	(0.002)	(0.187)	(0.002)	(0.198)
Fireplaces	0.101***	-2.741***	0.100***	-2.750***	0.100***	-2.748***	0.100***	-2.765***
	(0.002)	(0.171)	(0.002)	(0.173)	(0.002)	(0.173)	(0.002)	(0.183)
Photos	0.033***	-0.878***	0.033***	-0.885***	0.033***	-0.883***	0.033***	-0.890***
	(0.001)	(0.060)	(0.001)	(0.061)	(0.001)	(0.061)	(0.001)	(0.064)
Acres	0.430***	-11.316***	0.429***	-11.363***	0.429***	-11.358***	0.428***	-11.433***
	(0.004)	(0.743)	(0.004)	(0.753)	(0.004)	(0.752)	(0.004)	(0.793)
Pool	0.091***	-2.459***	0.091***	-2.474***	0.091***	-2.472***	0.091***	-2.489***
	(0.001)	(0.153)	(0.001)	(0.156)	(0.001)	(0.156)	(0.001)	(0.165)
Tenant	-0.068***	1.915***	-0.068***	1.924***	-0.068***	1.920***	-0.068***	1.921***
	(0.002)	(0.129)	(0.002)	(0.131)	(0.002)	(0.131)	(0.002)	(0.137)

Table 5. 3SLS for Sale Price and TOM with Agent Network Size (Degree centrality) (Cont.)

	(1)		*(2)*		*(3)*		*(4)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
Vacant	-0.045***	1.220***	-0.045***	1.221***	-0.044***	1.218***	-0.044***	1.223***
	(0.001)	(0.078)	(0.001)	(0.079)	(0.001)	(0.079)	(0.001)	(0.083)
No_HOA	-0.051***	1.375***	-0.051***	1.376***	-0.051***	1.374***	-0.050***	1.381***
	(0.001)	(0.089)	(0.001)	(0.090)	(0.001)	(0.090)	(0.001)	(0.095)
Vol_HOA	0.025***	-0.677***	0.025***	-0.682***	0.025***	-0.683***	0.025***	-0.689***
	(0.002)	(0.073)	(0.002)	(0.074)	(0.002)	(0.074)	(0.002)	(0.076)
Cash	-0.074***	1.918***	-0.074***	1.918***	-0.073***	1.913***	-0.072***	1.906***
	(0.002)	(0.138)	(0.002)	(0.139)	(0.002)	(0.138)	(0.002)	(0.143)
Government	-0.021***	0.593***	-0.021***	0.590***	-0.021***	0.591***	-0.021***	0.597***
	(0.001)	(0.040)	(0.001)	(0.041)	(0.001)	(0.041)	(0.001)	(0.042)
OtherFin	-0.021***	0.584***	-0.021***	0.582***	-0.021***	0.580***	-0.021***	0.580***
	(0.004)	(0.110)	(0.004)	(0.111)	(0.004)	(0.111)	(0.004)	(0.112)
Constant	6.898***	-184.450***	6.901***	-185.620***	6.904***	-185.601***	6.916***	-187.312***
	(0.024)	(11.620)	(0.024)	(11.825)	(0.024)	(11.817)	(0.024)	(12.538)
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		210,279		210,279		210,279		210,279
R-sq	0.89	-47.38	0.89	-47.92	0.89	-47.86	0.89	-48.64
AIC		-133,124		-131,453		-131,923		-122,531
BIC		-126,621		-124,868		-125,308		-115,865

Note. This table presents 3SLS results for four models. The dependent variables are the natural log-transformed sale price and TOM. Besides the standard set of controls that I use in all the regressions, Model 1 includes 1-year normalized degree centralities of agents. Model 2 includes 1-year normalized degree centralities and controls for agent experience. Model 3 includes 1-year normalized degree centralities and controls for agent experience, and specialization. Model 4 includes 1-year normalized degree centralities and controls for agent experience, specialization, and active listings inventory.
The sample period is from October 2003 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 6. 3SLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality)

	(1)		*(2)*		*(3)*		*(4)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
LA_BPower	0.004	-0.141	0.014*	-0.400**	0.015**	-0.428**	0.015**	-0.552***
	(0.004)	(0.116)	(0.006)	(0.155)	(0.006)	(0.155)	(0.006)	(0.161)
SA_BPower	0.044***	-1.222***	0.037***	-0.803***	0.038***	-0.850***	0.022**	-0.488*
	(0.006)	(0.168)	(0.007)	(0.208)	(0.007)	(0.209)	(0.007)	(0.208)
LA_Experience			-0.003**	0.078**	-0.003***	0.083**	-0.004**	0.000
			(0.001)	(0.027)	(0.001)	(0.027)	(0.001)	(0.037)
SA_Experience			-0.002	-0.002	-0.002	0.008	-0.012***	0.214***
			(0.001)	(0.034)	(0.001)	(0.034)	(0.001)	(0.046)
LA_Experience_M			0.001**	-0.029***	0.001	-0.020*	0.001	-0.027**
			(0.000)	(0.009)	(0.000)	(0.009)	(0.000)	(0.009)
SA_Experience_M			0.004***	-0.097***	0.003***	-0.087***	0.003***	-0.074***
			(0.000)	(0.009)	(0.000)	(0.009)	(0.000)	(0.009)
ExclList					-0.008**	0.233**	-0.008**	0.221**
					(0.003)	(0.080)	(0.003)	(0.081)
ExclSell					-0.005***	0.122***	-0.002	0.078*
					(0.001)	(0.037)	(0.001)	(0.037)
LA_Inventory							0.000	0.063***
							(0.001)	(0.018)
SA_Inventory							0.010***	-0.222***
							(0.001)	(0.027)
InHouse	0.006**	-0.168**	0.007***	-0.180**	0.006**	-0.176**	0.006**	-0.169**
	(0.002)	(0.055)	(0.002)	(0.055)	(0.002)	(0.055)	(0.002)	(0.056)
Previous	0.019***	-0.511***	0.017***	-0.452***	0.017***	-0.458***	0.017***	-0.473***
	(0.002)	(0.067)	(0.002)	(0.066)	(0.002)	(0.066)	(0.002)	(0.068)
TOM	0.010***		0.010***		0.010***		0.009***	
	(0.002)		(0.002)		(0.002)		(0.002)	
Sale Price		27.027***		27.084***		27.072***		27.526***
		(1.687)		(1.700)		(1.699)		(1.826)
Density	-0.025***		-0.025***		-0.025***		-0.025***	
	(0.001)		(0.001)		(0.001)		(0.001)	
Competition		0.627***		0.626***		0.625***		0.636***
		(0.030)		(0.030)		(0.030)		(0.033)
PriceReduced	-0.031***	1.107***	-0.031***	1.104***	-0.031***	1.104***	-0.031***	1.129***

Table 6. 3SLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) (Cont.)

	(1)		*(2)*		*(3)*		*(4)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.001)	(0.044)	(0.001)	(0.044)	(0.001)	(0.044)	(0.001)	(0.049)
AtypBeds	-0.044***	1.233***	-0.044***	1.231***	-0.044***	1.230***	-0.044***	1.247***
	(0.002)	(0.087)	(0.002)	(0.087)	(0.002)	(0.087)	(0.002)	(0.092)
AtypBaths	0.033***	-0.865***	0.033***	-0.860***	0.033***	-0.859***	0.033***	-0.870***
	(0.002)	(0.078)	(0.002)	(0.078)	(0.002)	(0.078)	(0.002)	(0.081)
AtypFirep	0.056***	-1.456***	0.056***	-1.464***	0.056***	-1.464***	0.056***	-1.490***
	(0.002)	(0.114)	(0.002)	(0.115)	(0.002)	(0.115)	(0.002)	(0.122)
AtypAge	0.097***	-2.610***	0.097***	-2.621***	0.097***	-2.619***	0.097***	-2.656***
	(0.004)	(0.196)	(0.004)	(0.198)	(0.004)	(0.198)	(0.004)	(0.208)
AtypGar	0.087***	-2.279***	0.087***	-2.285***	0.087***	-2.284***	0.087***	-2.328***
	(0.005)	(0.201)	(0.005)	(0.203)	(0.005)	(0.202)	(0.005)	(0.213)
Bathrooms	0.104***	-2.790***	0.105***	-2.812***	0.105***	-2.811***	0.105***	-2.869***
	(0.004)	(0.208)	(0.004)	(0.210)	(0.004)	(0.210)	(0.004)	(0.223)
Beds	-0.104***	2.699***	-0.103***	2.693***	-0.103***	2.690***	-0.103***	2.723***
	(0.005)	(0.232)	(0.005)	(0.232)	(0.005)	(0.232)	(0.005)	(0.243)
SqFt	0.662***	-17.924***	0.662***	-17.946***	0.662***	-17.937***	0.661***	-18.212***
	(0.003)	(1.137)	(0.003)	(1.144)	(0.003)	(1.143)	(0.003)	(1.225)
Age	-0.085***	2.289***	-0.085***	2.299***	-0.085***	2.298***	-0.085***	2.338***
	(0.001)	(0.144)	(0.001)	(0.145)	(0.001)	(0.145)	(0.001)	(0.156)
Garages	0.107***	-2.945***	0.107***	-2.940***	0.107***	-2.938***	0.107***	-2.985***
	(0.002)	(0.186)	(0.002)	(0.187)	(0.002)	(0.187)	(0.002)	(0.200)
Fireplaces	0.101***	-2.749***	0.100***	-2.746***	0.100***	-2.745***	0.100***	-2.785***
	(0.002)	(0.172)	(0.002)	(0.173)	(0.002)	(0.173)	(0.002)	(0.185)
Photos	0.033***	-0.883***	0.033***	-0.886***	0.033***	-0.884***	0.033***	-0.898***
	(0.001)	(0.060)	(0.001)	(0.061)	(0.001)	(0.061)	(0.001)	(0.064)
Acres	0.430***	-11.351***	0.429***	-11.354***	0.429***	-11.350***	0.428***	-11.518***
	(0.004)	(0.747)	(0.004)	(0.751)	(0.004)	(0.751)	(0.004)	(0.802)
Pool	0.091***	-2.467***	0.091***	-2.472***	0.091***	-2.470***	0.091***	-2.508***
	(0.001)	(0.154)	(0.001)	(0.155)	(0.001)	(0.155)	(0.001)	(0.166)
Tenant	-0.068***	1.922***	-0.068***	1.923***	-0.068***	1.919***	-0.068***	1.938***
	(0.002)	(0.130)	(0.002)	(0.131)	(0.002)	(0.130)	(0.002)	(0.138)
Vacant	-0.045***	1.224***	-0.045***	1.221***	-0.045***	1.217***	-0.044***	1.233***

Table 6. 3SLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) (Cont.)

	(1)		*(2)*		*(3)*		*(4)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.001)	(0.078)	(0.001)	(0.079)	(0.001)	(0.078)	(0.001)	(0.084)
No_HOA	-0.051***	1.380***	-0.051***	1.375***	-0.051***	1.373***	-0.050***	1.391***
	(0.001)	(0.090)	(0.001)	(0.090)	(0.001)	(0.090)	(0.001)	(0.096)
Vol_HOA	0.025***	-0.678***	0.025***	-0.681***	0.025***	-0.682***	0.025***	-0.694***
	(0.002)	(0.073)	(0.002)	(0.074)	(0.002)	(0.074)	(0.002)	(0.076)
Cash	-0.074***	1.920***	-0.074***	1.917***	-0.073***	1.912***	-0.072***	1.920***
	(0.002)	(0.138)	(0.002)	(0.138)	(0.002)	(0.138)	(0.002)	(0.145)
Government	-0.021***	0.597***	-0.021***	0.589***	-0.021***	0.591***	-0.021***	0.601***
	(0.001)	(0.041)	(0.001)	(0.040)	(0.001)	(0.041)	(0.001)	(0.043)
OtherFin	-0.021***	0.590***	-0.021***	0.584***	-0.021***	0.583***	-0.021***	0.587***
	(0.004)	(0.111)	(0.004)	(0.111)	(0.004)	(0.111)	(0.004)	(0.113)
Constant	6.899***	-185.037***	6.898***	-185.360***	6.901***	-185.352***	6.914***	-188.679***
	(0.024)	(11.704)	(0.024)	(11.792)	(0.024)	(11.786)	(0.024)	(12.688)
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		210,279		210,279		210,279		210,279
R-sq	0.89	-47.69	0.89	-47.84	0.89	-47.80	0.89	-49.39
AIC		-131,975		-132,341		-132,777		-120,174
BIC		-125,483		-125,757		-126,162		-113,507

Note. This table presents 3SLS results for four models. Besides the standard set of controls in all the regressions, Model 1 includes 1-year normalized betweenness centralities of agents. Model 2 includes 1-year normalized betweenness centralities and controls for agent experience. Model 3 includes 1-year normalized betweenness centralities and controls for agent experience, as well as specialization. Model 4 includes 1-year normalized betweenness centralities and controls for agent experience, specialization, and active listings inventory. The sample period is from October 2003 to March 2022.

Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 7. 3SLS for Sale Price and TOM with Agent Influence (Eigenvector Centrality)

	(1)		*(2)*		*(3)*		*(4)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
LA_Influence	-0.058***	1.422***	-0.086***	2.230***	-0.084***	2.166***	-0.090***	1.934***
	(0.013)	(0.373)	(0.019)	(0.525)	(0.019)	(0.525)	(0.019)	(0.565)
SA_Influence	0.025	-0.807	-0.109***	3.569***	-0.106***	3.486***	-0.180***	5.299***
	(0.017)	(0.455)	(0.023)	(0.653)	(0.024)	(0.653)	(0.024)	(0.745)
LA_Experience			0.001	-0.042	0.001	-0.038	0.000	-0.092*
			(0.001)	(0.028)	(0.001)	(0.028)	(0.001)	(0.037)
SA_Experience			0.005***	-0.201***	0.005***	-0.193***	-0.004**	0.016)
			(0.001)	(0.036)	(0.001)	(0.036)	(0.001)	(0.041)
LA_Experience_M			0.001***	-0.032***	0.001*	-0.024**	0.001	-0.029**
			0.000)	(0.009)	(0.000)	(0.009)	(0.000)	(0.010)
SA_Experience_M			0.004***	-0.100***	0.003***	-0.092***	0.003***	-0.080***
			0.000)	(0.009)	0.000)	(0.010)	0.000)	(0.009)
ExclList					-0.008**	0.209**	-0.008**	0.203*
					(0.003)	(0.079)	(0.003)	(0.082)
ExclSell					-0.004**	0.104**	(0.002)	0.056)
					(0.001)	(0.037)	(0.001)	(0.037)
LA_Inventory							(0.001)	0.041*
							(0.001)	(0.018)
SA_Inventory							0.011***	-0.253***
							(0.001)	(0.029)
InHouse	0.006**	-0.165**	0.006**	-0.169**	0.006**	-0.165**	0.005**	-0.156**
	(0.002)	(0.055)	(0.002)	(0.055)	(0.002)	(0.055)	(0.002)	(0.056)
Previous	0.022***	-0.590***	0.019***	-0.492***	0.019***	-0.498***	0.019***	-0.519***
	(0.002)	(0.070)	(0.002)	(0.067)	(0.002)	(0.067)	(0.002)	(0.070)
TOM	0.010***		0.010***		0.010***		0.009***	
	(0.002)		(0.002)		(0.002)		(0.002)	
Sale Price		27.167***		27.049***		27.038***		27.748***
		(1.705)		-1.695		(1.694)		(1.855)
Density	-0.025***		-0.025***		-0.025***		-0.025***	
	(0.001)		(0.001)		(0.001)		(0.001)	
Competition		0.629***		0.622***		0.622***		0.638***
		(0.031)		(0.030)		(0.030)		(0.033)
PriceReduced	-0.031***	1.114***	-0.031***	1.099***	-0.031***	1.099***	-0.031***	1.136***

Table 7. 3SLS for Sale Price and TOM with Agent Influence (Eigenvector Centrality) (Cont.)

	(1)		*(2)*		*(3)*		*(4)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.001)	(0.044)	(0.001)	(0.044)	(0.001)	(0.044)	(0.001)	(0.049)
AtypBeds	-0.044***	1.241***	-0.044***	1.228***	-0.044***	1.227***	-0.044***	1.256***
	(0.002)	(0.088)	(0.002)	(0.087)	(0.002)	(0.087)	(0.002)	(0.093)
AtypBaths	0.033***	-0.870***	0.033***	-0.859***	0.033***	-0.858***	0.033***	-0.876***
	(0.002)	(0.078)	(0.002)	(0.078)	(0.002)	(0.077)	(0.002)	(0.082)
AtypFirep	0.056***	-1.464***	0.056***	-1.463***	0.056***	-1.462***	0.056***	-1.503***
	(0.002)	(0.115)	(0.002)	(0.115)	(0.002)	(0.115)	(0.002)	(0.123)
AtypAge	0.097***	-2.625***	0.097***	-2.619***	0.097***	-2.617***	0.097***	-2.676***
	(0.004)	(0.198)	(0.004)	(0.197)	(0.004)	(0.197)	(0.004)	(0.211)
AtypGar	0.087***	-2.288***	0.087***	-2.276***	0.087***	-2.275***	0.087***	-2.341***
	(0.005)	(0.203)	(0.005)	(0.202)	(0.005)	(0.202)	(0.005)	(0.215)
Bathrooms	0.104***	-2.806***	0.105***	-2.808***	0.105***	-2.807***	0.105***	-2.893***
	(0.004)	(0.210)	(0.004)	(0.209)	(0.004)	(0.209)	(0.004)	(0.226)
Beds	-0.104***	2.710***	-0.103***	2.686***	-0.103***	2.684***	-0.103***	2.740***
	(0.005)	(0.234)	(0.005)	(0.232)	(0.005)	(0.232)	(0.005)	(0.246)
SqFt	0.662***	-18.021***	0.662***	-17.922***	0.662***	-17.915***	0.660***	-18.355***
	(0.003)	(1.149)	(0.003)	(1.141)	(0.003)	(1.140)	(0.003)	(1.244)
Age	-0.085***	2.304***	-0.085***	2.300***	-0.085***	2.300***	-0.085***	2.361***
	(0.001)	(0.146)	(0.001)	(0.145)	(0.001)	(0.145)	(0.001)	(0.159)
Garages	0.107***	-2.961***	0.107***	-2.935***	0.107***	-2.933***	0.107***	-3.009***
	(0.002)	(0.188)	(0.002)	(0.186)	(0.002)	(0.186)	(0.002)	(0.203)
Fireplaces	0.101***	-2.761***	0.100***	-2.739***	0.100***	-2.738***	0.100***	-2.802***
	(0.002)	(0.174)	(0.002)	(0.172)	(0.002)	(0.172)	(0.002)	(0.187)
Photos	0.033***	-0.891***	0.033***	-0.888***	0.033***	-0.886***	0.033***	-0.909***
	(0.001)	(0.061)	(0.001)	(0.061)	(0.001)	(0.061)	(0.001)	(0.066)
Acres	0.430***	-11.413***	0.429***	-11.344***	0.429***	-11.340***	0.428***	-11.613***
	(0.004)	(0.755)	(0.004)	(0.750)	(0.004)	(0.749)	(0.004)	(0.814)
Pool	0.091***	-2.480***	0.091***	-2.468***	0.091***	-2.467***	0.091***	-2.528***
	(0.001)	(0.156)	(0.001)	(0.155)	(0.001)	(0.155)	(0.001)	(0.169)
Tenant	-0.069***	1.937***	-0.068***	1.923***	-0.068***	1.920***	-0.068***	1.957***
	(0.002)	(0.132)	(0.002)	(0.131)	(0.002)	(0.130)	(0.002)	(0.140)
Vacant	-0.045***	1.230***	-0.045***	1.219***	-0.045***	1.216***	-0.044***	1.243***

Table 7. 3SLS for Sale Price and TOM with Agent Influence (Eigenvector Centrality) (Cont.)

	(1)		*(2)*		*(3)*		*(4)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**Price**	**TOM**	**Price**
	(0.001)	(0.079)	(0.001)	(0.078)	(0.001)	(0.078)	(0.001)	(0.085)
No_HOA	-0.051***	1.388***	-0.051***	1.374***	-0.051***	1.373***	-0.050***	1.404***
	(0.001)	(0.091)	(0.001)	(0.090)	(0.001)	(0.090)	(0.001)	(0.097)
Vol_HOA	0.025***	-0.680***	0.025***	-0.680***	0.025***	-0.680***	0.025***	-0.699***
	(0.002)	(0.074)	(0.002)	(0.074)	(0.002)	(0.074)	(0.002)	(0.077)
Cash	-0.074***	1.924***	-0.074***	1.915***	-0.073***	1.910***	-0.072***	1.935***
	(0.002)	(0.139)	(0.002)	(0.138)	(0.002)	(0.138)	(0.002)	(0.147)
Government	-0.021***	0.602***	-0.021***	0.586***	-0.021***	0.588***	-0.021***	0.603***
	(0.001)	(0.041)	(0.001)	(0.040)	(0.001)	(0.040)	(0.001)	(0.043)
OtherFin	-0.022***	0.600***	-0.021***	0.587***	-0.021***	0.586***	-0.021***	0.594***
	(0.004)	(0.111)	(0.004)	(0.111)	(0.004)	(0.110)	(0.004)	(0.114)
Constant	6.899***	-186.007***	6.892***	-184.970***	6.894***	-184.952***	6.910***	-190.102***
	(0.024)	(11.827)	(0.024)	(11.748)	(0.024)	(11.742)	(0.024)	(12.883)
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		210,279		210,279		210,279		210,279
R-sq	0.89	-48.19	0.89	-47.71	0.89	-47.67	0.89	-50.19
AIC		-130,688		-134,852		-135,243		-118,787
BIC		-124,196		-128,278		-128,628		-112,120

Note. This table presents 3SLS results for four models. Besides the standard set of controls in all the regressions, Model 1 includes 1-year normalized eigenvector centralities of agents. Model 2 includes 1-year normalized eigenvector centralities and controls for agent experience. Model 3 includes 1-year normalized eigenvector centralities and controls for agent experience, as well as specialization. Model 4 includes 1-year normalized eigenvector centralities and controls for agent experience, specialization, and active listings inventory. The sample period is from October 2003 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 8. 3SLS for Sale Price and TOM with Agent Network Size (Degree centrality) by Market Cycles

	2003^-2004		*2005-2010*		*2011-2019*		*2020-2022^*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
LA_NetSize	0.122**	-2.610***	0.002	-0.252	0.016*	-0.760**	-0.024	0.209
	(0.039)	(0.603)	(0.014)	(0.269)	(0.008)	(0.274)	(0.019)	(0.406)
SA_NetSize	0.046	0.003	-0.002	0.199	0.028**	-0.922**	0.049**	-0.879**
	(0.064)	(0.997)	(0.017)	(0.340)	(0.009)	(0.353)	(0.015)	(0.337)
LA_Experience	-0.011*	0.192*	0.002	-0.119	-0.004*	0.034	-0.005	0.019
	(0.005)	(0.091)	(0.003)	(0.061)	(0.002)	(0.067)	(0.003)	(0.062)
SA_Experience	-0.020*	0.135	-0.001	-0.089	-0.023***	0.675***	-0.004	0.034
	(0.008)	(0.136)	(0.003)	(0.068)	(0.002)	(0.124)	(0.003)	(0.063)
LA_Experience_M	0.000	-0.011	0.002	-0.051**	0.001*	-0.043**	0.001	-0.025
	(0.002)	(0.031)	(0.001)	(0.019)	(0.000)	(0.015)	(0.001)	(0.014)
SA_Experience_M	0.006**	-0.090**	0.004***	-0.074***	0.002***	-0.089***	0.002***	-0.039**
	(0.002)	(0.034)	(0.001)	(0.015)	(0.000)	(0.016)	(0.001)	(0.012)
ExclList	-0.014	0.268	-0.046***	0.906***	0.006	-0.204	-0.005	0.104
	(0.013)	(0.203)	(0.008)	(0.176)	(0.004)	(0.136)	(0.004)	(0.093)
ExclSell	0.010	-0.142	-0.002	0.047	-0.008***	0.298***	-0.007**	0.166***
	(0.005)	(0.087)	(0.003)	(0.055)	(0.002)	(0.077)	(0.002)	(0.050)
LA_Inventory	-0.007*	0.170***	-0.007***	0.203***	0.001	0.032	0.005**	-0.020
	(0.003)	(0.046)	(0.001)	(0.026)	(0.001)	(0.032)	(0.002)	(0.035)
SA_Inventory	0.013***	-0.153*	0.005***	-0.051	0.011***	-0.351***	0.006***	-0.068
	(0.003)	(0.062)	(0.001)	(0.029)	(0.001)	(0.060)	(0.002)	(0.039)
InHouse	0.008	-0.131	0.008*	-0.167*	0.006*	-0.216*	0.012*	-0.266*
	(0.008)	(0.120)	(0.004)	(0.077)	(0.003)	(0.093)	(0.005)	(0.113)
Previous	-0.007	0.126	0.013**	-0.255**	0.021***	-0.722***	0.023***	-0.461***
	(0.010)	(0.150)	(0.004)	(0.092)	(0.003)	(0.129)	(0.006)	(0.129)
TOM	0.029**		0.016***		0.004		0.017***	
	(0.009)		(0.003)		(0.003)		(0.005)	
Sale Price		15.467***		19.991***		35.199***		20.482***
		(2.595)		(1.771)		(4.227)		(2.704)
Density	-0.034***		-0.032***		-0.022***		-0.023***	
	(0.004)		(0.002)		(0.001)		(0.002)	
Competition		0.475***		0.616***		0.727***		0.431***
		(0.068)		(0.039)		(0.071)		(0.043)
PriceReduced	-0.041***	0.798***	-0.034***	0.910***	-0.029***	1.347***	-0.030***	0.865***

Table 8. 3SLS for Sale Price and TOM with Agent Network Size (Degree centrality) by Market Cycles (Cont.)

