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The Good, the Bad, and the Ordinary: Estimating Agent Value-Added Using Real Estate Transactions

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Abstract: Despite the ubiquity and expense of full-service real estate agents, there is limited empirical evidence of their efficacy. This paper uses data on residential property listings and transactions in three large metro areas spanning more than 20 years to estimate the distributions of real estate agent value-added with respect to both price and time-to-sale outcomes. Controlling for detailed property characteristics and, in some specifications, property fixed effects, we document considerable heterogeneity in the final prices negotiated by real estate agents on both the buy-side and the sell-side of the market, as well as in the time that it takes agents to sell properties. In addition, we show that homes sold using "flat-fee" brokers who provide sellers access to the local Multiple Listing Service (MLS) database but do not provide additional services transact at prices that are from 1 percent to 4 percent *higher* than the average sale conducted with a full-service agent. While the average agent does not appear to provide enough value-add to justify their high expense, we document the existence of a small fraction of high-performing agents. We show that high performance is persistent and that these agents achieve better outcomes in cold, thin markets compared to booming markets.

JEL classification: D01, D8, J24, G5, L8, R31

Key words: market intermediaries, value-added, bargaining, negotiation, agemcy theory, real estate, prices, time on the market

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1 Introduction

In many types of financial transactions, economic actors rely on third party agents to help facilitate and ultimately close deals. Examples of these types of arrangements include investment bankers for mergers, acquisitions and initial public offerings, executive search and compensation firms for filling top management positions, and attorneys for resolving competing claims and contract disputes. While these agents are often highly compensated and thus, quite costly, the benefits of hiring these experts are often difficult to quantify due to the complexity and scope of their responsibilities as well as the numerous frictions that often characterize principal-agent relationships like misaligned incentives and asymmetric information.

Real estate agents facilitating residential transactions are among the most frequently utilized of all agents. For many households, buying and selling a home is one of the most consequential financial transactions they will make in their lifetimes. It has immediate and far-reaching implications for their economic and financial well-being, and thus, it is unsurprising that most households rely on the help of experts in this context. In the U.S. approximately 90% of residential real estate transactions are assisted by agents, with approximately $100 billion in commissions paid for their professional services annually.[1] The typical real estate commission in the U.S. is between 5 and 6 percent of the final transaction price, and these high commissions have persisted over time with little variation across geographies despite large differences in home values (Hsieh and Moretti, 2003).

Many commentators and market participants have questioned whether such high commissions can be justified by the services that agents provide home buyers and sellers. Collusive behavior has long been suspected in the industry, and a recent antitrust lawsuit that was settled in the state of Missouri against the National Association of Realtors (NAR), the largest industry trade group for real estate agents, suggests that those suspicions may be warranted.[2]

However, real estate agents do provide numerous services intended to help facilitate a sale that may justify their high compensation. On the sell-side, these include helping sellers prepare, price, and market their properties, while on the buy-side most agent services involve

[1] See "Powerful Realtor Group Agrees to Slash Commissions to Settle Lawsuits 2017", New York Times, March 2024. `https://www.nytimes.com/2024/03/15/realestate/national-association-realtors-commission-settlement.html`

[2] On March 15, 2024, the NAR, in addition to a cash settlement of nearly $420 million, agreed to a change in the pay structure in the industry as it pertains to the services and compensation of buy-side agents. See "The 6% commission on buying or selling a home is gone after Realtors association agrees to seismic settlement" CNN, March 2024 `https://www.cnn.com/2024/03/15/economy/nar-realtor-commissions-settlement/index.html`

helping potential buyers in the search process. Many agents are likely better informed about the state of local housing markets and the value of any particular house at a given time compared to home buyers and sellers.[3] Until fairly recently, real estate agents had a very specific information advantage over buyers and sellers in the form of their exclusive access to Multiple Listing Services (MLS) databases that provide detailed information on properties for sale in a given housing market. This information gap has narrowed though with the rise of public, online real estate transaction platforms since the mid-2000s.[4] [5] In addition, agents on both sides of the market typically help negotiate the terms of a transaction. Many agents are likely more experienced in property negotiations compared to their clients and may be able to secure a better price or to complete a sale more quickly.

Previous studies in the literature have explored various aspects of how agents provide value to home buyers and sellers. However, due to data limitations, most research has focused on small geographic areas and narrow time periods, and as a result, there is no consensus in the literature about how, or even if, real estate agents add value to the process of buying and selling a home. Furthermore, there is evidence that misaligned incentives between sellers and their agents can lead to market distortions that detract from value in some cases.[6]

In this paper, we investigate the distribution of real estate agent performance using detailed information on the near universe of residential property listings from MLS databases in three large metro areas over a 20-year period. In particular, we benchmark agent performance on price and time-to-sale outcomes against flat-fee broker listings that do not employee the services of a listing agent, but, at the discretion of the home seller, may still pay a buyer's agent commission. We separately recover the agents' average effect on price when they serve as a buyer's agent.

With these measures of agent performance, we can answer a number of questions that remain largely unanswered in the literature. First, what fraction of listing agents have enough skill to generate a transaction price that warrants a 3 percent seller's commission? Second, by splitting our sample by time we ask whether high performance is persistent or fleeting.

[3] A recent study by Agarwal et al. (2019) finds that real estate agents use their information advantages to buy their own houses at a discount, while Levitt and Syverson (2008) and Rutherford et al. (2005) find that agents list and sell their own houses at a premium but relative to their clients' listings. Consistent empirical evidence is documented by Shen and Ross (2021).

[