	2003^-2004		*2005-2010*		*2011-2019*		*2020-2022^*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.006)	(0.083)	(0.003)	(0.053)	(0.002)	(0.109)	(0.003)	(0.069)
AtypBeds	-0.013	0.207	-0.042***	0.884***	-0.043***	1.566***	-0.022***	0.466***
	(0.011)	(0.174)	(0.005)	(0.113)	(0.003)	(0.193)	(0.004)	(0.098)
AtypBaths	0.050***	-0.754***	0.074***	-1.444***	0.025***	-0.838***	0.018***	-0.350***
	(0.010)	(0.203)	(0.004)	(0.159)	(0.002)	(0.136)	(0.004)	(0.095)
AtypFirep	0.050***	-0.723***	0.053***	-1.020***	0.047***	-1.598***	0.065***	-1.292***
	(0.010)	(0.214)	(0.005)	(0.135)	(0.003)	(0.228)	(0.005)	(0.209)
AtypAge	0.053	-0.853	0.118***	-2.362***	0.075***	-2.611***	0.018**	-0.348**
	(0.028)	(0.452)	(0.012)	(0.322)	(0.006)	(0.379)	(0.006)	(0.131)
AtypGar	0.064**	-0.915*	0.090***	-1.766***	0.080***	-2.725***	0.100***	-1.983***
	(0.021)	(0.365)	(0.009)	(0.248)	(0.006)	(0.419)	(0.011)	(0.353)
Bathrooms	0.123***	-1.922***	0.093***	-1.833***	0.099***	-3.444***	0.124***	-2.511***
	(0.025)	(0.400)	(0.009)	(0.239)	(0.005)	(0.461)	(0.008)	(0.383)
Beds	-0.082**	1.175*	-0.138***	2.644***	-0.093***	3.169***	-0.096***	1.899***
	(0.028)	(0.550)	(0.011)	(0.348)	(0.007)	(0.472)	(0.010)	(0.333)
SqFt	0.742***	-11.423***	0.764***	-15.286***	0.645***	-22.768***	0.521***	-10.679***
	(0.029)	(2.187)	(0.007)	(1.373)	(0.005)	(2.764)	(0.006)	(1.421)
Age	-0.060***	0.930***	-0.049***	0.984***	-0.103***	3.637***	-0.089***	1.815***
	(0.004)	(0.164)	(0.002)	(0.092)	(0.001)	(0.438)	(0.002)	(0.241)
Garages	0.117***	-1.847***	0.137***	-2.791***	0.101***	-3.611***	0.074***	-1.550***
	(0.010)	(0.329)	(0.005)	(0.254)	(0.003)	(0.432)	(0.004)	(0.215)
Fireplaces	0.102***	-1.612***	0.111***	-2.249***	0.109***	-3.871***	0.082***	-1.704***
	(0.011)	(0.266)	(0.005)	(0.207)	(0.002)	(0.461)	(0.003)	(0.227)
Photos	0.002	0.187	0.051***	-0.981***	0.036***	-1.262***	0.027***	-0.556***
	(0.016)	(0.240)	(0.005)	(0.149)	(0.001)	(0.156)	(0.001)	(0.079)
Acres	0.186***	-2.764***	0.336***	-6.508***	0.512***	-17.690***	0.494***	-9.872***
	(0.016)	(0.530)	(0.008)	(0.635)	(0.006)	(2.192)	(0.011)	(1.392)
Pool	0.088***	-1.368***	0.097***	-1.940***	0.084***	-2.970***	0.084***	-1.739***
	(0.005)	(0.228)	(0.002)	(0.175)	(0.001)	(0.355)	(0.002)	(0.231)
Tenant	-0.066***	1.045***	-0.075***	1.552***	-0.061***	2.224***	-0.067***	1.447***
	(0.012)	(0.253)	(0.006)	(0.179)	(0.003)	(0.271)	(0.006)	(0.206)
Vacant	-0.044***	0.697***	-0.072***	1.443***	-0.037***	1.306***	-0.023***	0.485***

Table 8. 3SLS for Sale Price and TOM with Agent Network Size (Degree centrality) by Market Cycles (Cont.)

	2003^-2004		*2005-2010*		*2011-2019*		*2020-2022^*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.004)	(0.130)	(0.002)	(0.132)	(0.001)	(0.160)	(0.002)	(0.069)
No_HOA	-0.070***	1.103***	-0.063***	1.267***	-0.055***	1.955***	-0.037***	0.751***
	(0.007)	(0.185)	(0.003)	(0.122)	(0.001)	(0.237)	(0.002)	(0.110)
Vol_HOA	-0.022*	0.350*	0.009*	-0.190*	0.021***	-0.756***	0.022***	-0.463***
	(0.009)	(0.143)	(0.004)	(0.080)	(0.003)	(0.140)	(0.006)	(0.140)
Cash	-0.061***	0.907***	-0.075***	1.486***	-0.081***	2.763***	-0.041***	0.716***
	(0.010)	(0.232)	(0.004)	(0.157)	(0.002)	(0.361)	(0.003)	(0.140)
Government	0.010*	-0.148*	-0.009***	0.194***	-0.024***	0.878***	-0.013***	0.308***
	(0.004)	(0.074)	(0.002)	(0.042)	(0.001)	(0.105)	(0.002)	(0.045)
OtherFin	-0.033**	0.504*	-0.009	0.198	-0.028***	0.985***	-0.034**	0.727**
	(0.012)	(0.206)	(0.007)	(0.132)	(0.005)	(0.217)	(0.010)	(0.228)
Constant	6.214***	-95.757***	6.119***	-121.154***	6.953***	-242.585***	8.007***	-162.550***
	(0.159)	(15.386)	(0.045)	(11.003)	(0.032)	(29.467)	(0.043)	(21.876)
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		8,301		48,442		118,019		35,517
R-sq	0.92	-11.40	0.90	-25.00	0.90	-83.72	0.90	-26.60

Note. This table presents 3SLS results for the full models for four periods. The dependent variables are the natural log-transformed sale price and TOM. In addition to the standard set of controls in all the regressions, all models include 1-year normalized degree centralities and controls for agent experience, specialization, and active listings inventory.
The sample period is from October 2003 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 9. 3SLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) by Market Cycles

	2003^-2004		*2005-2010*		*2011-2019*		*2020-2022^*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
LA_BPower	0.140**	-2.798***	0.025*	-0.614*	-0.007	0.125	-0.046*	0.836*
	(0.043)	(0.711)	(0.012)	(0.243)	(0.007)	(0.252)	(0.019)	(0.417)
SA_BPower	-0.042	1.293	-0.014	0.416	0.010	-0.286	0.043**	-0.711*
	(0.071)	(1.109)	(0.015)	(0.309)	(0.009)	(0.341)	(0.013)	(0.300)
LA_Experience	-0.010	0.162	-0.001	-0.083	-0.002	-0.058	-0.004	-0.009
	(0.005)	(0.091)	(0.003)	(0.060)	(0.002)	(0.062)	(0.003)	(0.059)
SA_Experience	-0.014*	0.075	0.000	-0.105	-0.021***	0.607***	-0.003	0.007
	(0.007)	(0.115)	(0.003)	(0.061)	(0.002)	(0.115)	(0.003)	(0.058)
LA_Experience_M	0.000	-0.015	0.002	-0.053**	0.001*	-0.046**	0.001	-0.025
	(0.002)	(0.032)	(0.001)	(0.018)	(0.000)	(0.015)	(0.001)	(0.014)
SA_Experience_M	0.006**	-0.086*	0.004***	-0.072***	0.003***	-0.093***	0.002***	-0.041***
	(0.002)	(0.035)	(0.001)	(0.015)	(0.000)	(0.017)	(0.001)	(0.012)
ExclList	-0.016	0.292	-0.047***	0.908***	0.006	-0.223	-0.005	0.098
	(0.013)	(0.205)	(0.008)	(0.176)	(0.004)	(0.137)	(0.004)	(0.093)
ExclSell	0.011	-0.150	-0.002	0.044	-0.008***	0.293***	-0.007**	0.168***
	(0.005)	(0.088)	(0.003)	(0.055)	(0.002)	(0.077)	(0.002)	(0.051)
LA_Inventory	-0.005	0.135**	-0.007***	0.206***	0.002*	0.006	0.005**	-0.024
	(0.003)	(0.044)	(0.001)	(0.026)	(0.001)	(0.032)	(0.002)	(0.035)
SA_Inventory	0.014***	-0.159*	0.005***	-0.052	0.012***	-0.372***	0.006***	-0.072
	(0.003)	(0.064)	(0.001)	(0.029)	(0.001)	(0.063)	(0.002)	(0.039)
InHouse	0.008	-0.125	0.008*	-0.167*	0.006*	-0.213*	0.012*	-0.262*
	(0.007)	(0.121)	(0.004)	(0.077)	(0.003)	(0.094)	(0.005)	(0.113)
Previous	-0.007	0.111	0.013**	-0.251**	0.021***	-0.756***	0.023***	-0.472***
	(0.010)	(0.151)	(0.004)	(0.092)	(0.003)	(0.133)	(0.006)	(0.129)
TOM	0.028**		0.017***		0.004		0.017***	
	(0.009)		(0.003)		(0.003)		(0.005)	
Sale Price		15.582***		19.973***		35.522***		20.522***
		(2.612)		(1.764)		(4.295)		(2.712)
Density	-0.034***		-0.032***		-0.022***		-0.023***	
	(0.004)		(0.002)		(0.001)		(0.002)	
Competition		0.482***		0.615***		0.733***		0.432***
		(0.068)		(0.039)		(0.072)		(0.043)
PriceReduced	-0.041***	0.812***	-0.034***	0.909***	-0.029***	1.356***	-0.030***	0.867***

Table 9. 3SLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) by Market Cycles (Cont.)

	2003^-2004		*2005-2010*		*2011-2019*		*2020-2022^*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.006)	(0.083)	(0.003)	(0.053)	(0.002)	(0.111)	(0.003)	(0.069)
AtypBeds	-0.013	0.210	-0.042***	0.883***	-0.043***	1.580***	-0.022***	0.467***
	(0.011)	(0.175)	(0.005)	(0.113)	(0.003)	(0.196)	(0.004)	(0.098)
AtypBaths	0.050***	-0.757***	0.074***	-1.442***	0.025***	-0.845***	0.018***	-0.349***
	(0.010)	(0.205)	(0.004)	(0.159)	(0.002)	(0.138)	(0.004)	(0.096)
AtypFirep	0.050***	-0.732***	0.053***	-1.019***	0.047***	-1.613***	0.065***	-1.294***
	(0.010)	(0.215)	(0.005)	(0.135)	(0.003)	(0.231)	(0.005)	(0.209)
AtypAge	0.053	-0.854	0.118***	-2.360***	0.075***	-2.637***	0.018**	-0.347**
	(0.028)	(0.454)	(0.012)	(0.321)	(0.006)	(0.384)	(0.006)	(0.131)
AtypGar	0.063**	-0.909*	0.091***	-1.766***	0.080***	-2.749***	0.100***	-1.986***
	(0.021)	(0.367)	(0.009)	(0.248)	(0.006)	(0.425)	(0.011)	(0.354)
Bathrooms	0.123***	-1.940***	0.093***	-1.831***	0.099***	-3.477***	0.124***	-2.516***
	(0.025)	(0.403)	(0.009)	(0.238)	(0.005)	(0.468)	(0.008)	(0.384)
Beds	-0.082**	1.187*	-0.138***	2.641***	-0.093***	3.193***	-0.096***	1.903***
	(0.028)	(0.553)	(0.011)	(0.347)	(0.007)	(0.479)	(0.010)	(0.334)
SqFt	0.742***	-11.514***	0.764***	-15.272***	0.645***	-22.977***	0.521***	-10.698***
	(0.029)	(2.202)	(0.007)	(1.367)	(0.005)	(2.807)	(0.006)	(1.425)
Age	-0.060***	0.937***	-0.049***	0.983***	-0.103***	3.672***	-0.089***	1.819***
	(0.004)	(0.165)	(0.002)	(0.091)	(0.001)	(0.445)	(0.002)	(0.242)
Garages	0.118***	-1.864***	0.137***	-2.788***	0.101***	-3.644***	0.074***	-1.553***
	(0.010)	(0.331)	(0.005)	(0.253)	(0.003)	(0.438)	(0.004)	(0.216)
Fireplaces	0.102***	-1.622***	0.111***	-2.247***	0.109***	-3.905***	0.082***	-1.708***
	(0.011)	(0.268)	(0.005)	(0.206)	(0.002)	(0.468)	(0.003)	(0.227)
Photos	0.002	0.185	0.051***	-0.982***	0.036***	-1.275***	0.027***	-0.557***
	(0.016)	(0.242)	(0.005)	(0.149)	(0.001)	(0.158)	(0.001)	(0.080)
Acres	0.186***	-2.775***	0.336***	-6.502***	0.512***	-17.852***	0.494***	-9.892***
	(0.016)	(0.533)	(0.008)	(0.633)	(0.006)	(2.227)	(0.011)	(1.396)
Pool	0.088***	-1.377***	0.097***	-1.938***	0.084***	-2.996***	0.084***	-1.743***
	(0.005)	(0.229)	(0.002)	(0.174)	(0.001)	(0.361)	(0.002)	(0.231)
Tenant	-0.066***	1.048***	-0.076***	1.552***	-0.061***	2.247***	-0.067***	1.449***
	(0.012)	(0.255)	(0.006)	(0.179)	(0.003)	(0.276)	(0.006)	(0.206)
Vacant	-0.044***	0.703***	-0.072***	1.441***	-0.037***	1.319***	-0.023***	0.486***

Table 9. 3SLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) by Market Cycles (Cont.)

	2003^-2004		*2005-2010*		*2011-2019*		*2020-2022^*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.004)	(0.131)	(0.002)	(0.131)	(0.001)	(0.162)	(0.002)	(0.069)
No_HOA	-0.070***	1.108***	-0.063***	1.265***	-0.056***	1.975***	-0.037***	0.752***
	(0.007)	(0.185)	(0.003)	(0.121)	(0.001)	(0.241)	(0.002)	(0.111)
Vol_HOA	-0.021*	0.351*	0.009*	-0.191*	0.021***	-0.763***	0.022***	-0.464***
	(0.009)	(0.143)	(0.004)	(0.080)	(0.003)	(0.142)	(0.006)	(0.141)
Cash	-0.061***	0.916***	-0.075***	1.485***	-0.081***	2.788***	-0.041***	0.717***
	(0.010)	(0.234)	(0.004)	(0.156)	(0.002)	(0.367)	(0.003)	(0.140)
Government	0.010*	-0.151*	-0.009***	0.194***	-0.024***	0.886***	-0.013***	0.309***
	(0.004)	(0.074)	(0.002)	(0.042)	(0.001)	(0.107)	(0.002)	(0.045)
OtherFin	-0.033**	0.509*	-0.010	0.201	-0.028***	1.003***	-0.034**	0.728**
	(0.012)	(0.207)	(0.007)	(0.132)	(0.005)	(0.220)	(0.010)	(0.228)
Constant	6.212***	-96.435***	6.120***	-121.054***	6.951***	-244.769***	8.007***	-162.868***
	(0.159)	(15.474)	(0.045)	(10.962)	(0.032)	(29.931)	(0.043)	(21.938)
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		8,301		48,442		118,019		35,517
R-sq	0.92	-11.58	0.90	-24.95	0.90	-85.29	0.90	-26.71

Note. This table presents 3SLS results for the full models for four periods. The dependent variables are the natural log-transformed sale price and TOM. In addition to the standard set of controls in all the regressions, all models include 1-year normalized betweenness centralities and controls for agent experience, specialization, and active listings inventory.
The sample period is from October 2003 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 10. 3SLS for Sale Price and TOM with Agent Influence (Eigenvector centrality) by Market Cycles

	2003^-2004		*2005-2010*		*2011-2019*		*2020-2022^*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
LA_Influence	0.315***	-6.163***	-0.296***	5.499***	-0.121***	3.797***	-0.208***	3.851**
	(0.085)	(1.464)	(0.049)	(1.143)	(0.023)	(0.999)	(0.053)	(1.241)
SA_Influence	-0.029	1.838	-0.712***	15.056***	-0.095**	3.597**	0.032	-0.389
	(0.127)	(1.983)	(0.066)	(1.803)	(0.029)	(1.116)	(0.045)	(0.924)
LA_Experience	-0.011*	0.177	0.009**	-0.275***	0.002	-0.165**	-0.003	-0.043
	(0.005)	(0.092)	(0.003)	(0.058)	(0.002)	(0.064)	(0.003)	(0.058)
SA_Experience	-0.016*	0.080	0.020***	-0.516***	-0.017***	0.485***	0.000	-0.052
	(0.007)	(0.119)	(0.003)	(0.070)	(0.002)	(0.105)	(0.003)	(0.057)
LA_Experience_M	0.000	-0.008	0.002*	-0.059**	0.001**	-0.049**	0.001	-0.026
	(0.002)	(0.031)	(0.001)	(0.019)	(0.000)	(0.016)	(0.001)	(0.014)
SA_Experience_M	0.006**	-0.090**	0.004***	-0.084***	0.003***	-0.097***	0.002***	-0.041***
	(0.002)	(0.034)	(0.001)	(0.016)	(0.000)	(0.017)	(0.001)	(0.012)
ExclList	-0.014	0.263	-0.046***	0.905***	0.007	-0.241	-0.005	0.097
	(0.013)	(0.203)	(0.008)	(0.177)	(0.004)	(0.139)	(0.004)	(0.093)
ExclSell	0.011*	-0.152	-0.001	0.028	-0.008***	0.280***	-0.006**	0.160**
	(0.005)	(0.088)	(0.003)	(0.055)	(0.002)	(0.077)	(0.002)	(0.050)
LA_Inventory	-0.006	0.143**	-0.005***	0.165***	0.003**	-0.017	0.005**	-0.031
	(0.003)	(0.044)	(0.001)	(0.025)	(0.001)	(0.034)	(0.002)	(0.035)
SA_Inventory	0.014***	-0.156*	0.007***	-0.094**	0.013***	-0.402***	0.006***	-0.065
	(0.003)	(0.063)	(0.001)	(0.031)	(0.001)	(0.067)	(0.002)	(0.039)
InHouse	0.008	-0.125	0.007	-0.141	0.005*	-0.205*	0.012*	-0.259*
	(0.008)	(0.120)	(0.004)	(0.077)	(0.003)	(0.094)	(0.005)	(0.113)
Previous	-0.007	0.114	0.016***	-0.306**	0.022***	-0.798***	0.023***	-0.478***
	(0.010)	(0.150)	(0.004)	(0.094)	(0.003)	(0.137)	(0.006)	(0.130)
TOM	0.028**		0.016***		0.003		0.017***	
	(0.009)		(0.003)		(0.003)		(0.005)	
Sale Price		15.474***		20.139***		35.842***		20.536***
		(2.583)		(1.789)		(4.374)		(2.714)
Density	-0.034***		-0.032***		-0.022***		-0.023***	
	(0.004)		(0.002)		(0.001)		(0.002)	
Competition		0.479***		0.614***		0.737***		0.432***
		(0.067)		(0.039)		(0.073)		(0.043)
PriceReduced	-0.041***	0.806***	-0.034***	0.915***	-0.029***	1.364***	-0.030***	0.869***

Table 10. 3SLS for Sale Price and TOM with Agent Influence (Eigenvector centrality) by Market Cycles (Cont.)

	2003^-2004		*2005-2010*		*2011-2019*		*2020-2022^*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.006)	(0.082)	(0.003)	(0.054)	(0.002)	(0.113)	(0.003)	(0.069)
AtypBeds	-0.013	0.202	-0.042***	0.881***	-0.043***	1.594***	-0.022***	0.467***
	(0.011)	(0.174)	(0.005)	(0.114)	(0.003)	(0.200)	(0.004)	(0.098)
AtypBaths	0.050***	-0.752***	0.074***	-1.454***	0.025***	-0.852***	0.018***	-0.347***
	(0.010)	(0.203)	(0.004)	(0.161)	(0.002)	(0.140)	(0.004)	(0.095)
AtypFirep	0.050***	-0.725***	0.053***	-1.031***	0.047***	-1.628***	0.065***	-1.293***
	(0.010)	(0.214)	(0.005)	(0.136)	(0.003)	(0.235)	(0.005)	(0.209)
AtypAge	0.053	-0.849	0.118***	-2.381***	0.075***	-2.660***	0.018**	-0.348**
	(0.028)	(0.451)	(0.012)	(0.324)	(0.006)	(0.390)	(0.006)	(0.131)
AtypGar	0.064**	-0.913*	0.091***	-1.782***	0.080***	-2.769***	0.100***	-1.984***
	(0.021)	(0.365)	(0.009)	(0.251)	(0.006)	(0.431)	(0.011)	(0.354)
Bathrooms	0.124***	-1.940***	0.093***	-1.852***	0.099***	-3.508***	0.124***	-2.518***
	(0.025)	(0.400)	(0.009)	(0.241)	(0.005)	(0.475)	(0.008)	(0.385)
Beds	-0.082**	1.187*	-0.138***	2.653***	-0.093***	3.215***	-0.096***	1.905***
	(0.028)	(0.550)	(0.011)	(0.350)	(0.007)	(0.485)	(0.010)	(0.334)
SqFt	0.742***	-11.426***	0.763***	-15.381***	0.645***	-23.179***	0.521***	-10.705***
	(0.029)	(2.178)	(0.007)	(1.386)	(0.005)	(2.858)	(0.006)	(1.426)
Age	-0.060***	0.930***	-0.049***	1.004***	-0.103***	3.709***	-0.089***	1.823***
	(0.004)	(0.163)	(0.002)	(0.094)	(0.001)	(0.454)	(0.002)	(0.243)
Garages	0.117***	-1.845***	0.136***	-2.799***	0.101***	-3.676***	0.074***	-1.555***
	(0.010)	(0.327)	(0.005)	(0.255)	(0.003)	(0.446)	(0.004)	(0.216)
Fireplaces	0.102***	-1.614***	0.110***	-2.241***	0.109***	-3.938***	0.082***	-1.709***
	(0.011)	(0.265)	(0.004)	(0.207)	(0.002)	(0.476)	(0.003)	(0.228)
Photos	0.003	0.182	0.051***	-0.983***	0.036***	-1.290***	0.027***	-0.559***
	(0.016)	(0.240)	(0.005)	(0.149)	(0.001)	(0.162)	(0.001)	(0.080)
Acres	0.186***	-2.764***	0.336***	-6.561***	0.512***	-18.012***	0.494***	-9.897***
	(0.016)	(0.528)	(0.008)	(0.642)	(0.006)	(2.267)	(0.011)	(1.396)
Pool	0.088***	-1.365***	0.097***	-1.958***	0.084***	-3.022***	0.084***	-1.745***
	(0.005)	(0.226)	(0.002)	(0.177)	(0.001)	(0.367)	(0.002)	(0.232)
Tenant	-0.066***	1.040***	-0.075***	1.553***	-0.061***	2.271***	-0.067***	1.454***
	(0.012)	(0.252)	(0.006)	(0.180)	(0.003)	(0.281)	(0.006)	(0.207)
Vacant	-0.044***	0.696***	-0.071***	1.439***	-0.037***	1.332***	-0.023***	0.490***

Table 10. 3SLS for Sale Price and TOM with Agent Influence (Eigenvector centrality) by Market Cycles (Cont.)

	2003^-2004		*2005-2010*		*2011-2019*		*2020-2022^*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.004)	(0.129)	(0.002)	(0.132)	(0.001)	(0.165)	(0.002)	(0.070)
No_HOA	-0.069***	1.100***	-0.063***	1.270***	-0.056***	1.994***	-0.037***	0.752***
	(0.007)	(0.183)	(0.003)	(0.123)	(0.001)	(0.246)	(0.002)	(0.111)
Vol_HOA	-0.021*	0.350*	0.009*	-0.190*	0.021***	-0.770***	0.022***	-0.467***
	(0.009)	(0.142)	(0.004)	(0.081)	(0.003)	(0.144)	(0.006)	(0.141)
Cash	-0.061***	0.910***	-0.075***	1.496***	-0.081***	2.813***	-0.040***	0.714***
	(0.010)	(0.232)	(0.004)	(0.158)	(0.002)	(0.373)	(0.003)	(0.140)
Government	0.010*	-0.151*	-0.009***	0.187***	-0.024***	0.892***	-0.013***	0.307***
	(0.004)	(0.074)	(0.002)	(0.042)	(0.001)	(0.108)	(0.002)	(0.045)
OtherFin	-0.033**	0.512*	-0.008	0.177	-0.028***	1.021***	-0.034**	0.729**
	(0.012)	(0.205)	(0.007)	(0.132)	(0.005)	(0.224)	(0.010)	(0.228)
Constant	6.214***	-95.804***	6.120***	-122.062***	6.950***	-246.939***	8.007***	-162.984***
	(0.159)	(15.301)	(0.045)	(11.119)	(0.032)	(30.472)	(0.043)	(21.950)
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		8,301		48,442		118,019		35,517
R-sq	0.92	-11.41	0.90	-25.29	0.90	-86.82	0.90	-26.74

Note. This table presents 3SLS results for the full models for four periods. The dependent variables are the natural log-transformed sale price and TOM. In addition to the standard set of controls in all the regressions, all models include 1-year normalized eigenvector centralities and controls for agent experience, specialization, and active listings inventory.

^The sample period from October 2003 to March 2022.

Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 11. 3SLS for Sale Price and TOM with Agent Network Size (Degree centrality) by Listing and Selling Brokerage Sizes

	Small_Small		*Small_Large*		*Large_Small*		*Large_Large*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
LA_NetSize	0.024	-0.773*	-0.016	0.225	0.050***	-1.793***	0.038***	-1.306***
	(0.014)	(0.330)	(0.013)	(0.413)	(0.012)	(0.411)	(0.011)	(0.329)
SA_NetSize	0.058***	-1.251**	-0.008	0.353	0.038**	-1.026*	0.019	-0.440
	(0.015)	(0.387)	(0.016)	(0.495)	(0.015)	(0.474)	(0.014)	(0.403)
LA_Experience	0.005	-0.185**	-0.001	-0.065	-0.014***	0.342***	-0.011***	0.246**
	(0.003)	(0.065)	(0.003)	(0.087)	(0.003)	(0.102)	(0.003)	(0.087)
SA_Experience	-0.013***	0.218**	-0.008*	0.077	-0.020***	0.487***	-0.009**	0.145
	(0.003)	(0.077)	(0.003)	(0.112)	(0.003)	(0.122)	(0.003)	(0.094)
LA_Experience_M	-0.001	0.010	-0.001	0.014	0.002**	-0.080***	0.003***	-0.089***
	(0.001)	(0.016)	(0.001)	(0.020)	(0.001)	(0.023)	(0.001)	(0.022)
SA_Experience_M	0.001*	-0.029*	0.004***	-0.128***	0.001*	-0.031	0.004***	-0.127***
	(0.001)	(0.013)	(0.001)	(0.027)	(0.001)	(0.016)	(0.001)	(0.023)
ExclList	-0.010*	0.240*	-0.012**	0.349*	-0.006	0.178	0.000	-0.007
	(0.005)	(0.117)	(0.004)	(0.149)	(0.007)	(0.223)	(0.009)	(0.257)
ExclSell	-0.001	0.036	-0.001	0.042	-0.003	0.111	0.000	-0.005
	(0.002)	(0.058)	(0.003)	(0.090)	(0.002)	(0.074)	(0.003)	(0.078)
LA_Inventory	-0.002	0.106***	0.003*	-0.009	-0.001	0.102**	-0.003*	0.148***
	(0.001)	(0.031)	(0.001)	(0.046)	(0.001)	(0.038)	(0.001)	(0.034)
SA_Inventory	0.007***	-0.130**	0.008***	-0.178**	0.009***	-0.211***	0.007***	-0.129**
	(0.001)	(0.040)	(0.001)	(0.060)	(0.001)	(0.057)	(0.001)	(0.046)
Previous	-0.000	0.002	0.035***	-1.088***	0.018***	-0.536***	0.023***	-0.638***
	(0.005)	(0.105)	(0.005)	(0.220)	(0.005)	(0.162)	(0.003)	(0.128)
TOM	0.016***		0.003		0.006		0.009*	
	(0.004)		(0.004)		(0.004)		(0.004)	
Sale Price		23.195***		30.880***		29.801***		28.224***
		(2.572)		(4.745)		(4.185)		(3.753)
Density	-0.023***		-0.027***		-0.024***		-0.024***	
	(0.002)		(0.002)		(0.002)		(0.001)	
Competition		0.508***		0.776***		0.672***		0.632***
		(0.042)		(0.095)		(0.075)		(0.069)
PriceReduced	-0.036***	1.061***	-0.027***	1.157***	-0.027***	1.105***	-0.032***	1.167***
	(0.003)	(0.076)	(0.003)	(0.116)	(0.003)	(0.102)	(0.003)	(0.099)
AtypBeds	-0.053***	1.256***	-0.034***	1.080***	-0.041***	1.276***	-0.044***	1.262***

Table 11. 3SLS for Sale Price and TOM with Agent Network Size (Degree centrality) by Listing and Selling Brokerage Sizes (Cont.)

	Small_Small		*Small_Large*		*Large_Small*		*Large_Large*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.004)	(0.157)	(0.004)	(0.193)	(0.004)	(0.199)	(0.004)	(0.183)
AtypBaths	0.036***	-0.816***	0.033***	-0.964***	0.035***	-1.005***	0.030***	-0.815***
	(0.004)	(0.138)	(0.004)	(0.197)	(0.004)	(0.188)	(0.003)	(0.150)
AtypFirep	0.062***	-1.410***	0.062***	-1.849***	0.055***	-1.573***	0.047***	-1.276***
	(0.005)	(0.201)	(0.005)	(0.333)	(0.004)	(0.264)	(0.004)	(0.215)
AtypAge	0.089***	-2.073***	0.099***	-3.017***	0.091***	-2.720***	0.098***	-2.750***
	(0.008)	(0.286)	(0.008)	(0.529)	(0.008)	(0.456)	(0.008)	(0.436)
AtypGar	0.114***	-2.548***	0.085***	-2.539***	0.092***	-2.661***	0.069***	-1.915***
	(0.010)	(0.389)	(0.010)	(0.536)	(0.009)	(0.482)	(0.008)	(0.358)
Bathrooms	0.124***	-2.861***	0.112***	-3.418***	0.080***	-2.345***	0.095***	-2.653***
	(0.008)	(0.368)	(0.009)	(0.605)	(0.008)	(0.408)	(0.008)	(0.411)
Beds	-0.088***	1.955***	-0.120***	3.584***	-0.085***	2.397***	-0.105***	2.872***
	(0.010)	(0.337)	(0.010)	(0.660)	(0.010)	(0.478)	(0.010)	(0.520)
SqFt	0.628***	-14.609***	0.663***	-20.511***	0.651***	-19.393***	0.693***	-19.595***
	(0.007)	(1.642)	(0.006)	(3.166)	(0.006)	(2.759)	(0.008)	(2.674)
Age	-0.088***	2.039***	-0.081***	2.498***	-0.088***	2.634***	-0.081***	2.280***
	(0.002)	(0.228)	(0.002)	(0.386)	(0.002)	(0.370)	(0.002)	(0.306)
Garages	0.108***	-2.556***	0.100***	-3.147***	0.112***	-3.406***	0.096***	-2.749***
	(0.004)	(0.288)	(0.005)	(0.493)	(0.004)	(0.479)	(0.004)	(0.367)
Fireplaces	0.105***	-2.460***	0.097***	-3.043***	0.095***	-2.849***	0.098***	-2.792***
	(0.004)	(0.274)	(0.004)	(0.468)	(0.004)	(0.403)	(0.004)	(0.368)
Photos	0.037***	-0.856***	0.031***	-0.953***	0.034***	-1.004***	0.025***	-0.695***
	(0.002)	(0.104)	(0.002)	(0.157)	(0.002)	(0.150)	(0.002)	(0.103)
Acres	0.409***	-9.257***	0.428***	-12.878***	0.437***	-12.766***	0.438***	-12.102***
	(0.009)	(1.104)	(0.009)	(2.065)	(0.009)	(1.873)	(0.008)	(1.668)
Pool	0.090***	-2.090***	0.093***	-2.896***	0.092***	-2.757***	0.087***	-2.483***
	(0.002)	(0.235)	(0.002)	(0.443)	(0.002)	(0.388)	(0.002)	(0.329)
Tenant	-0.064***	1.532***	-0.078***	2.489***	-0.066***	2.069***	-0.055***	1.617***
	(0.004)	(0.186)	(0.006)	(0.399)	(0.005)	(0.308)	(0.005)	(0.247)
Vacant	-0.046***	1.082***	-0.042***	1.320***	-0.041***	1.239***	-0.043***	1.236***
	(0.002)	(0.123)	(0.002)	(0.207)	(0.002)	(0.180)	(0.002)	(0.170)
No_HOA	-0.049***	1.144***	-0.053***	1.646***	-0.051***	1.537***	-0.048***	1.363***

Table 11. 3SLS for Sale Price and TOM with Agent Network Size (Degree centrality) by Listing and Selling Brokerage Sizes (Cont.)

	Small_Small		*Small_Large*		*Large_Small*		*Large_Large*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.002)	(0.135)	(0.002)	(0.262)	(0.002)	(0.222)	(0.002)	(0.186)
Vol_HOA	0.035***	-0.806***	0.022***	-0.712***	0.022***	-0.649***	0.016***	-0.470***
	(0.005)	(0.145)	(0.004)	(0.171)	(0.004)	(0.162)	(0.004)	(0.129)
Cash	-0.100***	2.244***	-0.059***	1.729***	-0.073***	2.072***	-0.045***	1.204***
	(0.003)	(0.278)	(0.003)	(0.307)	(0.003)	(0.331)	(0.003)	(0.199)
Government	-0.014***	0.338***	-0.025***	0.785***	-0.020***	0.620***	-0.027***	0.773***
	(0.002)	(0.050)	(0.002)	(0.125)	(0.002)	(0.095)	(0.002)	(0.103)
OtherFin	-0.044***	1.010***	-0.017*	0.569*	-0.019**	0.582*	0.009	-0.247
	(0.008)	(0.210)	(0.008)	(0.257)	(0.007)	(0.235)	(0.007)	(0.209)
Constant	7.054***	-162.159***	6.926***	-211.872***	7.044***	-208.346***	6.727***	-188.325***
	(0.048)	(18.332)	(0.048)	(33.068)	(0.045)	(29.620)	(0.048)	(25.197)
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		55,059		49,386		50,775		55,059
R-sq	0.89	-35.83	0.89	-62.73	0.90	-55.17	0.90	-48.46

Note. This table presents 3SLS results for the full model based on listing and selling brokerage sizes. To categorize a brokerage into small vs. large, I classify each listing and selling brokerage below and above median by the number of agents employed per calendar year. The dependent variables are the natural log-transformed sale price and TOM. Besides the standard set of controls in all the regressions, all models include 1-year normalized degree centralities and controls for agent experience, specialization, and active listings inventory.

The sample period is from October 2003 to March 2022.

Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 12. 3SLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) by Listing and Selling Brokerage Sizes

	Small_Small		*Small_Large*		*Large_Small*		*Large_Large*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
LA_BPower	0.003	-0.173	-0.036**	0.956*	0.047***	-1.571***	0.024*	-0.828**
	(0.013)	(0.305)	(0.012)	(0.413)	(0.012)	(0.396)	(0.010)	(0.303)
SA_BPower	0.056***	-1.212***	-0.028	0.981	0.042**	-1.132*	-0.006	0.281
	(0.014)	(0.361)	(0.017)	(0.534)	(0.014)	(0.458)	(0.014)	(0.412)
LA_Experience	0.007*	-0.243***	0.000	-0.116	-0.013***	0.295**	-0.010***	0.187*
	(0.003)	(0.063)	(0.003)	(0.084)	(0.003)	(0.099)	(0.002)	(0.083)
SA_Experience	-0.011***	0.185**	-0.006*	0.037	-0.019***	0.475***	-0.007*	0.073
	(0.003)	(0.071)	(0.003)	(0.104)	(0.003)	(0.117)	(0.003)	(0.086)
LA_Experience_M	-0.001	0.008	-0.001	0.014	0.003***	-0.087***	0.003***	-0.094***
	(0.001)	(0.016)	(0.001)	(0.020)	(0.001)	(0.023)	(0.001)	(0.023)
SA_Experience_M	0.001**	-0.033*	0.004***	-0.126***	0.001*	-0.034*	0.004***	-0.130***
	(0.001)	(0.013)	(0.001)	(0.027)	(0.001)	(0.016)	(0.001)	(0.023)
ExclList	-0.010*	0.237*	-0.012**	0.341*	-0.006	0.159	0.001	-0.035
	(0.005)	(0.118)	(0.004)	(0.149)	(0.007)	(0.224)	(0.009)	(0.260)
ExclSell	-0.001	0.038	-0.001	0.036	-0.003	0.115	0.001	-0.015
	(0.002)	(0.058)	(0.003)	(0.091)	(0.002)	(0.075)	(0.003)	(0.079)
LA_Inventory	-0.001	0.088**	0.003*	-0.018	0.000	0.076*	-0.002	0.123***
	(0.001)	(0.031)	(0.001)	(0.045)	(0.001)	(0.037)	(0.001)	(0.033)
SA_Inventory	0.008***	-0.139***	0.008***	-0.182**	0.009***	-0.218***	0.007***	-0.142**
	(0.001)	(0.041)	(0.001)	(0.060)	(0.001)	(0.058)	(0.001)	(0.047)
Previous	0.000	-0.010	0.036***	-1.110***	0.019***	-0.549***	0.023***	-0.662***
	(0.005)	(0.106)	(0.005)	(0.222)	(0.005)	(0.164)	(0.003)	(0.130)
TOM	0.016***		0.003		0.006		0.009*	
	(0.004)		(0.004)		(0.004)		(0.004)	
Sale Price		23.340***		30.944***		30.017***		28.486***
		(2.596)		(4.753)		(4.233)		(3.810)
Density	-0.023***		-0.027***		-0.024***		-0.024***	
	(0.002)		(0.002)		(0.002)		(0.001)	
Competition		0.510***		0.778***		0.677***		0.637***
		(0.042)		(0.095)		(0.076)		(0.070)

Table 12. 3SLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) by Listing and Selling Brokerage Sizes (Cont.)

	Small_Small		*Small_Large*		*Large_Small*		*Large_Large*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
PriceReduced	-0.036***	1.068***	-0.027***	1.159***	-0.027***	1.114***	-0.032***	1.178***
	(0.003)	(0.077)	(0.003)	(0.117)	(0.003)	(0.103)	(0.003)	(0.101)
AtypBeds	-0.053***	1.265***	-0.034***	1.081***	-0.041***	1.285***	-0.044***	1.273***
	(0.004)	(0.159)	(0.004)	(0.193)	(0.004)	(0.201)	(0.004)	(0.185)
AtypBaths	0.036***	-0.821***	0.032***	-0.965***	0.035***	-1.012***	0.030***	-0.822***
	(0.004)	(0.139)	(0.004)	(0.197)	(0.004)	(0.189)	(0.003)	(0.152)
AtypFirep	0.062***	-1.420***	0.062***	-1.852***	0.055***	-1.585***	0.047***	-1.287***
	(0.005)	(0.203)	(0.005)	(0.334)	(0.004)	(0.267)	(0.004)	(0.217)
AtypAge	0.089***	-2.086***	0.099***	-3.025***	0.091***	-2.739***	0.098***	-2.777***
	(0.008)	(0.288)	(0.008)	(0.530)	(0.008)	(0.460)	(0.008)	(0.442)
AtypGar	0.114***	-2.565***	0.085***	-2.536***	0.092***	-2.679***	0.069***	-1.930***
	(0.010)	(0.392)	(0.010)	(0.536)	(0.009)	(0.486)	(0.008)	(0.362)
Bathrooms	0.124***	-2.882***	0.112***	-3.425***	0.080***	-2.365***	0.095***	-2.678***
	(0.008)	(0.372)	(0.009)	(0.606)	(0.008)	(0.412)	(0.008)	(0.416)
Beds	-0.088***	1.965***	-0.120***	3.592***	-0.085***	2.411***	-0.105***	2.896***
	(0.010)	(0.339)	(0.010)	(0.661)	(0.010)	(0.482)	(0.010)	(0.526)
SqFt	0.628***	-14.698***	0.663***	-20.554***	0.650***	-19.533***	0.693***	-19.779***
	(0.007)	(1.657)	(0.006)	(3.172)	(0.006)	(2.791)	(0.008)	(2.714)
Age	-0.088***	2.053***	-0.081***	2.506***	-0.088***	2.652***	-0.081***	2.302***
	(0.002)	(0.230)	(0.002)	(0.387)	(0.002)	(0.374)	(0.002)	(0.310)
Garages	0.108***	-2.570***	0.100***	-3.152***	0.112***	-3.431***	0.096***	-2.774***
	(0.004)	(0.290)	(0.005)	(0.494)	(0.004)	(0.484)	(0.004)	(0.372)
Fireplaces	0.105***	-2.475***	0.097***	-3.048***	0.095***	-2.868***	0.098***	-2.816***
	(0.004)	(0.277)	(0.004)	(0.468)	(0.004)	(0.407)	(0.004)	(0.374)
Photos	0.037***	-0.861***	0.031***	-0.955***	0.034***	-1.013***	0.025***	-0.703***
	(0.002)	(0.105)	(0.002)	(0.158)	(0.002)	(0.152)	(0.002)	(0.105)
Acres	0.409***	-9.311***	0.428***	-12.907***	0.437***	-12.853***	0.438***	-12.216***
	(0.009)	(1.114)	(0.009)	(2.069)	(0.009)	(1.894)	(0.008)	(1.693)
Pool	0.090***	-2.103***	0.093***	-2.901***	0.092***	-2.776***	0.087***	-2.507***
	(0.002)	(0.237)	(0.002)	(0.444)	(0.002)	(0.392)	(0.002)	(0.334)
Tenant	-0.064***	1.542***	-0.078***	2.496***	-0.066***	2.087***	-0.055***	1.633***
	(0.004)	(0.188)	(0.005)	(0.400)	(0.005)	(0.311)	(0.005)	(0.251)

Table 12. 3SLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) by Listing and Selling Brokerage Sizes (Cont.)

	Small_Small		*Small_Large*		*Large_Small*		*Large_Large*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
Vacant	-0.046***	1.090***	-0.042***	1.325***	-0.041***	1.249***	-0.043***	1.246***
	(0.002)	(0.125)	(0.002)	(0.208)	(0.002)	(0.182)	(0.002)	(0.172)
No_HOA	-0.049***	1.152***	-0.053***	1.651***	-0.051***	1.547***	-0.048***	1.375***
	(0.002)	(0.136)	(0.002)	(0.262)	(0.002)	(0.224)	(0.002)	(0.189)
Vol_HOA	0.035***	-0.809***	0.022***	-0.713***	0.022***	-0.652***	0.016***	-0.473***
	(0.005)	(0.146)	(0.004)	(0.171)	(0.004)	(0.163)	(0.004)	(0.130)
Cash	-0.100***	2.257***	-0.059***	1.733***	-0.073***	2.087***	-0.045***	1.218***
	(0.003)	(0.280)	(0.003)	(0.307)	(0.003)	(0.335)	(0.003)	(0.202)
Government	-0.014***	0.340***	-0.025***	0.786***	-0.020***	0.627***	-0.027***	0.779***
	(0.002)	(0.051)	(0.002)	(0.125)	(0.002)	(0.096)	(0.002)	(0.105)
OtherFin	-0.044***	1.021***	-0.017*	0.573*	-0.020**	0.591*	0.009	-0.250
	(0.008)	(0.212)	(0.008)	(0.257)	(0.007)	(0.237)	(0.007)	(0.211)
Constant	7.054***	-163.168***	6.924***	-212.244***	7.044***	-209.865***	6.725***	-190.014***
	(0.048)	(18.505)	(0.048)	(33.118)	(0.045)	(29.967)	(0.048)	(25.569)
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		55,059		49,386		50,775		55,059
R-sq	0.89	-36.30	0.89	-62.98	0.90	-55.99	0.90	-49.38

Note. This table presents 3SLS results for the full model based on listing and selling brokerage sizes. To categorize a brokerage into small vs. large, I classify each listing and selling brokerage below and above median by the number of agents employed per calendar year. The dependent variables are the natural log-transformed sale price and TOM. Besides the standard set of controls in all the regressions, all models include 1-year normalized betweenness centralities and controls for agent experience, specialization, and active listings inventory.
The sample period is from October 2003 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 13. 3SLS for Sale Price and TOM with Agent Influence (Eigenvector centrality) by Listing and Selling Brokerage Sizes

	Small_Small		*Small_Large*		*Large_Small*		*Large_Large*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
LA_Influence	-0.214***	4.499***	-0.292***	8.517***	0.083*	-3.157**	0.042	-1.747
	(0.040)	(1.139)	(0.038)	(1.858)	(0.039)	(1.218)	(0.037)	(1.048)
SA_Influence	-0.153**	3.842**	-0.342***	10.990***	-0.061	2.170	-0.208***	6.329***
	(0.047)	(1.173)	(0.053)	(2.320)	(0.046)	(1.398)	(0.046)	(1.532)
LA_Experience	0.012***	-0.362***	0.005	-0.261**	-0.012***	0.259**	-0.009***	0.169*
	(0.003)	(0.068)	(0.003)	(0.087)	(0.003)	(0.097)	(0.003)	(0.083)
SA_Experience	-0.002	-0.023	0.002	-0.225*	-0.014***	0.317**	-0.001	-0.099
	(0.003)	(0.064)	(0.003)	(0.099)	(0.003)	(0.103)	(0.003)	(0.082)
LA_Experience_M	-0.001	0.004	-0.001	0.007	0.002***	-0.084***	0.003***	-0.091***
	(0.001)	(0.016)	(0.001)	(0.020)	(0.001)	(0.023)	(0.001)	(0.023)
SA_Experience_M	0.002**	-0.037**	0.004***	-0.138***	0.001*	-0.036*	0.005***	-0.137***
	(0.001)	(0.013)	(0.001)	(0.028)	(0.001)	(0.017)	(0.001)	(0.024)
ExclList	-0.010*	0.229	-0.012**	0.339*	-0.005	0.129	0.001	-0.048
	(0.005)	(0.119)	(0.004)	(0.149)	(0.007)	(0.225)	(0.009)	(0.260)
ExclSell	-0.000	0.017	-0.000	0.010	-0.003	0.096	0.001	-0.035
	(0.002)	(0.059)	(0.003)	(0.091)	(0.002)	(0.075)	(0.003)	(0.079)
LA_Inventory	-0.000	0.061	0.004**	-0.046	0.000	0.065	-0.002	0.118***
	(0.001)	(0.031)	(0.001)	(0.048)	(0.001)	(0.038)	(0.001)	(0.033)
SA_Inventory	0.009***	-0.167***	0.009***	-0.215***	0.010***	-0.244***	0.008***	-0.166***
	(0.001)	(0.044)	(0.001)	(0.064)	(0.001)	(0.061)	(0.001)	(0.049)
Previous	0.002	-0.040	0.038***	-1.167***	0.020***	-0.592***	0.024***	-0.688***
	(0.005)	(0.107)	(0.005)	(0.230)	(0.005)	(0.167)	(0.003)	(0.133)
TOM	0.016***		0.003		0.006		0.009*	
	(0.004)		(0.004)		(0.004)		(0.004)	
Sale Price		23.528***		31.152***		30.175***		28.551***
		(2.638)		(4.813)		(4.278)		(3.828)
Density	-0.023***		-0.027***		-0.024***		-0.024***	
	(0.002)		(0.002)		(0.002)		(0.001)	
Competition		0.512***		0.781***		0.678***		0.636***
		(0.042)		(0.096)		(0.076)		(0.070)
PriceReduced	-0.036***	1.076***	-0.027***	1.164***	-0.027***	1.118***	-0.032***	1.179***
	(0.003)	(0.079)	(0.003)	(0.118)	(0.003)	(0.104)	(0.003)	(0.101)
AtypBeds	-0.053***	1.274***	-0.034***	1.093***	-0.041***	1.291***	-0.044***	1.275***

Table 13. 3SLS for Sale Price and TOM with Agent Influence (Eigenvector centrality) by Listing and Selling Brokerage Sizes (Cont.)

	Small_Small		*Small_Large*		*Large_Small*		*Large_Large*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.004)	(0.161)	(0.004)	(0.195)	(0.004)	(0.203)	(0.004)	(0.186)
AtypBaths	0.036***	-0.825***	0.033***	-0.974***	0.035***	-1.015***	0.030***	-0.824***
	(0.004)	(0.141)	(0.004)	(0.199)	(0.004)	(0.191)	(0.003)	(0.152)
AtypFirep	0.062***	-1.434***	0.062***	-1.865***	0.055***	-1.594***	0.047***	-1.291***
	(0.005)	(0.205)	(0.005)	(0.337)	(0.004)	(0.269)	(0.004)	(0.218)
AtypAge	0.089***	-2.094***	0.098***	-3.034***	0.091***	-2.754***	0.099***	-2.789***
	(0.008)	(0.291)	(0.008)	(0.535)	(0.008)	(0.464)	(0.008)	(0.444)
AtypGar	0.113***	-2.571***	0.084***	-2.528***	0.092***	-2.699***	0.069***	-1.933***
	(0.010)	(0.395)	(0.010)	(0.539)	(0.009)	(0.491)	(0.008)	(0.363)
Bathrooms	0.124***	-2.906***	0.112***	-3.454***	0.080***	-2.378***	0.095***	-2.683***
	(0.008)	(0.377)	(0.009)	(0.614)	(0.008)	(0.416)	(0.008)	(0.418)
Beds	-0.088***	1.979***	-0.120***	3.606***	-0.085***	2.422***	-0.104***	2.893***
	(0.010)	(0.343)	(0.010)	(0.667)	(0.010)	(0.486)	(0.010)	(0.527)
SqFt	0.628***	-14.810***	0.662***	-20.682***	0.650***	-19.635***	0.693***	-19.819***
	(0.007)	(1.683)	(0.006)	(3.210)	(0.006)	(2.820)	(0.008)	(2.726)
Age	-0.088***	2.076***	-0.081***	2.528***	-0.088***	2.671***	-0.081***	2.309***
	(0.002)	(0.234)	(0.002)	(0.393)	(0.002)	(0.378)	(0.002)	(0.312)
Garages	0.108***	-2.589***	0.100***	-3.167***	0.112***	-3.450***	0.096***	-2.782***
	(0.004)	(0.295)	(0.005)	(0.499)	(0.004)	(0.490)	(0.004)	(0.374)
Fireplaces	0.105***	-2.492***	0.097***	-3.062***	0.095***	-2.882***	0.098***	-2.818***
	(0.004)	(0.281)	(0.004)	(0.473)	(0.004)	(0.411)	(0.004)	(0.375)
Photos	0.037***	-0.875***	0.031***	-0.968***	0.034***	-1.018***	0.025***	-0.705***
	(0.002)	(0.108)	(0.002)	(0.161)	(0.002)	(0.154)	(0.002)	(0.105)
Acres	0.409***	-9.383***	0.428***	-12.997***	0.437***	-12.916***	0.438***	-12.248***
	(0.009)	(1.131)	(0.009)	(2.095)	(0.009)	(1.913)	(0.008)	(1.701)
Pool	0.090***	-2.121***	0.093***	-2.919***	0.092***	-2.790***	0.087***	-2.512***
	(0.002)	(0.241)	(0.002)	(0.449)	(0.002)	(0.396)	(0.002)	(0.336)
Tenant	-0.064***	1.559***	-0.078***	2.526***	-0.066***	2.097***	-0.055***	1.633***
	(0.004)	(0.191)	(0.005)	(0.407)	(0.005)	(0.314)	(0.005)	(0.251)
Vacant	-0.047***	1.103***	-0.043***	1.338***	-0.041***	1.252***	-0.043***	1.246***
	(0.002)	(0.127)	(0.002)	(0.211)	(0.002)	(0.184)	(0.002)	(0.173)
No_HOA	-0.049***	1.164***	-0.053***	1.660***	-0.051***	1.557***	-0.048***	1.376***

Table 13. 3SLS for Sale Price and TOM with Agent Influence (Eigenvector centrality) by Listing and Selling Brokerage Sizes (Cont.)

	Small_Small		*Small_Large*		*Large_Small*		*Large_Large*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.002)	(0.139)	(0.002)	(0.265)	(0.002)	(0.227)	(0.002)	(0.189)
Vol_HOA	0.035***	-0.814***	0.023***	-0.722***	0.022***	-0.657***	0.016***	-0.471***
	(0.005)	(0.147)	(0.004)	(0.173)	(0.004)	(0.164)	(0.004)	(0.130)
Cash	-0.099***	2.271***	-0.059***	1.746***	-0.072***	2.092***	-0.045***	1.224***
	(0.003)	(0.284)	(0.003)	(0.311)	(0.003)	(0.337)	(0.003)	(0.203)
Government	-0.014***	0.341***	-0.024***	0.786***	-0.020***	0.628***	-0.026***	0.777***
	(0.002)	(0.051)	(0.002)	(0.125)	(0.002)	(0.096)	(0.002)	(0.105)
OtherFin	-0.044***	1.037***	-0.017*	0.573*	-0.019**	0.587*	0.009	-0.249
	(0.008)	(0.214)	(0.008)	(0.258)	(0.007)	(0.238)	(0.007)	(0.211)
Constant	7.051***	-164.420***	6.923***	-213.637***	7.039***	-210.803***	6.721***	-190.351***
	(0.048)	(18.794)	(0.048)	(33.528)	(0.045)	(30.257)	(0.048)	(25.676)
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		55,059		49,386		50,775		55,059
R-sq	0.89	-36.87	0.89	-63.74	0.90	-56.61	0.90	-49.59

Note. This table presents 3SLS results for the full model based on listing and selling brokerage sizes. To categorize a brokerage into small vs. large, I classify each listing and selling brokerage below and above median by the number of agents employed per calendar year. The dependent variables are the natural log-transformed sale price and TOM. Besides the standard set of controls in all the regressions, all models include 1-year normalized eigenvector centralities and controls for agent experience, specialization, and active listings inventory.
The sample period is from October 2003 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 14. 3SLS for Sale Price and TOM with Agent Network Size (Degree centrality) by Median Sale Price

	Below Median		*Above Median*	
	Price	**TOM**	**Price**	**TOM**
LA_NetSize	0.025**	-0.439***	-0.015*	0.099
	(0.008)	(0.023)	(0.007)	(0.195)
SA_NetSize	0.045***	0.121***	0.008	-0.097
	(0.009)	(0.028)	(0.009)	(0.223)
LA_Experience	0.000	-0.131***	-0.008***	0.099*
	(0.002)	(0.005)	(0.002)	(0.044)
SA_Experience	-0.009***	-0.155***	-0.008***	0.085
	(0.002)	(0.005)	(0.002)	(0.050)
LA_Experience_M	0.001	-0.017***	0.000	-0.005
	(0.000)	(0.001)	(0.000)	(0.010)
SA_Experience_M	0.001***	-0.003**	0.002***	-0.055***
	(0.000)	(0.001)	(0.000)	(0.009)
ExclList	-0.016***	-0.001	0.001	-0.027
	(0.004)	(0.010)	(0.003)	(0.078)
ExclSell	-0.003	0.015**	-0.002	0.057
	(0.002)	(0.005)	(0.001)	(0.038)
LA_Inventory	-0.005***	0.120***	0.007***	-0.085**
	(0.001)	(0.002)	(0.001)	(0.027)
SA_Inventory	0.004***	0.066***	0.008***	-0.153***
	(0.001)	(0.002)	(0.001)	(0.030)
InHouse	-0.008**	-0.013*	0.010***	-0.257***
	(0.002)	(0.007)	(0.002)	(0.063)
Previous	-0.001	0.008	0.028***	-0.720***
	(0.003)	(0.007)	(0.003)	(0.094)
TOM	-0.012***		0.006*	
	(0.002)		(0.003)	
Sale Price		0.772***		25.835***
		(0.014)		(2.367)
Density	0.010***		-0.026***	
	(0.001)		(0.001)	
Competition		0.340***		0.662***
		(0.003)		(0.044)
PriceReduced	-0.018***	0.459***	-0.022***	0.878***

Table 14. 3SLS for Sale Price and TOM with Agent Network Size (Degree centrality) by Median Sale Price (Cont.)

	Below Median		*Above Median*	
	Price	**TOM**	**Price**	**TOM**
	(0.002)	(0.004)	(0.002)	(0.046)
AtypBeds	-0.041***	0.198***	-0.018***	0.495***
	(0.004)	(0.013)	(0.002)	(0.063)
AtypBaths	0.007	0.027*	0.039***	-1.008***
	(0.004)	(0.011)	(0.002)	(0.105)
AtypFirep	-0.016***	0.079***	0.067***	-1.697***
	(0.003)	(0.010)	(0.002)	(0.171)
AtypAge	0.047***	-0.023*	0.079***	-2.047***
	(0.005)	(0.010)	(0.004)	(0.218)
AtypGar	-0.032**	0.147***	0.091***	-2.290***
	(0.011)	(0.030)	(0.005)	(0.259)
Bathrooms	0.027***	0.074***	0.078***	-1.993***
	(0.005)	(0.014)	(0.004)	(0.215)
Beds	-0.007	-0.104***	-0.140***	3.509***
	(0.006)	(0.017)	(0.005)	(0.370)
SqFt	0.453***	-0.849***	0.534***	-13.619***
	(0.005)	(0.023)	(0.004)	(1.303)
Age	-0.066***	0.091***	-0.074***	1.917***
	(0.001)	(0.003)	(0.001)	(0.178)
Garages	0.100***	-0.189***	0.061***	-1.590***
	(0.002)	(0.006)	(0.003)	(0.157)
Fireplaces	0.076***	-0.139***	0.059***	-1.513***
	(0.002)	(0.006)	(0.002)	(0.150)
Photos	0.041***	-0.021***	0.006***	-0.161***
	(0.001)	(0.003)	(0.001)	(0.028)
Acres	0.183***	0.302***	0.418***	-10.486***
	(0.007)	(0.022)	(0.005)	(1.020)
Pool	0.053***	-0.060***	0.083***	-2.153***
	(0.002)	(0.005)	(0.001)	(0.196)
Tenant	-0.046***	0.141***	-0.044***	1.217***
	(0.003)	(0.007)	(0.003)	(0.134)
Vacant	-0.039***	0.045***	-0.022***	0.567***

Table 14. 3SLS for Sale Price and TOM with Agent Network Size (Degree centrality) by Median Sale Price (Cont.)

	Below Median		*Above Median*	
	Price	**TOM**	**Price**	**TOM**
	(0.001)	(0.003)	(0.001)	(0.057)
No_HOA	-0.038***	0.020***	-0.046***	1.200***
	(0.001)	(0.005)	(0.001)	(0.113)
Vol_HOA	0.029***	-0.035***	-0.011***	0.281***
	(0.003)	(0.009)	(0.002)	(0.068)
Cash	-0.103***	-0.102***	0.005**	-0.197***
	(0.002)	(0.005)	(0.002)	(0.043)
Government	0.007***	0.018***	-0.033***	0.889***
	(0.001)	(0.003)	(0.001)	(0.081)
OtherFin	-0.038***	0.023	0.017***	-0.422**
	(0.004)	(0.012)	(0.005)	(0.130)
Constant	8.524***	omitted	8.129***	-209.644***
	(0.036)		(0.033)	(19.174)
YearxMonthFE	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes
N		102,201		108,078
R-sq	0.88	0.62	0.91	-30.35

Note. This table presents 3SLS results for the full model based on the median annual adjusted sale price. The dependent variables are the natural log-transformed sale price and TOM. In addition to the standard set of controls in all the regressions, all models include 1-year normalized degree centralities and controls for agent experience, specialization, and active listings inventory.
The sample period is from October 2003 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 15. 3SLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) by Median Sale Price

	Below Median		*Above Median*	
	Price	**TOM**	**Price**	**TOM**
LA_BPower	0.021**	-0.246***	-0.024***	0.462*
	(0.007)	(0.022)	(0.007)	(0.190)
SA_BPower	0.037***	0.115***	-0.008	0.344
	(0.009)	(0.029)	(0.008)	(0.214)
LA_Experience	0.001	-0.155***	-0.007***	0.074
	(0.002)	(0.005)	(0.002)	(0.043)
SA_Experience	-0.007***	-0.151***	-0.006***	0.042
	(0.002)	(0.005)	(0.002)	(0.046)
LA_Experience_M	0.001	-0.018***	0.000	-0.004
	(0.000)	(0.001)	(0.000)	(0.010)
SA_Experience_M	0.002***	-0.002*	0.002***	-0.055***
	(0.000)	(0.001)	(0.000)	(0.009)
ExclList	-0.016***	-0.005	0.001	-0.034
	(0.004)	(0.010)	(0.003)	(0.078)
ExclSell	-0.003	0.015**	-0.001	0.051
	(0.002)	(0.005)	(0.001)	(0.038)
LA_Inventory	-0.005***	0.111***	0.007***	-0.091***
	(0.001)	(0.002)	(0.001)	(0.026)
SA_Inventory	0.004***	0.067***	0.008***	-0.157***
	(0.001)	(0.002)	(0.001)	(0.030)
InHouse	-0.008**	-0.013*	0.010***	-0.253***
	(0.002)	(0.007)	(0.002)	(0.063)
Previous	-0.001	0.005	0.028***	-0.732***
	(0.003)	(0.007)	(0.003)	(0.094)
TOM	-0.012***		0.006*	
	(0.002)		(0.003)	
Sale Price		0.775***		25.872***
		(0.013)		(2.368)
Density	0.010***		-0.026***	
	(0.001)		(0.001)	
Competition		0.341***		0.663***
		(0.003)		(0.044)
PriceReduced	-0.018***	0.461***	-0.022***	0.879***

Table 15. 3SLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) by Median Sale Price (Cont.)

	Below Median		*Above Median*	
	Price	**TOM**	**Price**	**TOM**
	(0.002)	(0.004)	(0.002)	(0.046)
AtypBeds	-0.041***	0.198***	-0.018***	0.495***
	(0.004)	(0.013)	(0.002)	(0.063)
AtypBaths	0.007	0.027*	0.039***	-1.009***
	(0.004)	(0.011)	(0.002)	(0.105)
AtypFirep	-0.016***	0.079***	0.067***	-1.700***
	(0.003)	(0.010)	(0.002)	(0.171)
AtypAge	0.047***	-0.023*	0.079***	-2.051***
	(0.005)	(0.010)	(0.004)	(0.219)
AtypGar	-0.033**	0.148***	0.091***	-2.292***
	(0.011)	(0.030)	(0.005)	(0.259)
Bathrooms	0.027***	0.074***	0.078***	-1.996***
	(0.005)	(0.014)	(0.004)	(0.215)
Beds	-0.007	-0.104***	-0.140***	3.514***
	(0.006)	(0.017)	(0.005)	(0.370)
SqFt	0.453***	-0.853***	0.534***	-13.637***
	(0.005)	(0.022)	(0.004)	(1.303)
Age	-0.066***	0.092***	-0.074***	1.920***
	(0.001)	(0.004)	(0.001)	(0.178)
Garages	0.100***	-0.189***	0.061***	-1.592***
	(0.002)	(0.006)	(0.003)	(0.157)
Fireplaces	0.076***	-0.140***	0.058***	-1.514***
	(0.002)	(0.006)	(0.002)	(0.150)
Photos	0.041***	-0.022***	0.006***	-0.161***
	(0.001)	(0.003)	(0.001)	(0.028)
Acres	0.182***	0.303***	0.418***	-10.501***
	(0.007)	(0.022)	(0.005)	(1.021)
Pool	0.053***	-0.060***	0.083***	-2.156***
	(0.002)	(0.005)	(0.001)	(0.196)
Tenant	-0.046***	0.142***	-0.044***	1.219***
	(0.003)	(0.007)	(0.003)	(0.134)
Vacant	-0.039***	0.046***	-0.022***	0.567***

Table 15. 3SLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) by Median Sale Price (Cont.)

	Below Median		*Above Median*	
	Price	**TOM**	**Price**	**TOM**
	(0.001)	(0.003)	(0.001)	(0.057)
No_HOA	-0.038***	0.021***	-0.046***	1.202***
	(0.001)	(0.005)	(0.001)	(0.114)
Vol_HOA	0.029***	-0.034***	-0.011***	0.281***
	(0.003)	(0.009)	(0.002)	(0.068)
Cash	-0.103***	-0.102***	0.005**	-0.198***
	(0.002)	(0.005)	(0.002)	(0.043)
Government	0.007***	0.018***	-0.033***	0.889***
	(0.001)	(0.003)	(0.001)	(0.081)
OtherFin	-0.038***	0.025*	0.017***	-0.422**
	(0.004)	(0.012)	(0.005)	(0.130)
Constant	8.524***	omitted	8.128***	-209.904***
	(0.036)		(0.033)	(19.177)
YearxMonthFE	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes
N		102,201		108,078
R-sq	0.88	0.62	0.91	-30.44

Note. This table presents 3SLS results for the full model based on the median annual adjusted sale price. The dependent variables are the natural log-transformed sale price and TOM. In addition to the standard set of controls in all the regressions, all models include 1-year normalized betweenness centralities and controls for agent experience, specialization, and active listings inventory.
The sample period is from October 2003 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 16. 3SLS for Sale Price and TOM with Agent Influence (Eigenvector centrality) by Median Sale Price

	Below Median		*Above Median*	
	Price	**TOM**	**Price**	**TOM**
LA_Influence	-0.007	-0.957***	-0.165***	3.659***
	(0.023)	(0.075)	(0.022)	(0.718)
SA_Influence	-0.098***	0.532***	-0.125***	3.619***
	(0.029)	(0.089)	(0.027)	(0.751)
LA_Experience	0.003	-0.149***	-0.005**	0.015
	(0.002)	(0.005)	(0.002)	(0.041)
SA_Experience	-0.001	-0.157***	-0.003	-0.046
	(0.002)	(0.005)	(0.002)	(0.044)
LA_Experience_M	0.001	-0.018***	0.000	-0.008
	(0.000)	(0.001)	(0.000)	(0.010)
SA_Experience_M	0.002***	-0.003**	0.002***	-0.058***
	(0.000)	(0.001)	(0.000)	(0.010)
ExclList	-0.015***	-0.006	0.001	-0.043
	(0.004)	(0.010)	(0.003)	(0.079)
ExclSell	-0.002	0.015**	-0.001	0.044
	(0.002)	(0.005)	(0.001)	(0.038)
LA_Inventory	-0.005***	0.113***	0.007***	-0.106***
	(0.001)	(0.002)	(0.001)	(0.028)
SA_Inventory	0.005***	0.066***	0.009***	-0.168***
	(0.001)	(0.002)	(0.001)	(0.031)
InHouse	-0.008***	-0.013	0.009***	-0.249***
	(0.002)	(0.007)	(0.002)	(0.063)
Previous	0.000	0.004	0.029***	-0.753***
	(0.003)	(0.007)	(0.003)	(0.096)
TOM	-0.012***		0.006*	
	(0.002)		(0.003)	
Sale Price		0.775***		26.023***
		(0.015)		(2.395)
Density	0.010***		-0.026***	
	(0.001)		(0.001)	
Competition		0.341***		0.666***
		(0.003)		(0.045)
PriceReduced	-0.018***	0.460***	-0.022***	0.883***

Table 16. 3SLS for Sale Price and TOM with Agent Influence (Eigenvector centrality) by Median Sale Price (Cont.)

	Below Median		*Above Median*	
	Price	**TOM**	**Price**	**TOM**
	(0.002)	(0.004)	(0.002)	(0.047)
AtypBeds	-0.041***	0.198***	-0.018***	0.497***
	(0.004)	(0.013)	(0.002)	(0.064)
AtypBaths	0.007	0.027*	0.039***	-1.015***
	(0.004)	(0.011)	(0.002)	(0.106)
AtypFirep	-0.016***	0.079***	0.067***	-1.712***
	(0.003)	(0.010)	(0.002)	(0.173)
AtypAge	0.047***	-0.023*	0.079***	-2.067***
	(0.005)	(0.010)	(0.004)	(0.221)
AtypGar	-0.033**	0.149***	0.091***	-2.302***
	(0.011)	(0.030)	(0.005)	(0.261)
Bathrooms	0.027***	0.074***	0.078***	-2.008***
	(0.005)	(0.014)	(0.004)	(0.218)
Beds	-0.007	-0.104***	-0.140***	3.535***
	(0.006)	(0.016)	(0.005)	(0.374)
SqFt	0.453***	-0.852***	0.534***	-13.715***
	(0.005)	(0.023)	(0.004)	(1.318)
Age	-0.066***	0.092***	-0.074***	1.934***
	(0.001)	(0.004)	(0.001)	(0.180)
Garages	0.100***	-0.189***	0.061***	-1.603***
	(0.002)	(0.006)	(0.003)	(0.159)
Fireplaces	0.076***	-0.140***	0.058***	-1.520***
	(0.002)	(0.006)	(0.002)	(0.151)
Photos	0.041***	-0.022***	0.007***	-0.164***
	(0.001)	(0.003)	(0.001)	(0.028)
Acres	0.182***	0.302***	0.418***	-10.561***
	(0.007)	(0.022)	(0.005)	(1.032)
Pool	0.053***	-0.060***	0.083***	-2.170***
	(0.002)	(0.005)	(0.001)	(0.199)
Tenant	-0.046***	0.141***	-0.045***	1.230***
	(0.003)	(0.007)	(0.003)	(0.136)
Vacant	-0.039***	0.045***	-0.022***	0.572***

Table 16. 3SLS for Sale Price and TOM with Agent Influence (Eigenvector centrality) by Median Sale Price (Cont.)

	Below Median		*Above Median*	
	Price	**TOM**	**Price**	**TOM**
	(0.001)	(0.003)	(0.001)	(0.058)
No_HOA	-0.038***	0.021***	-0.046***	1.208***
	(0.001)	(0.005)	(0.001)	(0.115)
Vol_HOA	0.029***	-0.034***	-0.011***	0.282***
	(0.003)	(0.009)	(0.002)	(0.069)
Cash	-0.103***	-0.102***	0.005**	-0.199***
	(0.002)	(0.005)	(0.002)	(0.043)
Government	0.007***	0.018***	-0.033***	0.892***
	(0.001)	(0.003)	(0.001)	(0.081)
OtherFin	-0.038***	0.024*	0.017***	-0.421**
	(0.004)	(0.012)	(0.005)	(0.131)
Constant	8.520***	omitted	8.127***	-211.123***
	(0.036)		(0.033)	(19.399)
YearxMonthFE	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes
N		102,201		108,078
R-sq	0.88	0.62	0.91	-30.79

Note. This table presents 3SLS results for the full model based on the median annual sale price. The dependent variables are the natural log-transformed sale price and TOM. In addition to the standard set of controls in all the regressions, all models include 1-year normalized eigenvector centralities and controls for agent experience, specialization, and active listings inventory.
The sample period is from October 2003 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 17. 3SLS for Sale Price and TOM with Agent Network Size (Degree centrality) by Sale Price Segments

	Below $100,000		*$100,000 - $500,000*		*Above $500,000*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**
LA_NetSize	0.020	-0.566***	0.016**	-1.056***	-0.089***	0.890
	(0.020)	(0.064)	(0.005)	(0.262)	(0.026)	(0.466)
SA_NetSize	0.126***	0.212**	0.009	-0.313	-0.070	1.036*
	(0.025)	(0.072)	(0.007)	(0.313)	(0.038)	(0.522)
LA_Experience	0.011**	-0.169***	-0.005***	0.116*	-0.019*	0.083
	(0.004)	(0.013)	(0.001)	(0.057)	(0.008)	(0.128)
SA_Experience	0.001	-0.186***	-0.009***	0.276***	0.014	-0.370***
	(0.004)	(0.011)	(0.001)	(0.070)	(0.010)	(0.111)
LA_Experience_M	-0.001	-0.025***	0.001**	-0.055***	-0.004	0.023
	(0.001)	(0.003)	(0.000)	(0.014)	(0.002)	(0.030)
SA_Experience_M	0.001	-0.006*	0.003***	-0.128***	-0.002	0.032
	(0.001)	(0.003)	(0.000)	(0.015)	(0.002)	(0.021)
ExclList	-0.053***	0.038	-0.001	0.027	-0.032	0.346
	(0.010)	(0.024)	(0.002)	(0.105)	(0.019)	(0.248)
ExclSell	0.005	-0.007	-0.003*	0.148**	-0.002	0.030
	(0.004)	(0.012)	(0.001)	(0.054)	(0.007)	(0.089)
LA_Inventory	-0.014***	0.155***	0.001*	0.025	0.013**	-0.051
	(0.002)	(0.006)	(0.001)	(0.027)	(0.004)	(0.074)
SA_Inventory	-0.007***	0.089***	0.009***	-0.371***	0.003	0.042
	(0.002)	(0.005)	(0.001)	(0.047)	(0.004)	(0.050)
InHouse	-0.015**	-0.018	0.010***	-0.458***	0.004	-0.055
	(0.005)	(0.015)	(0.002)	(0.086)	(0.008)	(0.097)
Previous	-0.010	0.012	0.014***	-0.631***	0.037***	-0.455**
	(0.006)	(0.016)	(0.002)	(0.101)	(0.007)	(0.156)
TOM	0.012*		-0.001		0.027*	
	(0.005)		(0.001)		(0.013)	
Sale Price		0.877***		46.804***		12.203***
		(0.034)		(4.002)		(3.497)
Density	0.015***		-0.022***		-0.021***	
	(0.003)		(0.001)		(0.005)	
Competition		0.319***		0.961***		0.313***
		(0.007)		(0.066)		(0.039)
PriceReduced	-0.028***	0.475***	-0.019***	1.220***	-0.069***	1.155***

Table 17. 3SLS for Sale Price and TOM with Agent Network Size (Degree centrality) by Sale Price Segments (Cont.)

	Below $100,000		*$100,000 - $500,000*		*Above $500,000*	
	Price	**TOM**	**Price**	**Price**	**TOM**	**Price**
	(0.004)	(0.009)	(0.001)	(0.075)	(0.009)	(0.192)
AtypBeds	-0.063*	0.432***	-0.048***	2.295***	0.023*	-0.299*
	(0.025)	(0.067)	(0.002)	(0.203)	(0.009)	(0.136)
AtypBaths	-0.118***	0.287**	0.050***	-2.323***	-0.088***	1.014**
	(0.029)	(0.098)	(0.002)	(0.220)	(0.009)	(0.341)
AtypFirep	-0.041*	0.232***	0.027***	-1.245***	-0.040***	0.480**
	(0.017)	(0.065)	(0.002)	(0.147)	(0.008)	(0.178)
AtypAge	-0.012*	0.039**	0.097***	-4.561***	0.221***	-2.686***
	(0.005)	(0.014)	(0.004)	(0.429)	(0.017)	(0.794)
AtypGar	-0.039	0.115	0.009	-0.342	0.034***	-0.429**
	(0.030)	(0.089)	(0.005)	(0.254)	(0.007)	(0.146)
Bathrooms	0.113***	-0.089***	0.031***	-1.429***	0.261***	-3.177***
	(0.009)	(0.024)	(0.003)	(0.205)	(0.018)	(0.955)
Beds	0.102***	-0.305***	-0.073***	3.347***	-0.347***	4.134**
	(0.012)	(0.034)	(0.004)	(0.359)	(0.042)	(1.323)
SqFt	0.254***	-0.936***	0.613***	-28.758***	0.768***	-8.783**
	(0.011)	(0.052)	(0.003)	(2.480)	(0.027)	(2.863)
Age	-0.098***	0.152***	-0.063***	2.931***	-0.110***	1.347***
	(0.003)	(0.010)	(0.001)	(0.253)	(0.004)	(0.385)
Garages	0.080***	-0.148***	0.085***	-4.009***	-0.048**	0.577*
	(0.003)	(0.010)	(0.002)	(0.348)	(0.016)	(0.250)
Fireplaces	0.039***	-0.071***	0.060***	-2.850***	0.158***	-1.908**
	(0.004)	(0.012)	(0.002)	(0.249)	(0.014)	(0.590)
Photos	0.052***	-0.022***	0.018***	-0.852***	-0.003	0.047
	(0.002)	(0.006)	(0.001)	(0.080)	(0.003)	(0.034)
Acres	0.027	0.286***	0.444***	-20.431***	0.213***	-2.469**
	(0.017)	(0.055)	(0.004)	(1.801)	(0.016)	(0.791)
Pool	0.020***	0.015	0.088***	-4.118***	0.059***	-0.760***
	(0.006)	(0.020)	(0.001)	(0.352)	(0.005)	(0.204)
Tenant	-0.043***	0.136***	-0.054***	2.633***	-0.059***	0.786**
	(0.005)	(0.014)	(0.002)	(0.236)	(0.017)	(0.285)
Vacant	-0.031***	0.017*	-0.033***	1.581***	-0.035***	0.432**

Table 17. 3SLS for Sale Price and TOM with Agent Network Size (Degree centrality) by Sale Price Segments (Cont.)

	Below $100,000		*$100,000 - $500,000*		*Above $500,000*	
	Price	**TOM**	**Price**	**Price**	**TOM**	**Price**
	(0.002)	(0.007)	(0.001)	(0.138)	(0.007)	(0.148)
No_HOA	-0.003	-0.043	-0.061***	2.847***	0.008	-0.039
	(0.009)	(0.024)	(0.001)	(0.245)	(0.008)	(0.110)
Vol_HOA	0.076***	-0.123***	0.012***	-0.577***	-0.005	0.058
	(0.013)	(0.037)	(0.002)	(0.104)	(0.012)	(0.150)
Cash	-0.164***	-0.106***	-0.033***	1.463***	0.058***	-0.753***
	(0.004)	(0.012)	(0.001)	(0.149)	(0.006)	(0.211)
Government	0.053***	-0.032***	-0.034***	1.616***	-0.046***	0.565**
	(0.002)	(0.008)	(0.001)	(0.138)	(0.012)	(0.215)
OtherFin	-0.048***	-0.022	-0.001	0.072	0.049**	-0.610*
	(0.008)	(0.023)	(0.003)	(0.150)	(0.018)	(0.279)
Constant	9.446***	omitted	7.377***	-343.421***	6.479***	-81.202***
	(0.092)		(0.020)	(29.548)	(0.201)	(21.722)
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes
N		22,872		179,498		22,872
R-sq	0.58	0.61	0.87	-96.34	0.73	-6.75

Note. This table presents 3SLS results for the full model based on three sale price segments. The dependent variables are the natural log-transformed sale price and TOM. In addition to the standard set of controls in all the regressions, all models include 1-year normalized degree centralities and controls for agent experience, specialization, and active listings inventory.
The sample period is from October 2003 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 18. 3SLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) by Sale Price Segments

	Below $100,000		*$100,000 - $500,000*		*Above $500,000*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**
LA_BPower	0.025	-0.311***	0.003	-0.305	-0.070**	0.745
	(0.020)	(0.063)	(0.005)	(0.243)	(0.024)	(0.392)
SA_BPower	0.130***	0.187*	0.002	0.052	-0.092*	1.306*
	(0.029)	(0.080)	(0.007)	(0.309)	(0.038)	(0.558)
LA_Experience	0.011**	-0.201***	-0.003**	0.040	-0.022**	0.112
	(0.004)	(0.012)	(0.001)	(0.054)	(0.008)	(0.136)
SA_Experience	0.004	-0.178***	-0.008***	0.240***	0.014	-0.364***
	(0.004)	(0.010)	(0.001)	(0.066)	(0.010)	(0.103)
LA_Experience_M	-0.001	-0.027***	0.001***	-0.059***	-0.004	0.025
	(0.001)	(0.003)	0.000	(0.014)	(0.002)	(0.031)
SA_Experience_M	0.001	-0.005*	0.003***	-0.130***	-0.003	0.036
	(0.001)	(0.002)	(0.000)	(0.016)	(0.002)	(0.022)
ExclList	-0.054***	0.033	0.000	0.011	-0.033	0.346
	(0.010)	(0.024)	(0.002)	(0.106)	(0.019)	(0.247)
ExclSell	0.005	-0.006	-0.003*	0.145**	-0.002	0.025
	(0.004)	(0.012)	(0.001)	(0.054)	(0.007)	(0.089)
LA_Inventory	-0.014***	0.144***	0.002**	-0.001	0.011**	-0.037
	(0.002)	(0.005)	(0.001)	(0.027)	(0.004)	(0.068)
SA_Inventory	-0.007***	0.091***	0.009***	-0.380***	0.003	0.047
	(0.002)	(0.005)	(0.001)	(0.047)	(0.004)	(0.048)
InHouse	-0.016**	-0.018	0.009***	-0.458***	0.004	-0.054
	(0.005)	(0.015)	(0.002)	(0.087)	(0.008)	(0.097)
Previous	-0.010	0.010	0.014***	-0.657***	0.037***	-0.448**
	(0.006)	(0.016)	(0.002)	(0.102)	(0.007)	(0.153)
TOM	0.011*		-0.001		0.028*	
	(0.005)		(0.001)		(0.013)	
Sale Price		0.881***		47.181***		12.160***
		(0.034)		(4.057)		(3.468)
Density	0.015***		-0.022***		-0.021***	
	(0.003)		(0.001)		(0.005)	
Competition		0.320***		0.968***		0.312***
		(0.007)		(0.067)		(0.039)
PriceReduced	-0.028***	0.477***	-0.019***	1.230***	-0.069***	1.150***

Table 18. 3SLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) by Sale Price Segments (Cont.)

	Below $100,000		*$100,000 - $500,000*		*Above $500,000*	
	Price	**TOM**	**Price**	**Price**	**TOM**	**Price**
	(0.004)	(0.009)	(0.001)	(0.076)	(0.009)	(0.189)
AtypBeds	-0.063*	0.432***	-0.048***	2.313***	0.023*	-0.299*
	(0.025)	(0.067)	(0.002)	(0.206)	(0.009)	(0.136)
AtypBaths	-0.118***	0.288**	0.050***	-2.342***	-0.088***	1.010**
	(0.029)	(0.098)	(0.002)	(0.222)	(0.009)	(0.338)
AtypFirep	-0.042*	0.233***	0.027***	-1.255***	-0.040***	0.476**
	(0.017)	(0.065)	(0.002)	(0.149)	(0.008)	(0.177)
AtypAge	-0.013*	0.040**	0.097***	-4.598***	0.221***	-2.677***
	(0.005)	(0.014)	(0.004)	(0.434)	(0.017)	(0.788)
AtypGar	-0.039	0.113	0.009	-0.344	0.034***	-0.428**
	(0.030)	(0.089)	(0.005)	(0.256)	(0.007)	(0.145)
Bathrooms	0.113***	-0.091***	0.031***	-1.443***	0.261***	-3.163***
	(0.009)	(0.024)	(0.003)	(0.207)	(0.018)	(0.947)
Beds	0.102***	-0.304***	-0.073***	3.373***	-0.348***	4.131**
	(0.012)	(0.035)	(0.004)	(0.363)	(0.042)	(1.316)
SqFt	0.254***	-0.940***	0.613***	-28.989***	0.769***	-8.759**
	(0.011)	(0.053)	(0.003)	(2.514)	(0.027)	(2.842)
Age	-0.098***	0.153***	-0.063***	2.956***	-0.110***	1.343***
	(0.003)	(0.010)	(0.001)	(0.257)	(0.004)	(0.382)
Garages	0.080***	-0.148***	0.085***	-4.040***	-0.048**	0.577*
	(0.003)	(0.010)	(0.002)	(0.353)	(0.016)	(0.248)
Fireplaces	0.038***	-0.071***	0.060***	-2.872***	0.158***	-1.896**
	(0.004)	(0.012)	(0.002)	(0.253)	(0.014)	(0.584)
Photos	0.053***	-0.023***	0.018***	-0.860***	-0.003	0.045
	(0.002)	(0.006)	(0.001)	(0.081)	(0.003)	(0.034)
Acres	0.027	0.288***	0.444***	-20.596***	0.213***	-2.462**
	(0.017)	(0.055)	(0.004)	(1.825)	(0.016)	(0.785)
Pool	0.020***	0.015	0.088***	-4.152***	0.059***	-0.758***
	(0.006)	(0.020)	(0.001)	(0.357)	(0.005)	(0.203)
Tenant	-0.043***	0.138***	-0.054***	2.657***	-0.059***	0.784**
	(0.005)	(0.014)	(0.002)	(0.239)	(0.017)	(0.284)
Vacant	-0.031***	0.017*	-0.033***	1.595***	-0.036***	0.432**

Table 18. 3SLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) by Sale Price Segments (Cont.)

	Below $100,000		*$100,000 - $500,000*		*Above $500,000*	
	Price	**TOM**	**Price**	**Price**	**TOM**	**Price**
	(0.002)	(0.007)	(0.001)	(0.140)	(0.007)	(0.148)
No_HOA	-0.003	-0.044	-0.061***	2.870***	0.008	-0.037
	(0.009)	(0.024)	(0.001)	(0.249)	(0.008)	(0.109)
Vol_HOA	0.076***	-0.122***	0.012***	-0.580***	-0.005	0.062
	(0.013)	(0.037)	(0.002)	(0.105)	(0.012)	(0.149)
Cash	-0.164***	-0.105***	-0.033***	1.475***	0.058***	-0.751***
	(0.004)	(0.012)	(0.001)	(0.151)	(0.006)	(0.209)
Government	0.053***	-0.032***	-0.034***	1.628***	-0.047***	0.568**
	(0.002)	(0.008)	(0.001)	(0.140)	(0.012)	(0.216)
OtherFin	-0.048***	-0.019	-0.001	0.072	0.049**	-0.605*
	(0.008)	(0.023)	(0.003)	(0.151)	(0.018)	(0.277)
Constant	9.446***	omitted	7.376***	-346.132***	6.475***	-80.848***
	(0.092)		(0.020)	(29.954)	(0.201)	(21.520)
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes
N		22,872		179,498		22,872
R-sq	0.58	0.61	0.87	-96.34	0.73	-6.75

Note. This table presents 3SLS results for the full model based on three sale price segments. The dependent variables are the natural log-transformed sale price and TOM. In addition to the standard set of controls in all the regressions, all models include 1-year normalized betweenness centralities and controls for agent experience, specialization, and active listings inventory.
The sample period is from October 2003 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 19. 3SLS for Sale Price and TOM with Agent Influence (Eigenvector centrality) by Sale Price Segments

	Below $100,000		*$100,000 - $500,000*		*Above $500,000*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**
LA_Influence	0.125*	-1.243***	-0.031	0.762	-0.342***	3.663*
	(0.064)	(0.206)	(0.017)	(0.805)	(0.089)	(1.690)
SA_Influence	-0.170*	1.135***	-0.097***	4.918***	-0.449***	6.122**
	(0.081)	(0.228)	(0.021)	(1.048)	(0.130)	(2.238)
LA_Experience	0.010*	-0.192***	-0.002*	-0.002	-0.020*	0.088
	(0.004)	(0.012)	(0.001)	(0.054)	(0.008)	(0.131)
SA_Experience	0.016***	-0.193***	-0.005***	0.092	0.021*	-0.460***
	(0.004)	(0.010)	(0.001)	(0.062)	(0.010)	(0.116)
LA_Experience_M	-0.001	-0.027***	0.001***	-0.059***	-0.003	0.021
	(0.001)	(0.003)	(0.000)	(0.014)	(0.002)	(0.030)
SA_Experience_M	0.002*	-0.007**	0.003***	-0.134***	-0.003	0.034
	(0.001)	(0.003)	(0.000)	(0.016)	(0.002)	(0.022)
ExclList	-0.054***	0.031	0.000	0.000	-0.032	0.347
	(0.010)	(0.024)	(0.002)	(0.106)	(0.019)	(0.250)
ExclSell	0.006	-0.006	-0.002*	0.130*	-0.002	0.027
	(0.004)	(0.012)	(0.001)	(0.054)	(0.007)	(0.090)
LA_Inventory	-0.015***	0.146***	0.002***	-0.012	0.012**	-0.044
	(0.002)	(0.005)	(0.001)	(0.027)	(0.004)	(0.071)
SA_Inventory	-0.005*	0.089***	0.010***	-0.402***	0.003	0.042
	(0.002)	(0.005)	(0.001)	(0.049)	(0.004)	(0.050)
InHouse	-0.016**	-0.016	0.009***	-0.451***	0.004	-0.051
	(0.005)	(0.015)	(0.002)	(0.087)	(0.008)	(0.098)
Previous	-0.008	0.008	0.015***	-0.690***	0.036***	-0.448**
	(0.006)	(0.016)	(0.002)	(0.104)	(0.007)	(0.155)
TOM	0.012*		-0.001		0.027*	
	(0.005)		(0.001)		(0.013)	
Sale Price		0.880***		47.287***		12.298***
		(0.034)		(4.077)		(3.545)
Density	0.015***		-0.022***		-0.021***	
	(0.003)		(0.001)		(0.005)	
Competition		0.319***		0.969***		0.312***
		(0.007)		(0.067)		(0.039)
PriceReduced	-0.028***	0.476***	-0.019***	1.232***	-0.068***	1.156***

Table 19. 3SLS for Sale Price and TOM with Agent Influence (Eigenvector centrality) by Sale Price Segments (Cont.)

	Below $100,000		*$100,000 - $500,000*		*Above $500,000*	
	Price	**TOM**	**Price**	**Price**	**TOM**	**Price**
	(0.004)	(0.009)	(0.001)	(0.076)	(0.009)	(0.193)
AtypBeds	-0.064**	0.433***	-0.048***	2.318***	0.023*	-0.303*
	(0.024)	(0.067)	(0.002)	(0.207)	(0.009)	(0.138)
AtypBaths	-0.118***	0.291**	0.050***	-2.347***	-0.088***	1.020**
	(0.029)	(0.098)	(0.002)	(0.223)	(0.009)	(0.345)
AtypFirep	-0.041*	0.232***	0.028***	-1.259***	-0.040***	0.480**
	(0.017)	(0.065)	(0.002)	(0.149)	(0.008)	(0.180)
AtypAge	-0.013*	0.040**	0.097***	-4.610***	0.222***	-2.708***
	(0.005)	(0.014)	(0.004)	(0.436)	(0.017)	(0.805)
AtypGar	-0.040	0.114	0.009	-0.343	0.034***	-0.431**
	(0.030)	(0.089)	(0.005)	(0.256)	(0.007)	(0.147)
Bathrooms	0.113***	-0.090***	0.031***	-1.448***	0.260***	-3.188***
	(0.009)	(0.024)	(0.003)	(0.208)	(0.018)	(0.963)
Beds	0.104***	-0.306***	-0.073***	3.378***	-0.347***	4.162**
	(0.012)	(0.034)	(0.004)	(0.364)	(0.042)	(1.338)
SqFt	0.253***	-0.939***	0.613***	-29.051***	0.769***	-8.860**
	(0.011)	(0.052)	(0.003)	(2.526)	(0.027)	(2.902)
Age	-0.098***	0.153***	-0.063***	2.966***	-0.110***	1.357***
	(0.003)	(0.010)	(0.001)	(0.258)	(0.004)	(0.391)
Garages	0.080***	-0.148***	0.085***	-4.049***	-0.048**	0.580*
	(0.003)	(0.010)	(0.002)	(0.354)	(0.016)	(0.252)
Fireplaces	0.039***	-0.071***	0.060***	-2.876***	0.157***	-1.917**
	(0.004)	(0.012)	(0.002)	(0.254)	(0.014)	(0.596)
Photos	0.053***	-0.023***	0.018***	-0.863***	-0.003	0.042
	(0.002)	(0.006)	(0.001)	(0.081)	(0.003)	(0.034)
Acres	0.028	0.284***	0.444***	-20.642***	0.213***	-2.487**
	(0.017)	(0.055)	(0.004)	(1.834)	(0.016)	(0.801)
Pool	0.020***	0.016	0.088***	-4.161***	0.059***	-0.767***
	(0.006)	(0.020)	(0.001)	(0.359)	(0.005)	(0.208)
Tenant	-0.043***	0.136***	-0.055***	2.664***	-0.059***	0.791**
	(0.005)	(0.014)	(0.002)	(0.241)	(0.017)	(0.289)
Vacant	-0.031***	0.016*	-0.033***	1.598***	-0.035***	0.434**

Table 19. 3SLS for Sale Price and TOM with Agent Influence (Eigenvector centrality) by Sale Price Segments (Cont.)

	Below $100,000		*$100,000 - $500,000*		*Above $500,000*	
	Price	**TOM**	**Price**	**Price**	**TOM**	**Price**
	(0.002)	(0.007)	(0.001)	(0.140)	(0.007)	(0.150)
No_HOA	-0.003	-0.043	-0.061***	2.876***	0.008	-0.037
	(0.009)	(0.024)	(0.001)	(0.250)	(0.008)	(0.110)
Vol_HOA	0.076***	-0.122***	0.012***	-0.582***	-0.005	0.063
	(0.013)	(0.037)	(0.002)	(0.105)	(0.012)	(0.151)
Cash	-0.164***	-0.105***	-0.033***	1.477***	0.058***	-0.756***
	(0.004)	(0.012)	(0.001)	(0.152)	(0.006)	(0.213)
Government	0.053***	-0.032***	-0.034***	1.629***	-0.046***	0.570**
	(0.002)	(0.008)	(0.001)	(0.140)	(0.012)	(0.218)
OtherFin	-0.048***	-0.020	-0.001	0.072	0.049**	-0.606*
	(0.008)	(0.023)	(0.003)	(0.151)	(0.018)	(0.280)
Constant	9.440***	omitted	7.375***	-346.849***	6.487***	-81.882***
	(0.092)		(0.020)	(30.091)	(0.200)	(22.055)
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes
N		22,872		179,498		22,872
R-sq	0.58	0.61	0.87	-98.35	0.73	-6.86

Note. This table presents 3SLS results for the full model based on three sale price segments. The dependent variables are the natural log-transformed sale price and TOM. In addition to the standard set of controls in all the regressions, all models include 1-year normalized eigenvector centralities and controls for agent experience, specialization, and active listings inventory.
The sample period is from October 2003 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 20. 3SLS for Sale Price and TOM with Agent Network Size (Degree centrality) and Mispricing

	Mispricing (1)		*With Mispricing (2)*		*Without Mispricing (3)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**
LA_NetSize	0.027***	-0.846***	0.027***	-0.921***	0.053***	-0.456***
	(0.006)	(0.143)	(0.007)	(0.176)	(0.014)	(0.037)
SA_NetSize	0.034***	-0.694***	0.032***	-0.706**	0.049**	0.047
	(0.007)	(0.175)	(0.008)	(0.218)	(0.016)	(0.046)
Mispricing	-0.759***	17.816***				
	(0.058)	(1.472)				
LA_Experience	-0.006***	0.063	-0.004**	0.022	-0.008**	-0.127***
	(0.001)	(0.032)	(0.002)	(0.039)	(0.003)	(0.008)
SA_Experience	-0.014***	0.217***	-0.013***	0.211***	-0.015***	-0.144***
	(0.001)	(0.039)	(0.002)	(0.049)	(0.003)	(0.008)
LA_Experience_M	0.000	-0.017*	0.001	-0.024*	0.001	-0.015***
	(0.000)	(0.008)	(0.000)	(0.010)	(0.001)	(0.002)
SA_Experience_M	0.002***	-0.056***	0.003***	-0.070***	0.002**	-0.002
	(0.000)	(0.007)	(0.000)	(0.009)	(0.001)	(0.002)
ExclList	-0.008**	0.168*	-0.009**	0.210*	-0.009	0.001
	(0.003)	(0.066)	(0.003)	(0.082)	(0.006)	(0.015)
ExclSell	-0.002	0.057	-0.002	0.066	-0.005	0.012
	(0.001)	(0.030)	(0.001)	(0.037)	(0.003)	(0.008)
LA_Inventory	-0.000	0.074***	-0.000	0.078***	-0.003*	0.116***
	(0.001)	(0.015)	(0.001)	(0.019)	(0.001)	(0.004)
SA_Inventory	0.010***	-0.176***	0.009***	-0.180***	0.010***	0.067***
	(0.001)	(0.021)	(0.001)	(0.026)	(0.002)	(0.004)
InHouse	0.007***	-0.175***	0.003	-0.090	0.017***	-0.042***
	(0.002)	(0.045)	(0.002)	(0.056)	(0.004)	(0.011)
Previous	0.019***	-0.420***	0.017***	-0.411***	0.014**	0.007
	(0.002)	(0.055)	(0.002)	(0.068)	(0.005)	(0.012)
TOM	0.014***		0.011***		0.013**	
	(0.002)		(0.002)		(0.004)	
Sale Price		22.838***		24.927***		0.554***
		(1.285)		(1.692)		(0.019)
Density	-0.027***		-0.026***		-0.027***	
	(0.001)		(0.001)		(0.002)	
Competition		0.576***		0.596***		0.293***

Table 20. 3SLS for Sale Price and TOM with Agent Network Size (Degree centrality) and Mispricing (Cont.)

	Mispricing (1)		*With Mispricing (2)*		*Without Mispricing (3)*	
	Price	**TOM**	**Price**	**Price**	**TOM**	**Price**
		(0.025)		(0.032)		(0.005)
PriceReduced	-0.032***	0.974***	-0.033***	1.083***	-0.029***	0.468***
	(0.001)	(0.035)	(0.002)	(0.047)	(0.003)	(0.006)
AtypBeds	-0.043***	1.004***	-0.044***	1.124***	-0.045***	0.172***
	(0.002)	(0.068)	(0.002)	(0.088)	(0.005)	(0.012)
AtypBaths	0.035***	-0.759***	0.033***	-0.797***	0.025***	0.107***
	(0.002)	(0.063)	(0.002)	(0.079)	(0.004)	(0.010)
AtypFirep	0.059***	-1.308***	0.055***	-1.313***	0.058***	0.084***
	(0.002)	(0.092)	(0.002)	(0.113)	(0.006)	(0.012)
AtypAge	0.095***	-2.160***	0.097***	-2.409***	0.098***	-0.056***
	(0.004)	(0.151)	(0.004)	(0.198)	(0.009)	(0.017)
AtypGar	0.092***	-2.034***	0.080***	-1.934***	0.120***	0.063*
	(0.005)	(0.164)	(0.005)	(0.191)	(0.013)	(0.027)
Bathrooms	0.103***	-2.336***	0.110***	-2.711***	0.085***	0.065**
	(0.004)	(0.162)	(0.005)	(0.217)	(0.009)	(0.020)
Beds	-0.108***	2.381***	-0.107***	2.561***	-0.082***	-0.097***
	(0.005)	(0.186)	(0.006)	(0.242)	(0.010)	(0.025)
SqFt	0.661***	-15.117***	0.662***	-16.530***	0.652***	-0.470***
	(0.003)	(0.865)	(0.004)	(1.144)	(0.007)	(0.027)
Age	-0.082***	1.870***	-0.086***	2.141***	-0.081***	0.057***
	(0.001)	(0.107)	(0.001)	(0.146)	(0.002)	(0.005)
Garages	0.104***	-2.415***	0.109***	-2.762***	0.097***	-0.153***
	(0.002)	(0.140)	(0.002)	(0.190)	(0.005)	(0.010)
Fireplaces	0.098***	-2.256***	0.102***	-2.574***	0.092***	-0.129***
	(0.002)	(0.129)	(0.002)	(0.175)	(0.004)	(0.009)
Photos	0.030***	-0.687***	0.035***	-0.869***	0.023***	0.013**
	(0.001)	(0.044)	(0.001)	(0.064)	(0.002)	(0.005)
Acres	0.437***	-9.751***	0.422***	-10.269***	0.450***	0.316***
	(0.004)	(0.577)	(0.005)	(0.735)	(0.011)	(0.026)
Pool	0.091***	-2.090***	0.090***	-2.265***	0.091***	-0.067***
	(0.001)	(0.118)	(0.001)	(0.154)	(0.002)	(0.006)
Tenant	-0.063***	1.503***	-0.068***	1.777***	-0.065***	0.127***

Table 20. 3SLS for Sale Price and TOM with Agent Network Size (Degree centrality) and Mispricing (Cont.)

	Mispricing (1)		*With Mispricing (2)*		*Without Mispricing (3)*	
	Price	**TOM**	**Price**	**Price**	**TOM**	**Price**
	(0.002)	(0.098)	(0.003)	(0.132)	(0.006)	(0.014)
Vacant	-0.042***	0.961***	-0.046***	1.158***	-0.036***	0.032***
	(0.001)	(0.057)	(0.001)	(0.081)	(0.002)	(0.005)
No_HOA	-0.050***	1.138***	-0.051***	1.279***	-0.046***	0.013
	(0.001)	(0.068)	(0.001)	(0.090)	(0.002)	(0.007)
Vol_HOA	0.025***	-0.569***	0.023***	-0.590***	0.034***	-0.049***
	(0.002)	(0.060)	(0.002)	(0.073)	(0.005)	(0.012)
Cash	-0.058***	1.237***	-0.074***	1.771***	-0.051***	-0.160***
	(0.002)	(0.094)	(0.002)	(0.138)	(0.004)	(0.009)
Government	-0.026***	0.621***	-0.019***	0.500***	-0.027***	0.059***
	(0.001)	(0.036)	(0.001)	(0.038)	(0.002)	(0.005)
OtherFin	-0.020***	0.478***	-0.022***	0.552***	-0.019*	0.045*
	(0.004)	(0.091)	(0.004)	(0.113)	(0.009)	(0.022)
Constant	6.927***	-156.732***	6.889***	-170.221***	6.970***	omitted
	(0.024)	(8.957)	(0.027)	(11.712)	(0.052)	
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes
N		22,872		179,498		22,872
R-sq	0.58	0.61	0.87	-96.34	0.73	-6.75

Note. This table presents 3SLS results for the full model and mispricing. The dependent variables are the natural log-transformed sale price and TOM. Besides the standard set of controls I use in all the regressions, all models include 1-year normalized degree centralities and controls for agent experience, specialization, and active listings inventory. Model 1 includes Mispricing, calculated as |(ln(sale price) – ln(list price))|. Model 2 limits the sample to transactions where mispricing was present. Model 3 limits the sample to transactions with no mispricing.
The sample period is from October 2003 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 21. 3SLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) and Mispricing

	Mispricing (1)		*With Mispricing (2)*		*Without Mispricing (3)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**
LA_BPower	0.014*	-0.440***	0.011	-0.410*	0.040**	-0.280***
	(0.006)	(0.133)	(0.006)	(0.163)	(0.013)	(0.035)
SA_BPower	0.020**	-0.357*	0.020*	-0.384	0.029	0.067
	(0.007)	(0.170)	(0.008)	(0.213)	(0.016)	(0.045)
Mispricing	-0.759***	17.924***				
	(0.058)	(1.481)				
LA_Experience	-0.005***	0.016	-0.002	-0.034	-0.006*	-0.150***
	(0.001)	(0.031)	(0.001)	(0.037)	(0.003)	(0.008)
SA_Experience	-0.012***	0.172***	-0.011***	0.167***	-0.013***	-0.144***
	(0.001)	(0.036)	(0.002)	(0.045)	(0.003)	(0.008)
LA_Experience_M	0.000	-0.020*	0.001	-0.027**	0.001	-0.016***
	(0.000)	(0.008)	(0.000)	(0.010)	(0.001)	(0.002)
SA_Experience_M	0.003***	-0.058***	0.003***	-0.072***	0.002**	-0.002
	(0.000)	(0.007)	(0.000)	(0.009)	(0.001)	(0.002)
ExclList	-0.007**	0.160*	-0.008**	0.199*	-0.009	-0.003
	(0.003)	(0.067)	(0.003)	(0.082)	(0.006)	(0.015)
ExclSell	-0.002	0.054	-0.002	0.063	-0.004	0.012
	(0.001)	(0.030)	(0.001)	(0.038)	(0.003)	(0.008)
LA_Inventory	0.000	0.057***	0.000	0.059**	-0.002	0.108***
	(0.001)	(0.015)	(0.001)	(0.018)	(0.001)	(0.004)
SA_Inventory	0.010***	-0.186***	0.010***	-0.190***	0.011***	0.068***
	(0.001)	(0.021)	(0.001)	(0.026)	(0.001)	(0.004)
InHouse	0.007***	-0.175***	0.003	-0.089	0.017***	-0.042***
	(0.002)	(0.046)	(0.002)	(0.056)	(0.004)	(0.011)
Previous	0.019***	-0.436***	0.017***	-0.429***	0.014**	0.003
	(0.002)	(0.055)	(0.002)	(0.068)	(0.005)	(0.012)
TOM	0.013***		0.011***		0.013**	
	(0.002)		(0.002)		(0.004)	
Sale Price		22.971***		25.105***		0.556***
		(1.297)		(1.711)		(0.019)
Density	-0.027***		-0.026***		-0.027***	
	(0.001)		(0.001)		(0.002)	
Competition		0.579***		0.599***		0.294***

Table 21. 3SLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) and Mispricing (Cont.)

	Mispricing (1)		*With Mispricing (2)*		*Without Mispricing (3)*	
	Price	**TOM**	**Price**	**Price**	**TOM**	**Price**
		(0.025)		(0.032)		(0.005)
PriceReduced	-0.032***	0.979***	-0.033***	1.091***	-0.029***	0.469***
	(0.001)	(0.035)	(0.002)	(0.048)	(0.003)	(0.006)
AtypBeds	-0.043***	1.009***	-0.044***	1.131***	-0.045***	0.173***
	(0.002)	(0.068)	(0.002)	(0.088)	(0.005)	(0.012)
AtypBaths	0.035***	-0.763***	0.033***	-0.802***	0.025***	0.107***
	(0.002)	(0.063)	(0.002)	(0.079)	(0.004)	(0.010)
AtypFirep	0.059***	-1.315***	0.055***	-1.323***	0.058***	0.085***
	(0.002)	(0.093)	(0.002)	(0.114)	(0.006)	(0.012)
AtypAge	0.095***	-2.173***	0.097***	-2.427***	0.098***	-0.057***
	(0.004)	(0.153)	(0.004)	(0.200)	(0.009)	(0.017)
AtypGar	0.092***	-2.044***	0.080***	-1.946***	0.120***	0.062*
	(0.005)	(0.166)	(0.005)	(0.193)	(0.013)	(0.027)
Bathrooms	0.103***	-2.350***	0.110***	-2.731***	0.085***	0.064**
	(0.004)	(0.163)	(0.005)	(0.219)	(0.009)	(0.020)
Beds	-0.108***	2.394***	-0.107***	2.579***	-0.082***	-0.098***
	(0.005)	(0.187)	(0.006)	(0.244)	(0.010)	(0.025)
SqFt	0.661***	-15.205***	0.662***	-16.648***	0.652***	-0.472***
	(0.003)	(0.873)	(0.004)	(1.157)	(0.007)	(0.027)
Age	-0.082***	1.882***	-0.086***	2.158***	-0.081***	0.057***
	(0.001)	(0.108)	(0.001)	(0.148)	(0.002)	(0.005)
Garages	0.104***	-2.429***	0.109***	-2.781***	0.097***	-0.153***
	(0.002)	(0.141)	(0.002)	(0.192)	(0.005)	(0.010)
Fireplaces	0.098***	-2.268***	0.102***	-2.591***	0.092***	-0.129***
	(0.002)	(0.131)	(0.002)	(0.177)	(0.004)	(0.009)
Photos	0.030***	-0.692***	0.035***	-0.876***	0.023***	0.012*
	(0.001)	(0.045)	(0.001)	(0.065)	(0.002)	(0.005)
Acres	0.437***	-9.808***	0.422***	-10.341***	0.450***	0.316***
	(0.004)	(0.582)	(0.005)	(0.743)	(0.011)	(0.026)
Pool	0.091***	-2.102***	0.090***	-2.281***	0.091***	-0.067***
	(0.001)	(0.119)	(0.001)	(0.156)	(0.002)	(0.007)
Tenant	-0.063***	1.514***	-0.069***	1.792***	-0.065***	0.128***

Table 21. 3SLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) and Mispricing (Cont.)

	Mispricing (1)		*With Mispricing (2)*		*Without Mispricing (3)*	
	Price	**TOM**	**Price**	**Price**	**TOM**	**Price**
	(0.002)	(0.098)	(0.003)	(0.133)	(0.006)	(0.014)
Vacant	-0.042***	0.967***	-0.046***	1.167***	-0.036***	0.032***
	(0.001)	(0.058)	(0.001)	(0.082)	(0.002)	(0.005)
No_HOA	-0.050***	1.145***	-0.051***	1.288***	-0.046***	0.013*
	(0.001)	(0.069)	(0.001)	(0.091)	(0.002)	(0.007)
Vol_HOA	0.025***	-0.572***	0.023***	-0.594***	0.034***	-0.049***
	(0.002)	(0.060)	(0.002)	(0.073)	(0.005)	(0.012)
Cash	-0.057***	1.244***	-0.074***	1.783***	-0.051***	-0.159***
	(0.002)	(0.095)	(0.002)	(0.139)	(0.004)	(0.009)
Government	-0.026***	0.624***	-0.019***	0.503***	-0.027***	0.059***
	(0.001)	(0.037)	(0.001)	(0.039)	(0.002)	(0.005)
OtherFin	-0.020***	0.482***	-0.022***	0.558***	-0.019*	0.046*
	(0.004)	(0.091)	(0.004)	(0.114)	(0.009)	(0.022)
Constant	6.926***	-157.610***	6.888***	-171.397***	6.969***	omitted
	(0.024)	(9.036)	(0.027)	(11.841)	(0.052)	
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes
N		22,872		179,498		22,872
R-sq	0.58	0.61	0.87	-96.34	0.73	-6.75

Note. This table presents 3SLS results for the full model and mispricing. The dependent variables are the natural log-transformed sale price and TOM. Besides the standard set of controls I use in all the regressions, all models include 1-year normalized betweenness centralities and controls for agent experience, specialization, and active listings inventory. Model 1 includes Mispricing, calculated as |(ln(sale price) – ln(list price))|. Model 2 limits the sample to transactions where mispricing was present. Model 3 limits the sample to transactions with no mispricing.
The sample period is from October 2003 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 22. 3SLS for Sale Price and TOM with Agent Influence (Eigenvector centrality) and Mispricing

	Mispricing (1)		*With Mispricing (2)*		*Without Mispricing (3)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**
LA_Influence	-0.096***	1.706***	-0.095***	1.839**	-0.040	-0.914***
	(0.019)	(0.462)	(0.021)	(0.576)	(0.042)	(0.116)
SA_Influence	-0.184***	4.539***	-0.189***	5.080***	-0.142**	0.486***
	(0.024)	(0.597)	(0.027)	(0.759)	(0.052)	(0.139)
Mispricing	-0.759***	18.052***				
	(0.058)	(1.495)				
LA_Experience	-0.001	-0.061*	0.001	-0.113**	-0.002	-0.147***
	(0.001)	(0.031)	(0.002)	(0.037)	(0.003)	(0.008)
SA_Experience	-0.005**	0.008	-0.004*	-0.016	-0.006	-0.153***
	(0.001)	(0.034)	(0.002)	(0.042)	(0.003)	(0.008)
LA_Experience_M	0.001	-0.021**	0.001	-0.029**	0.001	-0.016***
	(0.000)	(0.008)	(0.000)	(0.010)	(0.001)	(0.002)
SA_Experience_M	0.003***	-0.063***	0.003***	-0.078***	0.002***	-0.002
	(0.000)	(0.007)	(0.000)	(0.010)	(0.001)	(0.002)
ExclList	-0.007*	0.144*	-0.008*	0.183*	-0.008	-0.004
	(0.003)	(0.067)	(0.003)	(0.083)	(0.006)	(0.015)
ExclSell	-0.001	0.036	-0.001	0.043	-0.004	0.011
	(0.001)	(0.030)	(0.001)	(0.038)	(0.003)	(0.008)
LA_Inventory	0.001	0.038*	0.001	0.040*	-0.001	0.109***
	(0.001)	(0.015)	(0.001)	(0.019)	(0.001)	(0.004)
SA_Inventory	0.011***	-0.211***	0.011***	-0.217***	0.012***	0.066***
	(0.001)	(0.022)	(0.001)	(0.028)	(0.001)	(0.004)
InHouse	0.007***	-0.164***	0.003	-0.077	0.016***	-0.041***
	(0.002)	(0.046)	(0.002)	(0.056)	(0.004)	(0.011)
Previous	0.021***	-0.475***	0.019***	-0.467***	0.017***	-0.000
	(0.002)	(0.057)	(0.002)	(0.070)	(0.005)	(0.012)
TOM	0.013***		0.011***		0.012**	
	(0.002)		(0.002)		(0.004)	
Sale Price		23.127***		25.280***		0.558***
		(1.314)		(1.735)		(0.019)
Density	-0.027***		-0.025***		-0.027***	
	(0.001)		(0.001)		(0.002)	
Competition		0.580***		0.601***		0.294***

Table 22. 3SLS for Sale Price and TOM with Agent Influence (Eigenvector centrality) and Mispricing (Cont.)

	Mispricing (1)		*With Mispricing (2)*		*Without Mispricing (3)*	
	Price	**TOM**	**Price**	**Price**	**TOM**	**Price**
		(0.025)		(0.032)		(0.005)
PriceReduced	-0.032***	0.984***	-0.033***	1.097***	-0.029***	0.469***
	(0.001)	(0.036)	(0.002)	(0.048)	(0.003)	(0.006)
AtypBeds	-0.043***	1.015***	-0.044***	1.137***	-0.045***	0.173***
	(0.002)	(0.069)	(0.002)	(0.089)	(0.005)	(0.012)
AtypBaths	0.035***	-0.768***	0.033***	-0.807***	0.025***	0.107***
	(0.002)	(0.064)	(0.002)	(0.080)	(0.004)	(0.010)
AtypFirep	0.059***	-1.325***	0.055***	-1.333***	0.058***	0.084***
	(0.002)	(0.094)	(0.002)	(0.115)	(0.006)	(0.012)
AtypAge	0.095***	-2.187***	0.097***	-2.442***	0.098***	-0.057***
	(0.004)	(0.154)	(0.004)	(0.202)	(0.009)	(0.017)
AtypGar	0.092***	-2.053***	0.080***	-1.954***	0.120***	0.061*
	(0.005)	(0.167)	(0.005)	(0.195)	(0.013)	(0.027)
Bathrooms	0.103***	-2.366***	0.110***	-2.751***	0.085***	0.065**
	(0.004)	(0.165)	(0.005)	(0.222)	(0.009)	(0.020)
Beds	-0.108***	2.406***	-0.107***	2.593***	-0.081***	-0.098***
	(0.005)	(0.189)	(0.006)	(0.246)	(0.010)	(0.025)
SqFt	0.661***	-15.304***	0.662***	-16.760***	0.651***	-0.473***
	(0.003)	(0.884)	(0.004)	(1.173)	(0.007)	(0.027)
Age	-0.082***	1.899***	-0.086***	2.177***	-0.081***	0.057***
	(0.001)	(0.110)	(0.001)	(0.150)	(0.002)	(0.005)
Garages	0.104***	-2.444***	0.109***	-2.800***	0.097***	-0.152***
	(0.002)	(0.143)	(0.002)	(0.195)	(0.005)	(0.010)
Fireplaces	0.098***	-2.279***	0.102***	-2.604***	0.092***	-0.130***
	(0.002)	(0.132)	(0.002)	(0.179)	(0.004)	(0.009)
Photos	0.030***	-0.700***	0.035***	-0.886***	0.023***	0.013**
	(0.001)	(0.046)	(0.001)	(0.066)	(0.002)	(0.005)
Acres	0.437***	-9.876***	0.421***	-10.414***	0.450***	0.315***
	(0.004)	(0.589)	(0.005)	(0.753)	(0.011)	(0.026)
Pool	0.091***	-2.116***	0.090***	-2.296***	0.091***	-0.067***
	(0.001)	(0.120)	(0.001)	(0.158)	(0.002)	(0.006)

Table 22. 3SLS for Sale Price and TOM with Agent Influence (Eigenvector centrality) and Mispricing (Cont.)

	Mispricing (1)		*With Mispricing (2)*		*Without Mispricing (3)*	
	Price	**TOM**	**Price**	**Price**	**TOM**	**Price**
Tenant	-0.063***	1.527***	-0.069***	1.807***	-0.065***	0.128***
	(0.002)	(0.100)	(0.003)	(0.135)	(0.006)	(0.014)
Vacant	-0.042***	0.974***	-0.046***	1.175***	-0.036***	0.032***
	(0.001)	(0.059)	(0.001)	(0.083)	(0.002)	(0.005)
No_HOA	-0.050***	1.153***	-0.051***	1.297***	-0.046***	0.014*
	(0.001)	(0.069)	(0.001)	(0.092)	(0.002)	(0.007)
Vol_HOA	0.024***	-0.575***	0.023***	-0.598***	0.034***	-0.049***
	(0.002)	(0.061)	(0.002)	(0.074)	(0.005)	(0.012)
Cash	-0.057***	1.252***	-0.074***	1.794***	-0.051***	-0.159***
	(0.002)	(0.096)	(0.002)	(0.141)	(0.004)	(0.009)
Government	-0.026***	0.625***	-0.019***	0.505***	-0.027***	0.059***
	(0.001)	(0.037)	(0.001)	(0.039)	(0.002)	(0.005)
OtherFin	-0.021***	0.488***	-0.022***	0.564***	-0.019*	0.047*
	(0.004)	(0.092)	(0.004)	(0.115)	(0.009)	(0.022)
Constant	6.922***	-158.599***	6.884***	-172.510***	6.964***	omitted
	(0.024)	(9.152)	(0.027)	(11.999)	(0.052)	
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes
N		22,872		179,498		22,872
R-sq	0.58	0.61	0.87	-96.34	0.73	-6.75

Note. This table presents 3SLS results for the full model and mispricing. The dependent variables are the natural log-transformed sale price and TOM. Besides the standard set of controls I use in all the regressions, all models include 1-year normalized eigenvector centralities and controls for agent experience, specialization, and active listings inventory. Model 1 includes Mispricing, calculated as |(ln(sale price) – ln(list price))|. Model 2 limits the sample to transactions where mispricing was present. Model 3 limits the sample to transactions with no mispricing.
The sample period is from October 2003 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 23. 3SLS for Sale Price and TOM with Agent Network Size (3-year Degree Centrality)

	(1)		(2)		(3)		(4)	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
LA_NetSize_3y	0.006	-0.227*	0.024***	-0.661***	0.026***	-0.707***	0.024***	-0.843***
	(0.004)	(0.106)	(0.006)	(0.186)	(0.006)	(0.187)	(0.006)	(0.192)
SA_NetSize_3y	0.057***	-1.662***	0.069***	-1.765***	0.070***	-1.805***	0.041***	-1.133***
	(0.005)	(0.179)	(0.008)	(0.268)	(0.008)	(0.269)	(0.008)	(0.251)
LA_Experience			-0.005***	0.129***	-0.005***	0.139***	-0.006***	0.058
			(0.001)	(0.037)	(0.001)	(0.038)	(0.002)	(0.046)
SA_Experience			-0.008***	0.172***	-0.009***	0.183***	-0.014***	0.314***
			(0.002)	(0.048)	(0.002)	(0.048)	(0.002)	(0.057)
LA_Experience_M			0.001	-0.020*	0.000	-0.011	0.000	-0.017
			(0.000)	(0.009)	(0.000)	(0.010)	(0.000)	(0.010)
SA_Experience_M			0.003***	-0.085***	0.003***	-0.073***	0.002***	-0.065***
			(0.000)	(0.010)	(0.000)	(0.010)	(0.000)	(0.010)
ExclList					-0.007*	0.212*	-0.007*	0.199*
					(0.003)	(0.087)	(0.003)	(0.088)
ExclSell					-0.005***	0.149***	-0.003*	0.109**
					(0.001)	(0.041)	(0.001)	(0.041)
LA_Inventory							0.000	0.066***
							(0.001)	(0.020)
SA_Inventory							0.009***	-0.204***
							(0.001)	(0.029)
InHouse	0.007***	-0.208***	0.008***	-0.226***	0.008***	-0.222***	0.007***	-0.216***
	(0.002)	(0.062)	(0.002)	(0.063)	(0.002)	(0.063)	(0.002)	(0.063)
Previous	0.018***	-0.506***	0.017***	-0.490***	0.018***	-0.496***	0.018***	-0.509***
	(0.002)	(0.074)	(0.002)	(0.075)	(0.002)	(0.075)	(0.002)	(0.077)
TOM	0.010***		0.009***		0.009***		0.008***	
	(0.002)		(0.002)		(0.002)		(0.002)	
Sale Price		28.433***		28.681***		28.655***		28.900***
		(1.984)		(2.025)		(2.021)		(2.140)
Density	-0.024***		-0.023***		-0.023***		-0.023***	
	(0.001)		(0.001)		(0.001)		(0.001)	
Competition		0.626***		0.630***		0.629***		0.635***
		(0.034)		(0.034)		(0.034)		(0.037)
PriceReduced	-0.031***	1.145***	-0.031***	1.152***	-0.031***	1.152***	-0.031***	1.167***

Table 23. 3SLS for Sale Price and TOM with Agent Network Size (3-year Degree Centrality) (Cont.)

	(1)		*(2)*		*(3)*		*(4)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.002)	(0.051)	(0.002)	(0.052)	(0.002)	(0.052)	(0.002)	(0.056)
AtypBeds	-0.044***	1.285***	-0.044***	1.295***	-0.044***	1.294***	-0.044***	1.303***
	(0.002)	(0.099)	(0.002)	(0.100)	(0.002)	(0.100)	(0.002)	(0.105)
AtypBaths	0.032***	-0.863***	0.031***	-0.865***	0.031***	-0.864***	0.031***	-0.867***
	(0.002)	(0.085)	(0.002)	(0.086)	(0.002)	(0.086)	(0.002)	(0.089)
AtypFirep	0.054***	-1.491***	0.054***	-1.508***	0.054***	-1.507***	0.054***	-1.521***
	(0.002)	(0.129)	(0.002)	(0.131)	(0.002)	(0.131)	(0.002)	(0.137)
AtypAge	0.092***	-2.604***	0.092***	-2.629***	0.092***	-2.626***	0.092***	-2.644***
	(0.004)	(0.217)	(0.004)	(0.221)	(0.004)	(0.221)	(0.004)	(0.230)
AtypGar	0.085***	-2.335***	0.085***	-2.356***	0.085***	-2.354***	0.085***	-2.379***
	(0.005)	(0.226)	(0.005)	(0.230)	(0.005)	(0.229)	(0.005)	(0.238)
Bathrooms	0.103***	-2.896***	0.103***	-2.936***	0.103***	-2.934***	0.104***	-2.969***
	(0.004)	(0.239)	(0.004)	(0.244)	(0.004)	(0.244)	(0.004)	(0.256)
Beds	-0.104***	2.862***	-0.104***	2.872***	-0.104***	2.868***	-0.103***	2.880***
	(0.005)	(0.265)	(0.005)	(0.268)	(0.005)	(0.267)	(0.005)	(0.277)
SqFt	0.652***	-18.574***	0.652***	-18.721***	0.652***	-18.703***	0.651***	-18.843***
	(0.003)	(1.311)	(0.003)	(1.337)	(0.003)	(1.335)	(0.003)	(1.410)
Age	-0.088***	2.495***	-0.088***	2.520***	-0.088***	2.518***	-0.088***	2.542***
	(0.001)	(0.175)	(0.001)	(0.179)	(0.001)	(0.179)	(0.001)	(0.189)
Garages	0.105***	-3.026***	0.104***	-3.045***	0.104***	-3.042***	0.104***	-3.067***
	(0.002)	(0.213)	(0.002)	(0.217)	(0.002)	(0.216)	(0.002)	(0.229)
Fireplaces	0.101***	-2.909***	0.101***	-2.927***	0.101***	-2.924***	0.101***	-2.945***
	(0.002)	(0.203)	(0.002)	(0.207)	(0.002)	(0.207)	(0.002)	(0.218)
Photos	0.033***	-0.937***	0.033***	-0.947***	0.033***	-0.945***	0.033***	-0.952***
	(0.001)	(0.070)	(0.001)	(0.072)	(0.001)	(0.071)	(0.001)	(0.075)
Acres	0.467***	-12.993***	0.466***	-13.081***	0.466***	-13.069***	0.465***	-13.160***
	(0.005)	(0.952)	(0.005)	(0.969)	(0.005)	(0.967)	(0.005)	(1.019)
Pool	0.090***	-2.579***	0.090***	-2.602***	0.090***	-2.599***	0.090***	-2.619***
	(0.001)	(0.180)	(0.001)	(0.184)	(0.001)	(0.183)	(0.001)	(0.194)
Tenant	-0.069***	2.023***	-0.068***	2.038***	-0.068***	2.033***	-0.068***	2.039***
	(0.003)	(0.150)	(0.003)	(0.152)	(0.003)	(0.152)	(0.003)	(0.159)
Vacant	-0.044***	1.265***	-0.044***	1.270***	-0.044***	1.266***	-0.044***	1.272***

Table 23. 3SLS for Sale Price and TOM with Agent Network Size (3-year Degree Centrality) (Cont.)

	(1)		*(2)*		*(3)*		*(4)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.001)	(0.090)	(0.001)	(0.091)	(0.001)	(0.091)	(0.001)	(0.096)
No_HOA	-0.052***	1.471***	-0.051***	1.476***	-0.051***	1.473***	-0.051***	1.481***
	(0.001)	(0.107)	(0.001)	(0.108)	(0.001)	(0.108)	(0.001)	(0.113)
Vol_HOA	0.027***	-0.788***	0.027***	-0.795***	0.027***	-0.796***	0.027***	-0.803***
	(0.002)	(0.086)	(0.002)	(0.087)	(0.002)	(0.087)	(0.002)	(0.090)
Cash	-0.075***	2.054***	-0.075***	2.057***	-0.074***	2.049***	-0.074***	2.047***
	(0.002)	(0.163)	(0.002)	(0.165)	(0.002)	(0.164)	(0.002)	(0.171)
Government	-0.022***	0.655***	-0.022***	0.656***	-0.022***	0.657***	-0.022***	0.664***
	(0.001)	(0.048)	(0.001)	(0.049)	(0.001)	(0.049)	(0.001)	(0.051)
OtherFin	-0.026***	0.759***	-0.026***	0.760***	-0.026***	0.757***	-0.026***	0.759***
	(0.004)	(0.130)	(0.004)	(0.132)	(0.004)	(0.131)	(0.004)	(0.133)
Constant	7.068***	-199.459***	7.068***	-201.168***	7.071***	-201.067***	7.084***	-203.032***
	(0.024)	(14.099)	(0.024)	(14.392)	(0.024)	(14.371)	(0.024)	(15.235)
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		194,662		194,662		194,662		194,662
R-sq	0.89	-53.56	0.89	-54.47	0.89	-54.36	0.89	-55.27
AIC		-121,806		-118,960		-119,506		-110,428
BIC		-115,841		-112,924		-113,419		-104,301

Note. This table presents 3SLS results for four models. The dependent variables are the natural log-transformed sale price and TOM. Besides the standard set of controls in all the regressions, Model 1 includes 3-year normalized degree centralities of agents. Model 2 includes 3-year normalized degree centralities and controls for agent experience. Model 3 includes 3-year normalized degree centralities and controls for agent experience and specialization. Model 4 includes 3-year normalized degree centralities and controls for agent experience, specialization, and active listings inventory.
The sample period is from October 2005 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 24. 3SLS for Sale Price and TOM with Agent Bridging Power (3-year Betweenness Centrality)

	(1)		*(2)*		*(3)*		*(4)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
LA_BPower_3y	0.002	-0.101	0.011	-0.300	0.012	-0.332	0.011	-0.391*
	(0.005)	(0.137)	(0.007)	(0.193)	(0.007)	(0.193)	(0.007)	(0.198)
SA_BPower_3y	0.046***	-1.382***	0.036***	-0.847**	0.038***	-0.894***	0.010	-0.252
	(0.007)	(0.213)	(0.009)	(0.269)	(0.009)	(0.270)	(0.009)	(0.268)
LA_Experience			-0.003*	0.058	-0.003*	0.064*	-0.004*	-0.012
			(0.001)	(0.031)	(0.001)	(0.031)	(0.001)	(0.043)
SA_Experience			-0.002	0.006	-0.002	0.016	-0.010***	0.206***
			(0.001)	(0.038)	(0.001)	(0.039)	(0.001)	(0.050)
LA_Experience_M			0.001*	-0.026**	0.001	-0.018	0.000	-0.024*
			(0.000)	(0.009)	(0.000)	(0.010)	(0.000)	(0.010)
SA_Experience_M			0.003***	-0.096***	0.003***	-0.084***	0.002***	-0.072***
			(0.000)	(0.010)	(0.000)	(0.010)	(0.000)	(0.010)
ExclList					-0.007*	0.191*	-0.007*	0.179*
					(0.003)	(0.086)	(0.003)	(0.088)
ExclSell					-0.005***	0.140***	-0.003*	0.098*
					(0.001)	(0.041)	(0.001)	(0.041)
LA_Inventory							0.001	0.053**
							(0.001)	(0.020)
SA_Inventory							0.009***	-0.226***
							(0.001)	(0.030)
InHouse	0.007***	-0.210***	0.008***	-0.224***	0.008***	-0.220***	0.007***	-0.214***
	(0.002)	(0.062)	(0.002)	(0.062)	(0.002)	(0.062)	(0.002)	(0.063)
Previous	0.020***	-0.577***	0.019***	-0.520***	0.019***	-0.525***	0.019***	-0.539***
	(0.002)	(0.076)	(0.002)	(0.076)	(0.002)	(0.076)	(0.002)	(0.078)
TOM	0.009***		0.009***		0.009***		0.008***	
	(0.002)		(0.002)		(0.002)		(0.002)	
Sale Price		28.511***		28.584***		28.558***		29.015***
		(1.994)		(2.010)		(2.007)		(2.154)
Density	-0.024***		-0.023***		-0.023***		-0.023***	
	(0.001)		(0.001)		(0.001)		(0.001)	
Competition		0.628***		0.628***		0.627***		0.637***
		(0.034)		(0.034)		(0.034)		(0.037)
PriceReduced	-0.031***	1.150***	-0.030***	1.147***	-0.031***	1.147***	-0.031***	1.172***

Table 24. 3SLS for Sale Price and TOM with Agent Bridging Power (3-year Betweenness Centrality) (Cont.)

	(1)		*(2)*		*(3)*		*(4)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.002)	(0.051)	(0.002)	(0.051)	(0.002)	(0.051)	(0.002)	(0.057)
AtypBeds	-0.044***	1.292***	-0.044***	1.292***	-0.044***	1.290***	-0.044***	1.309***
	(0.002)	(0.099)	(0.002)	(0.100)	(0.002)	(0.100)	(0.002)	(0.106)
AtypBaths	0.032***	-0.868***	0.032***	-0.864***	0.032***	-0.862***	0.031***	-0.871***
	(0.002)	(0.086)	(0.002)	(0.086)	(0.002)	(0.086)	(0.002)	(0.089)
AtypFirep	0.054***	-1.495***	0.054***	-1.503***	0.054***	-1.502***	0.054***	-1.527***
	(0.002)	(0.129)	(0.002)	(0.130)	(0.002)	(0.130)	(0.002)	(0.138)
AtypAge	0.092***	-2.608***	0.092***	-2.621***	0.092***	-2.618***	0.092***	-2.655***
	(0.004)	(0.218)	(0.004)	(0.220)	(0.004)	(0.220)	(0.004)	(0.231)
AtypGar	0.085***	-2.339***	0.085***	-2.346***	0.085***	-2.344***	0.085***	-2.387***
	(0.005)	(0.227)	(0.005)	(0.228)	(0.005)	(0.228)	(0.005)	(0.239)
Bathrooms	0.103***	-2.903***	0.103***	-2.924***	0.103***	-2.923***	0.104***	-2.980***
	(0.004)	(0.240)	(0.004)	(0.243)	(0.004)	(0.242)	(0.004)	(0.257)
Beds	-0.104***	2.867***	-0.104***	2.862***	-0.104***	2.857***	-0.103***	2.890***
	(0.005)	(0.266)	(0.005)	(0.266)	(0.005)	(0.266)	(0.005)	(0.279)
SqFt	0.652***	-18.628***	0.652***	-18.661***	0.652***	-18.644***	0.651***	-18.919***
	(0.003)	(1.318)	(0.003)	(1.328)	(0.003)	(1.326)	(0.003)	(1.419)
Age	-0.088***	2.502***	-0.088***	2.512***	-0.088***	2.511***	-0.088***	2.553***
	(0.001)	(0.176)	(0.001)	(0.178)	(0.001)	(0.177)	(0.001)	(0.190)
Garages	0.105***	-3.037***	0.104***	-3.034***	0.104***	-3.031***	0.104***	-3.079***
	(0.002)	(0.214)	(0.002)	(0.215)	(0.002)	(0.215)	(0.002)	(0.230)
Fireplaces	0.101***	-2.917***	0.101***	-2.917***	0.101***	-2.914***	0.101***	-2.956***
	(0.002)	(0.204)	(0.002)	(0.205)	(0.002)	(0.205)	(0.002)	(0.219)
Photos	0.033***	-0.942***	0.033***	-0.945***	0.033***	-0.943***	0.033***	-0.957***
	(0.001)	(0.071)	(0.001)	(0.071)	(0.001)	(0.071)	(0.001)	(0.076)
Acres	0.467***	-13.034***	0.466***	-13.043***	0.466***	-13.032***	0.465***	-13.216***
	(0.005)	(0.957)	(0.005)	(0.963)	(0.005)	(0.961)	(0.005)	(1.026)
Pool	0.090***	-2.586***	0.090***	-2.594***	0.090***	-2.591***	0.090***	-2.629***
	(0.001)	(0.181)	(0.001)	(0.183)	(0.001)	(0.182)	(0.001)	(0.195)
Tenant	-0.069***	2.032***	-0.069***	2.033***	-0.068***	2.029***	-0.068***	2.049***
	(0.003)	(0.151)	(0.003)	(0.152)	(0.003)	(0.151)	(0.003)	(0.160)
Vacant	-0.044***	1.270***	-0.044***	1.267***	-0.044***	1.264***	-0.044***	1.280***

Table 24. 3SLS for Sale Price and TOM with Agent Bridging Power (3-year Betweenness Centrality) (Cont.)

	(1)		*(2)*		*(3)*		*(4)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.001)	(0.091)	(0.001)	(0.091)	(0.001)	(0.091)	(0.001)	(0.097)
No_HOA	-0.052***	1.477***	-0.051***	1.473***	-0.051***	1.470***	-0.051***	1.488***
	(0.001)	(0.107)	(0.001)	(0.108)	(0.001)	(0.107)	(0.001)	(0.114)
Vol_HOA	0.027***	-0.788***	0.027***	-0.792***	0.027***	-0.792***	0.027***	-0.806***
	(0.002)	(0.087)	(0.002)	(0.087)	(0.002)	(0.087)	(0.002)	(0.090)
Cash	-0.075***	2.058***	-0.075***	2.057***	-0.075***	2.050***	-0.074***	2.060***
	(0.002)	(0.164)	(0.002)	(0.164)	(0.002)	(0.164)	(0.002)	(0.172)
Government	-0.022***	0.662***	-0.022***	0.654***	-0.022***	0.655***	-0.022***	0.666***
	(0.001)	(0.049)	(0.001)	(0.049)	(0.001)	(0.049)	(0.001)	(0.052)
OtherFin	-0.026***	0.766***	-0.026***	0.762***	-0.026***	0.759***	-0.026***	0.765***
	(0.004)	(0.131)	(0.004)	(0.131)	(0.004)	(0.131)	(0.004)	(0.134)
Constant	7.069***	-200.033***	7.065***	-200.396***	7.068***	-200.293***	7.083***	-203.799***
	(0.024)	(14.099)	(0.024)	(14.392)	(0.024)	(14.371)	(0.024)	(15.235)
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		194,662		194,662		194,662		194,662
R-sq	0.89	-53.88	0.89	-54.11	0.89	-54.01	0.89	-55.73
AIC		-120,722		-120,640		-121,166		-109,380
BIC		-114,767		-114,594		-115,079		-103,263

Note. This table presents 3SLS results for four models. The dependent variables are the natural log-transformed sale price and TOM. Besides the standard set of controls in all the regressions, Model 1 includes 3-year normalized betweenness centralities of agents. Model 2 includes 3-year normalized betweenness centralities and controls for agent experience. Model 3 includes 3-year normalized betweenness centralities and controls for agent experience and specialization. Model 4 includes 3-year normalized betweenness centralities and controls for agent experience, specialization, and active listings inventory.
The sample period is from October 2005 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table 25. 3SLS for Sale Price and TOM with Agent Influence (3-year Eigenvector Centrality)

	(1)		*(2)*		*(3)*		*(4)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
LA_Influence_3y	-0.041**	0.979*	-0.086***	2.484***	-0.083***	2.383***	-0.091***	2.222**
	(0.013)	(0.393)	(0.022)	(0.656)	(0.022)	(0.657)	(0.023)	(0.701)
SA_Influence_3y	0.072***	-2.251***	-0.066*	2.550**	-0.062*	2.443**	-0.174***	5.280***
	(0.017)	(0.515)	(0.027)	(0.778)	(0.027)	(0.777)	(0.028)	(0.904)
LA_Experience			0.002	-0.074*	0.002	-0.068	0.001	-0.123**
			(0.001)	(0.035)	(0.001)	(0.036)	(0.002)	(0.044)
SA_Experience			0.003*	-0.159***	0.003*	-0.150***	-0.004**	0.026
			(0.002)	(0.043)	(0.002)	(0.043)	(0.002)	(0.048)
LA_Experience_M			0.001**	-0.034***	0.001*	-0.027**	0.001*	-0.031**
			(0.000)	(0.010)	(0.000)	(0.010)	(0.000)	(0.010)
SA_Experience_M			0.004***	-0.102***	0.003***	-0.091***	0.003***	-0.083***
			(0.000)	(0.010)	(0.000)	(0.010)	(0.000)	(0.010)
ExclList					-0.006	0.159	-0.006	0.151
					(0.003)	(0.086)	(0.003)	(0.088)
ExclSell					-0.005**	0.130**	-0.002	0.081*
					(0.001)	(0.041)	(0.001)	(0.041)
LA_Inventory							0.001	0.040
							(0.001)	(0.020)
SA_Inventory							0.011***	-0.260***
							(0.001)	(0.033)
InHouse	0.007***	-0.208***	0.007***	-0.217***	0.007***	-0.213***	0.007**	-0.207**
	(0.002)	(0.062)	(0.002)	(0.062)	(0.002)	(0.062)	(0.002)	(0.063)
Previous	0.022***	-0.625***	0.020***	-0.561***	0.020***	-0.566***	0.021***	-0.589***
	(0.002)	(0.079)	(0.002)	(0.077)	(0.002)	(0.077)	(0.002)	(0.081)
TOM	0.009***		0.010***		0.010***		0.008***	
	(0.002)		(0.002)		(0.002)		(0.002)	
Sale Price		28.612***		28.533***		28.510***		29.168***
		(2.009)		(2.004)		(2.000)		(2.177)
Density	-0.023***		-0.023***		-0.023***		-0.023***	
	(0.001)		(0.001)		(0.001)		(0.001)	
Competition		0.629***		0.625***		0.624***		0.639***
		(0.034)		(0.034)		(0.034)		(0.037)
PriceReduced	-0.031***	1.154***	-0.030***	1.142***	-0.030***	1.142***	-0.031***	1.175***

Table 25. 3SLS for Sale Price and TOM with Agent Influence (3-year Eigenvector Centrality) (Cont.)

	(1)		*(2)*		*(3)*		*(4)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.002)	(0.052)	(0.002)	(0.051)	(0.002)	(0.051)	(0.002)	(0.057)
AtypBeds	-0.044***	1.297***	-0.044***	1.288***	-0.044***	1.287***	-0.044***	1.315***
	(0.002)	(0.100)	(0.002)	(0.100)	(0.002)	(0.099)	(0.002)	(0.106)
AtypBaths	0.032***	-0.871***	0.032***	-0.863***	0.032***	-0.862***	0.031***	-0.876***
	(0.002)	(0.086)	(0.002)	(0.086)	(0.002)	(0.086)	(0.002)	(0.090)
AtypFirep	0.054***	-1.501***	0.054***	-1.500***	0.054***	-1.499***	0.054***	-1.535***
	(0.002)	(0.130)	(0.002)	(0.130)	(0.002)	(0.130)	(0.002)	(0.139)
AtypAge	0.092***	-2.622***	0.092***	-2.618***	0.092***	-2.616***	0.092***	-2.668***
	(0.004)	(0.220)	(0.004)	(0.219)	(0.004)	(0.219)	(0.004)	(0.233)
AtypGar	0.085***	-2.348***	0.085***	-2.339***	0.085***	-2.337***	0.085***	-2.396***
	(0.005)	(0.228)	(0.005)	(0.228)	(0.005)	(0.227)	(0.005)	(0.241)
Bathrooms	0.103***	-2.914***	0.103***	-2.917***	0.103***	-2.916***	0.104***	-2.994***
	(0.004)	(0.242)	(0.004)	(0.242)	(0.004)	(0.242)	(0.004)	(0.259)
Beds	-0.104***	2.876***	-0.104***	2.857***	-0.104***	2.853***	-0.103***	2.903***
	(0.005)	(0.267)	(0.005)	(0.266)	(0.005)	(0.265)	(0.005)	(0.281)
SqFt	0.653***	-18.699***	0.652***	-18.631***	0.652***	-18.616***	0.651***	-19.017***
	(0.003)	(1.328)	(0.003)	(1.324)	(0.003)	(1.322)	(0.003)	(1.435)
Age	-0.088***	2.513***	-0.088***	2.510***	-0.088***	2.509***	-0.088***	2.568***
	(0.001)	(0.178)	(0.001)	(0.177)	(0.001)	(0.177)	(0.001)	(0.193)
Garages	0.105***	-3.048***	0.104***	-3.027***	0.104***	-3.024***	0.104***	-3.094***
	(0.002)	(0.216)	(0.002)	(0.214)	(0.002)	(0.214)	(0.002)	(0.232)
Fireplaces	0.101***	-2.926***	0.101***	-2.910***	0.101***	-2.908***	0.101***	-2.970***
	(0.002)	(0.206)	(0.002)	(0.205)	(0.002)	(0.204)	(0.002)	(0.222)
Photos	0.033***	-0.948***	0.033***	-0.947***	0.033***	-0.945***	0.033***	-0.966***
	(0.001)	(0.071)	(0.001)	(0.071)	(0.001)	(0.071)	(0.001)	(0.077)
Acres	0.467***	-13.085***	0.466***	-13.030***	0.466***	-13.019***	0.465***	-13.291***
	(0.005)	(0.964)	(0.005)	(0.960)	(0.005)	(0.959)	(0.005)	(1.037)
Pool	0.090***	-2.596***	0.090***	-2.590***	0.090***	-2.587***	0.090***	-2.644***
	(0.001)	(0.182)	(0.001)	(0.182)	(0.001)	(0.182)	(0.001)	(0.197)
Tenant	-0.069***	2.042***	-0.069***	2.032***	-0.069***	2.028***	-0.068***	2.063***
	(0.003)	(0.152)	(0.003)	(0.151)	(0.003)	(0.151)	(0.003)	(0.162)
Vacant	-0.044***	1.275***	-0.044***	1.268***	-0.044***	1.264***	-0.044***	1.290***

Table 25. 3SLS for Sale Price and TOM with Agent Influence (3-year Eigenvector Centrality) (Cont.)

	(1)		*(2)*		*(3)*		*(4)*	
	Price	**TOM**	**Price**	**TOM**	**Price**	**TOM**	**Price**	**TOM**
	(0.001)	(0.091)	(0.001)	(0.091)	(0.001)	(0.091)	(0.001)	(0.098)
No_HOA	-0.052***	1.482***	-0.052***	1.473***	-0.051***	1.471***	-0.051***	1.499***
	(0.001)	(0.108)	(0.001)	(0.107)	(0.001)	(0.107)	(0.001)	(0.116)
Vol_HOA	0.027***	-0.789***	0.027***	-0.789***	0.027***	-0.789***	0.027***	-0.807***
	(0.002)	(0.087)	(0.002)	(0.087)	(0.002)	(0.087)	(0.002)	(0.091)
Cash	-0.075***	2.066***	-0.075***	2.062***	-0.075***	2.055***	-0.074***	2.079***
	(0.002)	(0.165)	(0.002)	(0.165)	(0.002)	(0.164)	(0.002)	(0.175)
Government	-0.022***	0.664***	-0.022***	0.651***	-0.022***	0.652***	-0.022***	0.667***
	(0.001)	(0.049)	(0.001)	(0.048)	(0.001)	(0.049)	(0.001)	(0.052)
OtherFin	-0.027***	0.775***	-0.026***	0.765***	-0.026***	0.763***	-0.026***	0.772***
	(0.004)	(0.132)	(0.004)	(0.131)	(0.004)	(0.131)	(0.004)	(0.135)
Constant	7.069***	-200.735***	7.061***	-199.940***	7.064***	-199.847***	7.080***	-204.819***
	(0.024)	(14.278)	(0.024)	(14.228)	(0.024)	(14.210)	(0.024)	(15.494)
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		194,662		194,662		194,662		194,662
R-sq	0.89	-54.28	0.89	-53.92	0.89	-53.83	0.89	-56.32
AIC		-119,833		-122,377		-122,851		-108,381
BIC		-113,878		-116,341		-116,764		-102,253

Note. This table presents 3SLS results for four models. The dependent variables are the natural log-transformed sale price and TOM. Besides the standard set of controls in all the regressions; Model 1 includes 3-year normalized eigenvector centralities of agents. Model 2 includes 3-year normalized eigenvector centralities and controls for agent experience. Model 3 includes 3-year normalized eigenvector centralities and controls for agent experience, as well as specialization. Model 4 includes 3-year normalized eigenvector centralities and controls for agent experience, specialization, and active listings inventory.
The sample period is from October 2005 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Figure 1. A 2-by-2 Matrix of Network Explanatory Mechanisms and Goals modified from Borgatti & Foster (2003)

		Explanatory goals (styles)	
Explanatory mechanisms		*Social capital (performance variation)*	*Diffusion (social homogeneity)*
	Structuralist (topology)	Structural capital (actor position, connection patterns)	Environmental shaping (homogeneity in actors through similar attributes)
	Connectionist (flows)	Social access to resources (direct ties as information channels)	Contagion (spread of ideas, increasing homogeneity)

Figure 2. Total Agents, New Agents, and Agents Leaving the Market

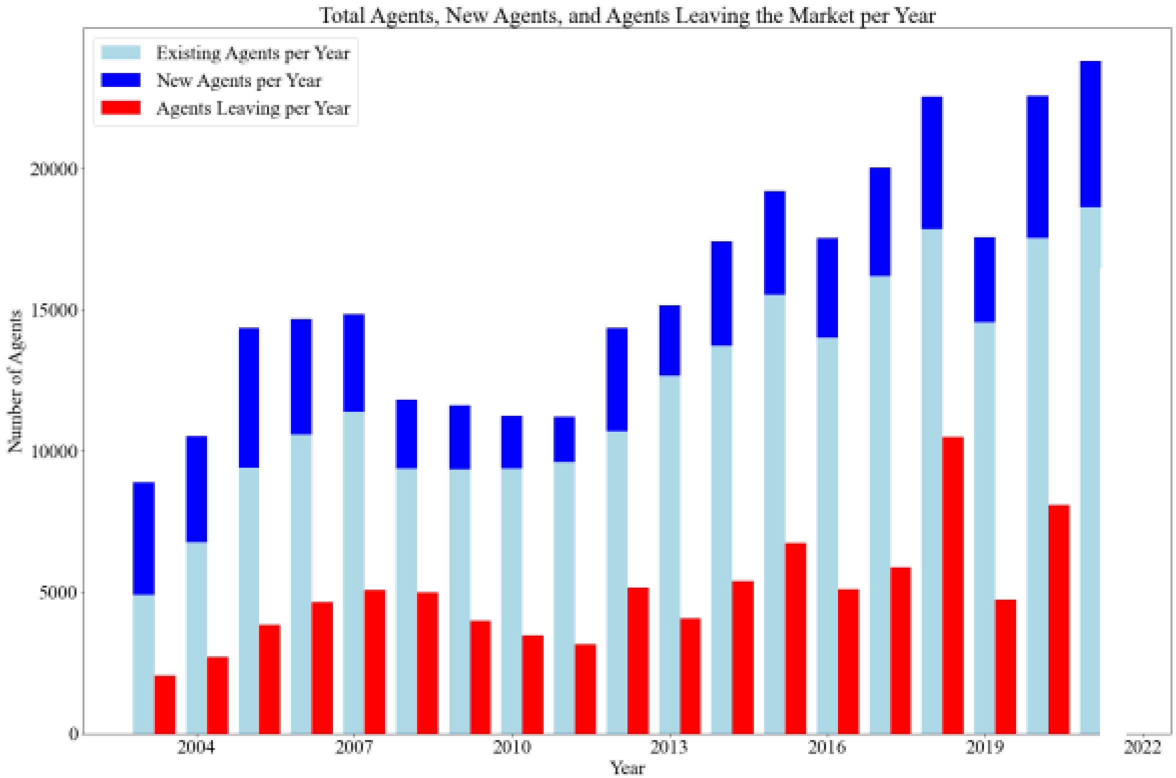


Figure 3. Exclusive Listing versus Selling Agents per Year

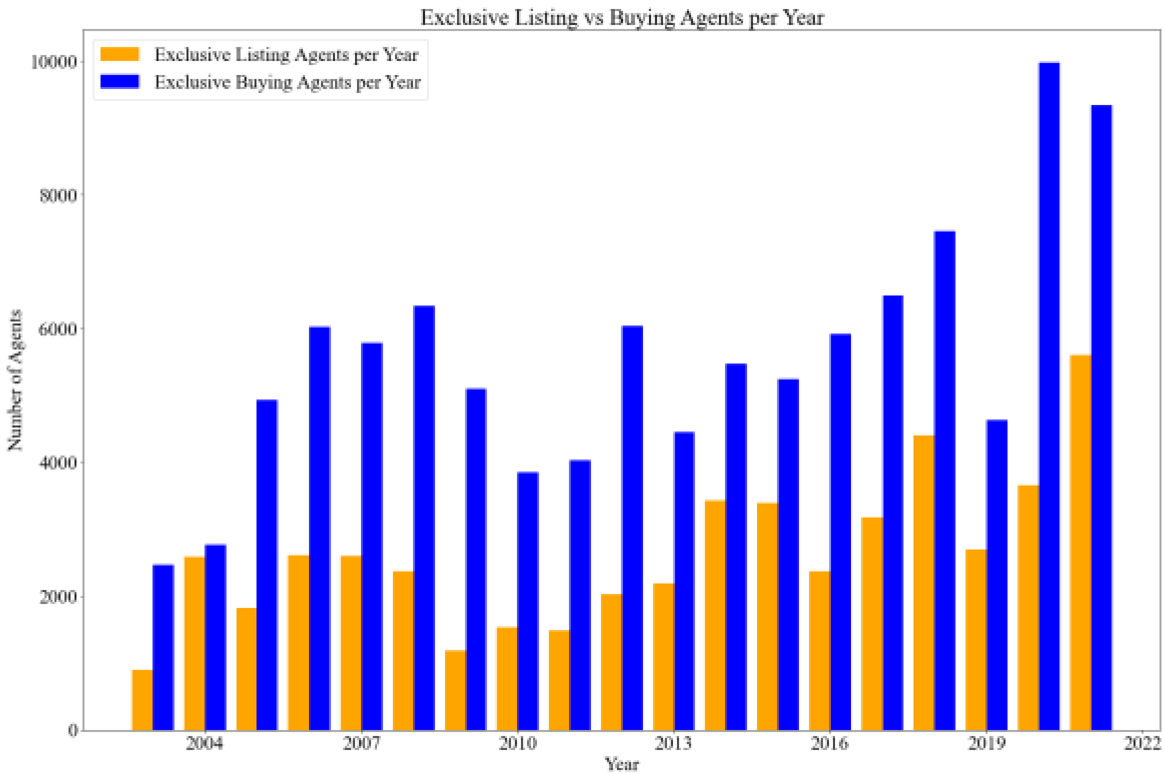
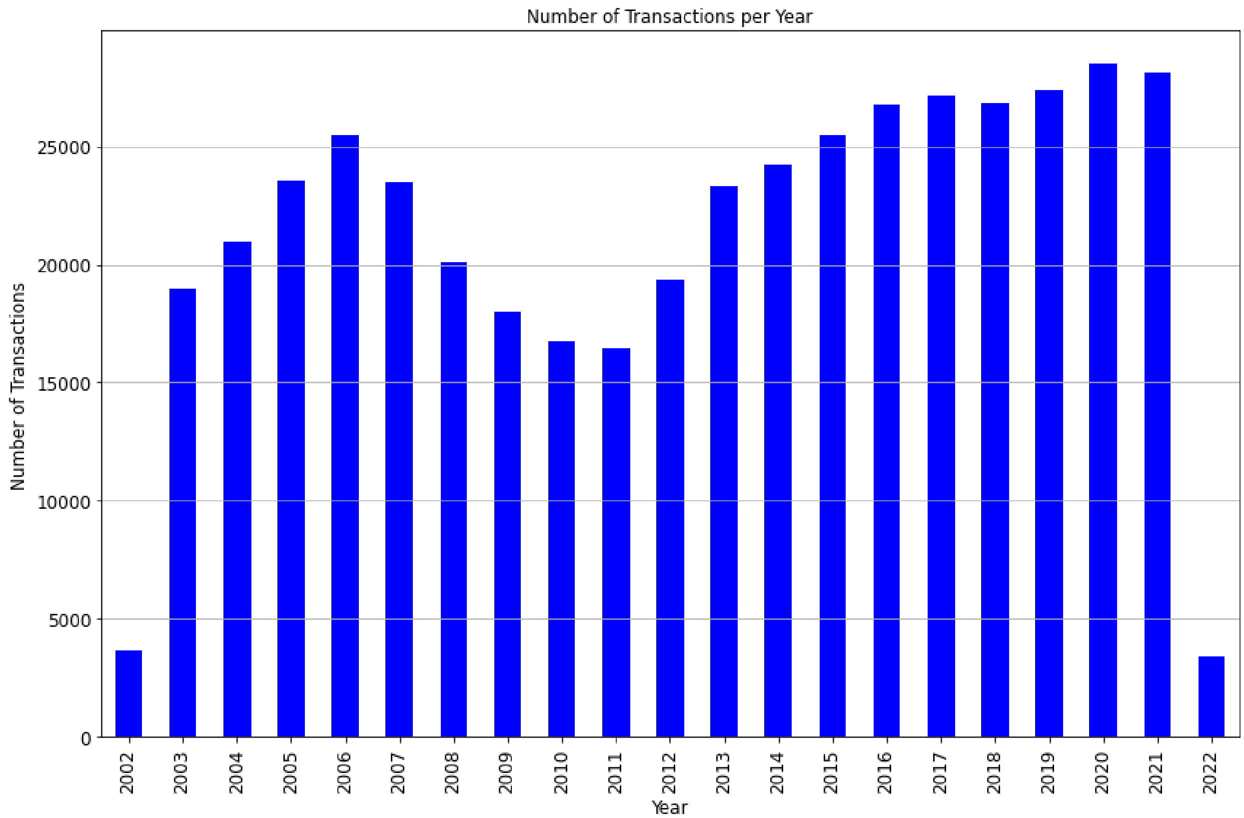


Figure 4. The Number of Transactions per Year



***The sample starts in October 2002 and ends in March 2022.*

APPENDIX A

Table A1. The correlations of agent network variables and other agent characteristics

	LA_NetSize	SA_NetSize	LA_NetSize_3y	SA_NetSize_3y	LA_BPower	SA_BPower	LA_BPower_3y	SA_BPower_3y	LA_Influence	SA_Influence	LA_Influence_3y	SA_Influence_3y	LA_Experience	SA_Experience	LA_Experience_M	SA_Experience_M	ExclList	ExclSell	LA_Inventory	SA_Inventory	InHouse	Previous	LA_TotTrans
LA_NetSize	-																						
SA_NetSize	.06	-																					
LA_NetSize_3y	.93	.04	-																				
SA_NetSize_3y	.04	.92	.05	-																			
LA_BPower	.96	.04	.90	.03	-																		
SA_BPower	.03	.94	.02	.86	.02	-																	
LA_BPower_3y	.89	.02	.96	.03	.91	.02	-																
SA_BPower_3y	.02	.86	.03	.94	.02	.88	.03	-															
LA_Influence	.92	.04	.88	.03	.92	.02	.84	.02	-														
SA_Influence	.04	.92	.03	.86	.02	.90	.02	.82	.04	-													
LA_Influence_3y	.90	.03	.95	.03	.86	.02	.90	.02	.91	.03	-												
SA_Influence_3y	.03	.89	.03	.96	.02	.82	.02	.90	.03	.89	.03	-											
LA_Experience	.75	.01	.78	.02	.65	.01	.69	.01	.70	.02	.78	.02	-										
SA_Experience	.02	.72	.02	.74	.01	.61	.01	.63	.02	.67	.02	.73	.03	-									
LA_Experience_M	.22	-.01	.28	.00	.17	.00	.20	.01	.21	.00	.29	.00	.24	-.03	-								
SA_Experience_M	-.01	.27	.00	.34	.00	.18	.01	.22	.00	.26	.00	.36	.00	.26	.10	-							
ExclList	-.09	-.01	-.09	-.01	-.06	.00	-.06	.00	-.09	.00	-.10	-.01	-.12	-.01	-.29	-.01	-						
ExclSell	-.02	-.14	-.02	-.17	-.01	-.06	-.01	-.10	-.01	-.12	-.01	-.17	.00	-.17	-.01	-.41	.02	-					
LA_Inventory	.72	.02	.71	.02	.61	.01	.60	.01	.64	.01	.69	.02	.77	.02	.25	-.01	-.11	-.01	-				
SA_Inventory	.01	.53	.02	.58	.01	.42	.01	.48	.02	.49	.02	.57	.02	.58	.01	.31	-.01	-.23	.04	-			
InHouse	.03	.03	.03	.03	.02	.01	.02	.02	.02	.02	.03	.03	.03	.04	-.01	.00	-.02	-.02	.04	.04	-		
Previous	.21	.17	.23	.18	.19	.13	.20	.15	.19	.15	.21	.18	.21	.16	.09	.11	-.02	-.04	.19	.11	.16	-	
LA_TotTrans	.58	.00	.64	.01	.48	.00	.52	.01	.55	.01	.66	.02	.75	.00	.76	.07	-.24	-.01	.64	.02	.02	.19	-
SA_TotTrans	.01	.58	.01	.65	.01	.43	.01	.48	.01	.54	.02	.66	.02	.72	.06	.80	-.01	-.37	.00	.56	.03	.18	.05

Table A2. Mean and median sale price (adjusted at base 2010 year) and TOM

	Mean Sale Price$_{2010}$	Mean TOM	Median Sale Price$_{2010}$	Median TOM
2003	177,430	92	132,825	80
2004	185,489	91	142,979	76
2003-2004	184,700	91	141,977	76
2005	196,524	92	150,374	76
2006	195,983	89	150,182	72
2007	203,044	90	154,816	73
2008	197,078	102	150,147	80
2009	178,520	105	141,349	82
2010	199,284	111	150,000	86
2005-2010	195,257	97	149,474	77
2011	203,957	118	152,498	93
2012	199,151	100	149,594	74
2013	194,009	81	147,302	60
2014	194,899	71	148,194	52
2015	193,881	61	154,021	48
2016	192,243	61	159,778	49
2017	197,030	59	162,931	45
2018	195,829	60	162,682	46
2019	198,722	65	165,716	49
2011-2019	196,083	70	158,084	51
2020	204,993	64	168,178	48
2021	238,417	48	196,849	39
2022	229,091	50	197,744	39
2020-2022	221,283	56	182,975	43

Note. This table presents the mean and median for sale price and TOM by years and market cycle periods. All sale prices are CPI adjusted with base year of 2010.

Table A3. Agent Turnover and Specialization

Year	Number of Transacti ons	Number of Agents	New Agents	Agents Leaving per Year	Agents Inactive Next Year	Agents Returnin g after One Year	Exclusive Listing during the Year	Exclusive Buying per Year
2002	4,060	3,861	2,880	444	744	-	599	1,300
2003	20,276	8,902	3,996	1,133	2,049	-	897	2,465
2004	22,497	10,513	3,743	1,467	2,714	105	2,586	2,763
2005	25,308	14,340	4,922	1,998	3,846	392	1,832	4,936
2006	27,428	14,646	4,062	2,567	4,650	637	2,608	6,026
2007	25,240	14,834	3,442	2,834	5,087	840	2,601	5,791
2008	21,241	11,806	2,438	2,372	4,984	841	2,364	6,346
2009	18,736	11,631	2,293	1,661	3,997	807	1,191	5,104
2010	17,693	11,242	1,875	1,430	3,465	845	1,540	3,850
2011	17,489	11,212	1,602	1,224	3,150	926	1,489	4,033
2012	20,159	14,351	3,640	2,908	5,165	906	2,030	6,039
2013	24,169	15,155	2,492	1,676	4,082	976	2,193	4,456
2014	25,070	17,416	3,693	3,017	5,403	1,181	3,432	5,476
2015	26,386	19,197	3,680	2,999	6,735	1,261	3,398	5,249
2016	27,710	17,526	3,541	2,598	5,116	936	2,370	5,918
2017	28,075	20,037	3,869	3,156	5,864	1,956	3,178	6,501
2018	27,744	22,518	4,677	5,358	10,486	1,274	4,409	7,465
2019	28,375	17,557	3,019	3,427	4,736	1,529	2,695	4,636
2020	29,348	22,537	5,000	7,729	8,073	3,395	3,655	9,972
2021	28,958	23,772	5,157	16,047	16,047	1,197	5,612	9,338
2022	3,521	4,931	624	4,600	4,600	344	1,847	2,422

APPENDIX B

Table B1. Filters applied to the raw MLS data and Agent Networks data

Panel A: MLS Data filters	
Variables	*Keep only*
Status	Closed
Transaction Type	For Sale
Property Sub Type	Single-Family
Seller Type	Standard/Individual
Year Built Details	Preowned
List Agent Office Name/Sell Agent Office Name	Non-iBuyers
Zip code	More than 99 observations in each zip code
Panel B: Agent Networks Data filters	
Variables	*Delete*
Listing and Selling Agents MLS Id	Self-loops (Listing agent is the same as Selling agent)
Listing or Selling Agents MLS Id	Any data entry errors like “99999999”, “0”, or non-MLS

Table B2. The list of the Zip codes included in all regressions as Postal Code FE

Tarrant County Zip Codes
75052, 75054, 76001, 76002, 76005, 76006, 76008, 76010, 76011, 76012, 76013, 76014, 76015, 76016, 76017, 76018, 76020, 76021, 76022, 76028, 76034, 76036, 76039, 76040, 76051, 76052, 76053, 76054, 76060, 76063, 76071, 76092, 76103, 76104, 76105, 76106, 76107, 76108, 76109, 76110, 76111, 76112, 76114, 76115, 76116, 76117, 76118, 76119, 76120, 76123, 76126, 76131, 76132, 76133, 76134, 76135, 76137, 76140, 76148, 76164, 76177, 76179, 76180, 76182, 76244, 76248, 76262

APPENDIX C

Normalization formula for the Degree Centrality:

$$D_{normalized}(i) = \frac{1}{N-1}\sum_{j=1}^{N} \min\,(1, \alpha_{ij}) \qquad (1)$$

Normalization formula for the Betweenness Centrality:

$$B_{normalized}(i) = \frac{1}{(n-1)(n-2)} \sum_{j \neq k \neq i} \frac{\sigma_{jk}(i)}{\sigma_{jk}} \qquad (2)$$

Normalization formula for the Eigenvector Centrality:

$$E_{normalized}(i) = \frac{E(i)}{\|E\|_2} = \frac{E(i)}{\sqrt{\sum_{k=1}^{n} E(k)^2}} \qquad (3)$$

APPENDIX D

Table D1. OLS for Sale Price and TOM with Agent Network Size (Degree centrality)

	Price				TOM			
	(1)	*(2)*	*(3)*	*(4)*	*(1)*	*(2)*	*(3)*	*(4)*
LA_NetSize	0.006	0.025***	0.026***	0.023***	-0.116***	-0.064***	-0.066***	-0.608***
	(0.004)	(0.006)	(0.006)	(0.006)	(0.011)	(0.018)	(0.018)	(0.018)
SA_NetSize	0.053***	0.062***	0.064***	0.035***	-0.104***	0.527***	0.524***	0.192***
	(0.005)	(0.007)	(0.007)	(0.008)	(0.015)	(0.023)	(0.023)	(0.023)
TOM	-0.005***	-0.005***	-0.005***	-0.007***				
	(0.001)	(0.001)	(0.001)	(0.001)				
Sale Price					-0.042***	-0.045***	-0.044***	-0.057***
					(0.008)	(0.008)	(0.008)	(0.007)
LA_Experience		-0.005***	-0.006***	-0.007***		-0.008*	-0.008*	-0.198***
		(0.001)	(0.001)	(0.001)		(0.003)	(0.003)	(0.004)
SA_Experience		-0.007***	-0.008***	-0.015***		-0.160***	-0.159***	-0.230***
		(0.001)	(0.001)	(0.001)		(0.004)	(0.004)	(0.004)
LA_Experience_M		0.001**	0.000	0.000		-0.006***	-0.006***	-0.022***
		(0.000)	(0.000)	(0.000)		(0.001)	(0.001)	(0.001)
SA_Experience_M		0.004***	0.003***	0.003***		0.003***	0.003***	-0.003***
		(0.000)	(0.000)	(0.000)		(0.001)	(0.001)	(0.001)
ExclList			-0.009**	-0.009**			0.013	-0.015
			(0.003)	(0.003)			(0.008)	(0.007)
ExclSell			-0.005***	-0.003*			0.009*	0.032***
			(0.001)	(0.001)			(0.004)	(0.004)
LA_Inventory				0.001				0.173***
				(0.001)				(0.002)
SA_Inventory				0.010***				0.110***
				(0.001)				(0.002)
InHouse	0.007***	0.007***	0.007***	0.007***	-0.019***	-0.015**	-0.015**	-0.029***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Previous	0.018***	0.017***	0.017***	0.018***	0.008	0.021***	0.021***	0.017**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)	(0.006)
PriceReduced	-0.028***	-0.028***	-0.028***	-0.028***	0.705***	0.698***	0.698***	0.651***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)

Table D1. OLS for Sale Price and TOM with Agent Network Size (Degree centrality) (Cont.)

	Price				TOM			
	(1)	*(2)*	*(3)*	*(4)*	*(1)*	*(2)*	*(3)*	*(4)*
AtypBeds	0.108***	0.109***	0.109***	0.109***	0.077***	0.077***	0.076***	0.075***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.010)	(0.010)	(0.010)	(0.010)
AtypBaths	-0.114***	-0.113***	-0.113***	-0.113***	-0.081***	-0.080***	-0.080***	-0.069***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.012)	(0.012)	(0.012)	(0.012)
AtypFirep	0.658***	0.657***	0.657***	0.656***	0.265***	0.265***	0.265***	0.241***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.009)	(0.009)	(0.009)	(0.008)
AtypAge	-0.084***	-0.084***	-0.084***	-0.084***	-0.001	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
AtypGar	0.103***	0.103***	0.103***	0.103***	-0.058***	-0.057***	-0.057***	-0.049***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Bathrooms	0.097***	0.096***	0.096***	0.096***	-0.024***	-0.023***	-0.023***	-0.022***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Beds	0.033***	0.033***	0.033***	0.033***	0.033***	0.033***	0.033***	0.030***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
SqFt	0.461***	0.460***	0.460***	0.459***	0.156***	0.155***	0.155***	0.139***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.011)	(0.011)	(0.011)	(0.011)
Age	0.091***	0.091***	0.091***	0.091***	-0.032***	-0.031***	-0.031***	-0.029***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Garages	-0.067***	-0.067***	-0.067***	-0.066***	0.160***	0.159***	0.159***	0.141***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.007)	(0.007)	(0.007)	(0.007)
Fireplaces	-0.044***	-0.044***	-0.044***	-0.044***	0.015***	0.015***	0.015***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)
Photos	-0.051***	-0.050***	-0.050***	-0.050***	0.000	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Acres	0.025***	0.025***	0.025***	0.025***	-0.021***	-0.022***	-0.022***	-0.019**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)	(0.006)
Pool	-0.075***	-0.075***	-0.074***	-0.073***	-0.267***	-0.261***	-0.261***	-0.238***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)
Tenant	-0.022***	-0.022***	-0.022***	-0.022***	0.063***	0.061***	0.061***	0.060***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Vacant	-0.021***	-0.021***	-0.021***	-0.020***	0.006	0.006	0.005	0.009
	(0.004)	(0.004)	(0.004)	(0.004)	(0.011)	(0.011)	(0.011)	(0.010)
No_HOA	-0.036***	-0.036***	-0.036***	-0.036***	0.019***	0.017**	0.017**	0.016**

Table D1. OLS for Sale Price and TOM with Agent Network Size (Degree centrality) (Cont.)

	Price				TOM			
	(1)	*(2)*	*(3)*	*(4)*	*(1)*	*(2)*	*(3)*	*(4)*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Vol_HOA	0.041***	0.041***	0.041***	0.041***	0.032***	0.033***	0.033***	0.027***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Cash	0.062***	0.062***	0.062***	0.062***	0.063***	0.063***	0.063***	0.058***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)	(0.005)
Government	0.097***	0.097***	0.097***	0.096***	0.013	0.012	0.012	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.008)	(0.008)	(0.008)	(0.007)
OtherFin	0.094***	0.094***	0.094***	0.094***	0.108***	0.109***	0.108***	0.099***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.011)	(0.011)	(0.011)	(0.010)
Constant	7.035***	7.029***	7.033***	7.050***	2.367***	2.450***	2.442***	2.782***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.072)	(0.072)	(0.072)	(0.069)
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	210,279	210,279	210,279	210,279	210,279	210,279	210,279	210,279
R-sq	0.89	0.89	0.89	0.89	0.45	0.45	0.45	0.49
AIC	-151,452	-151,668	-151,689	-151,958	293,185	291,561	291,556	277,394
BIC	-151,165	-151,340	-151,340	-151,588	293,472	291,889	291,905	277,763

Note. This table presents OLS results for four models. The dependent variables are the natural log-transformed adjusted sale price and TOM. Besides the standard set of controls in all the regressions, Model 1 includes 1-year normalized degree centralities of agents. Model 2 includes 1-year normalized degree centralities and controls for agent experience. Model 3 includes 1-year normalized degree centralities and controls for agent experience, and specialization. Model 4 includes 1-year normalized degree centralities and controls for agent experience, specialization, and active listings inventory.
The sample period is from October 2003 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table D2. OLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality)

	Price				**TOM**			
	(1)	*(2)*	*(3)*	*(4)*	*(1)*	*(2)*	*(3)*	*(4)*
LA_BPower	0.001	0.012	0.013*	0.010	-0.105***	-0.036*	-0.037*	-0.345***
	(0.004)	(0.006)	(0.006)	(0.006)	(0.013)	(0.018)	(0.018)	(0.017)
SA_ BPower	0.042***	0.038***	0.040***	0.022**	-0.070***	0.454***	0.450***	0.239***
	(0.006)	(0.008)	(0.008)	(0.008)	(0.018)	(0.023)	(0.023)	(0.022)
TOM	-0.005***	-0.005***	-0.005***	-0.007***				
	(0.001)	(0.001)	(0.001)	(0.001)				
Sale Price					-0.043***	-0.043***	-0.043***	-0.058***
					(0.008)	(0.008)	(0.008)	(0.007)
LA_Experience		-0.003**	-0.003**	-0.005***		-0.014***	-0.014***	-0.231***
		(0.001)	(0.001)	(0.001)		(0.003)	(0.003)	(0.004)
SA_Experience		-0.003*	-0.003**	-0.013***		-0.135***	-0.134***	-0.229***
		(0.001)	(0.001)	(0.001)		(0.004)	(0.004)	(0.004)
LA_Experience_M		0.001**	0.001	0.000		-0.006***	-0.006***	-0.024***
		(0.000)	(0.000)	(0.000)		(0.001)	(0.001)	(0.001)
SA_Experience_M		0.004***	0.003***	0.003***		0.005***	0.005***	-0.002*
		(0.000)	(0.000)	(0.000)		(0.001)	(0.001)	(0.001)
ExclList			-0.009**	-0.009**			0.012	-0.021**
			(0.003)	(0.003)			(0.008)	(0.007)
ExclSell			-0.005***	-0.003			0.008*	0.031***
			(0.001)	(0.001)			(0.004)	(0.004)
LA_Inventory				0.001*				0.161***
				(0.001)				(0.002)
SA_Inventory				0.011***				0.111***
				(0.001)				(0.002)
InHouse	0.007***	0.007***	0.007***	0.007***	-0.019***	-0.015**	-0.015**	-0.028***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Previous	0.020***	0.018***	0.018***	0.018***	0.001	0.023***	0.023***	0.013*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)	(0.006)
PriceReduced	-0.028***	-0.027***	-0.028***	-0.028***	0.705***	0.699***	0.699***	0.653***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)
AtypBeds	0.108***	0.109***	0.109***	0.109***	0.077***	0.077***	0.077***	0.075***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.010)	(0.010)	(0.010)	(0.010)
AtypBaths	-0.114***	-0.113***	-0.113***	-0.113***	-0.081***	-0.079***	-0.079***	-0.069***

Table D2. OLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) (Cont.)

	Price				TOM			
	(1)	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*
	(0.005)	(0.004)	(0.004)	(0.004)	(0.012)	(0.012)	(0.012)	(0.012)
AtypFirep	0.658***	0.657***	0.657***	0.656***	0.265***	0.264***	0.264***	0.242***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.009)	(0.009)	(0.009)	(0.008)
AtypAge	-0.084***	-0.084***	-0.084***	-0.084***	-0.001	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
AtypGar	0.103***	0.103***	0.103***	0.103***	-0.058***	-0.057***	-0.057***	-0.049***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Bathrooms	0.097***	0.096***	0.096***	0.096***	-0.023***	-0.023***	-0.023***	-0.022***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Beds	0.033***	0.033***	0.033***	0.033***	0.033***	0.033***	0.033***	0.030***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
SqFt	0.461***	0.460***	0.460***	0.459***	0.157***	0.155***	0.154***	0.141***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.011)	(0.011)	(0.011)	(0.011)
Age	0.091***	0.091***	0.091***	0.091***	-0.032***	-0.032***	-0.032***	-0.029***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Garages	-0.067***	-0.067***	-0.067***	-0.066***	0.160***	0.159***	0.159***	0.143***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.007)	(0.007)	(0.007)	(0.007)
Fireplaces	-0.044***	-0.044***	-0.044***	-0.044***	0.015***	0.015***	0.015***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)
Photos	-0.051***	-0.050***	-0.050***	-0.050***	0.000	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Acres	0.025***	0.025***	0.025***	0.025***	-0.021***	-0.022***	-0.022***	-0.018**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)	(0.006)
Pool	-0.075***	-0.075***	-0.074***	-0.073***	-0.267***	-0.261***	-0.261***	-0.238***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)
Tenant	-0.022***	-0.022***	-0.022***	-0.022***	0.063***	0.061***	0.061***	0.060***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Vacant	-0.021***	-0.021***	-0.021***	-0.020***	0.006	0.005	0.005	0.010
	(0.004)	(0.003)	(0.003)	(0.003)	(0.011)	(0.011)	(0.011)	(0.010)
No_HOA	-0.037***	-0.036***	-0.036***	-0.036***	0.019***	0.017**	0.017**	0.016**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Vol_HOA	0.041***	0.041***	0.041***	0.041***	0.032***	0.033***	0.033***	0.028***

Table D2. OLS for Sale Price and TOM with Agent Bridging Power (Betweenness centrality) (Cont.)

	Price				TOM			
	(1)	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Cash	0.062***	0.062***	0.062***	0.062***	0.063***	0.063***	0.063***	0.058***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)	(0.005)
Government	0.097***	0.097***	0.097***	0.096***	0.013	0.012	0.012	0.002
	(0.004)	(0.002)	(0.002)	(0.002)	(0.008)	(0.008)	(0.008)	(0.007)
OtherFin	0.094***	0.094***	0.094***	0.094***	0.108***	0.108***	0.108***	0.100***
	(0.005)	(0.003)	(0.003)	(0.003)	(0.011)	(0.011)	(0.011)	(0.010)
Constant	7.036***	7.027***	7.030***	7.049***	2.369***	2.438***	2.431***	2.803***
	(0.021)	(0.015)	(0.015)	(0.015)	(0.072)	(0.072)	(0.072)	(0.069)
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	210,279	210,279	210,279	210,279	210,279	210,279	210,279	210,279
R-sq	0.89	0.89	0.89	0.89	0.45	0.45	0.45	0.49
AIC	-151,393	-151,615	-151,634	-151,936	293,257	291,731	291,728	278,118
BIC	-151,106	-151,287	-151,285	-151,566	293,544	292,059	292,076	278,487

Note. This table presents OLS results for four models. The dependent variables are the natural log-transformed adjusted sale price and TOM. Besides the standard set of controls in all the regressions, Model 1 includes 1-year normalized betweenness centralities of agents. Model 2 includes 1-year normalized betweenness centralities and controls for agent experience. Model 3 includes 1-year normalized betweenness centralities and controls for agent experience, and specialization. Model 4 includes 1-year normalized betweenness centralities and controls for agent experience, specialization, and active listings inventory.
The sample period is from October 2003 to March 2022.
Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001

Table D3. OLS for Sale Price and TOM with Agent Influence (Eigenvector Centrality)

	Price				TOM			
	(1)	*(2)*	*(3)*	*(4)*	*(1)*	*(2)*	*(3)*	*(4)*
LA_Influence	-0.068***	-0.097***	-0.094***	-0.109***	-0.395***	-0.211***	-0.215***	-1.334***
	(0.013)	(0.019)	(0.019)	(0.019)	(0.041)	(0.057)	(0.057)	(0.057)
SA_ Influence	0.018	-0.108***	-0.104***	-0.184***	-0.260***	1.537***	1.530***	0.719***
	(0.017)	(0.024)	(0.024)	(0.024)	(0.051)	(0.070)	(0.070)	(0.071)
TOM	-0.005***	-0.005***	-0.005***	-0.008***				
	(0.001)	(0.001)	(0.001)	(0.001)				
Sale Price					-0.044***	-0.041***	-0.041***	-0.059***
					(0.008)	(0.008)	(0.008)	(0.007)
LA_Experience		0.002	0.001	-0.001		-0.010***	-0.010**	-0.222***
		(0.001)	(0.001)	(0.001)		(0.003)	(0.003)	(0.004)
SA_Experience		0.004***	0.004**	-0.006***		-0.146***	-0.145***	-0.231***
		(0.001)	(0.001)	(0.001)		(0.004)	(0.004)	(0.004)
LA_Experience_M		0.001***	0.001*	0.001		-0.006***	-0.006***	-0.023***
		(0.000)	(0.000)	(0.000)		(0.001)	(0.001)	(0.001)
SA_Experience_M		0.004***	0.004***	0.003***		0.003***	0.004***	-0.003***
		(0.000)	(0.000)	(0.000)		(0.001)	(0.001)	(0.001)
ExclList			-0.008**	-0.008**			0.012	-0.022**
			(0.003)	(0.003)			(0.008)	(0.007)
ExclSell			-0.004**	-0.002			0.010*	0.032***
			(0.001)	(0.001)			(0.004)	(0.004)
LA_Inventory				0.002***				0.163***
				(0.001)				(0.002)
SA_Inventory				0.012***				0.110***
				(0.001)				(0.002)
InHouse	0.007***	0.007***	0.007***	0.006**	-0.019***	-0.015**	-0.015**	-0.028***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Previous	0.023***	0.019***	0.020***	0.020***	0.004	0.022***	0.022***	0.012*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)	(0.006)
PriceReduced	-0.028***	-0.027***	-0.027***	-0.028***	0.705***	0.699***	0.699***	0.653***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)
AtypBeds	0.108***	0.109***	0.109***	0.109***	0.077***	0.077***	0.077***	0.075***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.010)	(0.010)	(0.010)	(0.010)
AtypBaths	-0.114***	-0.113***	-0.113***	-0.112***	-0.081***	-0.080***	-0.080***	-0.069***

Table D3. OLS for Sale Price and TOM with Agent Influence (Eigenvector Centrality) (Cont.)

	Price				TOM			
	(1)	*(2)*	*(3)*	*(4)*	*(1)*	*(2)*	*(3)*	*(4)*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.012)	(0.012)	(0.012)	(0.012)
AtypFirep	0.658***	0.657***	0.657***	0.656***	0.266***	0.263***	0.263***	0.242***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.009)	(0.009)	(0.009)	(0.008)
AtypAge	-0.084***	-0.084***	-0.084***	-0.084***	-0.001	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
AtypGar	0.103***	0.103***	0.103***	0.103***	-0.058***	-0.057***	-0.057***	-0.049***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Bathrooms	0.096***	0.096***	0.096***	0.096***	-0.024***	-0.023***	-0.023***	-0.022***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Beds	0.033***	0.033***	0.033***	0.033***	0.033***	0.032***	0.033***	0.031***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
SqFt	0.461***	0.460***	0.460***	0.459***	0.157***	0.154***	0.154***	0.141***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.011)	(0.011)	(0.011)	(0.011)
Age	0.091***	0.091***	0.091***	0.091***	-0.032***	-0.032***	-0.032***	-0.029***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Garages	-0.067***	-0.067***	-0.067***	-0.066***	0.160***	0.159***	0.159***	0.142***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.007)	(0.007)	(0.007)	(0.007)
Fireplaces	-0.044***	-0.044***	-0.044***	-0.044***	0.015***	0.015***	0.015***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)
Photos	-0.051***	-0.050***	-0.050***	-0.050***	0.000	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Acres	0.025***	0.025***	0.025***	0.025***	-0.021***	-0.021***	-0.021***	-0.018**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)	(0.006)
Pool	-0.075***	-0.075***	-0.074***	-0.073***	-0.267***	-0.259***	-0.260***	-0.238***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)
Tenant	-0.022***	-0.021***	-0.022***	-0.021***	0.063***	0.061***	0.061***	0.060***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Vacant	-0.021***	-0.021***	-0.021***	-0.021***	0.006	0.005	0.005	0.010
	(0.004)	(0.004)	(0.004)	(0.004)	(0.011)	(0.011)	(0.011)	(0.010)
No_HOA	-0.037***	-0.036***	-0.036***	-0.036***	0.019***	0.017**	0.017**	0.015**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Vol_HOA	0.041***	0.041***	0.041***	0.041***	0.032***	0.032***	0.032***	0.028***

Table D3. OLS for Sale Price and TOM with Agent Influence (Eigenvector Centrality) (Cont.)

	Price				TOM			
	(1)	*(2)*	*(3)*	*(4)*	*(1)*	*(2)*	*(3)*	*(4)*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Cash	0.062***	0.062***	0.062***	0.062***	0.063***	0.062***	0.062***	0.058***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)	(0.005)
Government	0.097***	0.097***	0.097***	0.096***	0.013	0.012	0.012	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.008)	(0.008)	(0.008)	(0.007)
OtherFin	0.094***	0.093***	0.093***	0.094***	0.108***	0.108***	0.108***	0.100***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.011)	(0.011)	(0.011)	(0.010)
Constant	7.037***	7.023***	7.026***	7.047***	2.380***	2.417***	2.409***	2.805***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.072)	(0.072)	(0.072)	(0.069)
YearxMonthFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PostalcodeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	210,279	210,279	210,279	210,279	210,279	210,279	210,279	210,279
R-sq	0.89	0.89	0.89	0.89	0.45	0.45	0.45	0.49
AIC	-151,371	-151,631	-151,645	-152,010	293,216	291,639	291,634	277,975
BIC	-151,084	-151,303	-151,296	-151,641	293,504	291,968	291,983	278,344

Note. This table presents OLS results for four models. The dependent variables are the natural log-transformed adjusted sale price and TOM. In addition to the standard set of controls in all the regressions, Model 1 includes 1-year normalized eigenvector centralities of agents. Model 2 includes 1-year normalized eigenvector centralities and controls for agent experience. Model 3 includes 1-year normalized eigenvector centralities and controls for agent experience and specialization. Model 4 includes 1-year normalized betweenness centralities and controls for agent experience, specialization, and active listings inventory.

The sample period is from October 2003 to March 2022.

Robust standard errors are in parentheses. *p<0.05, **p<0.01, and ***p<0.001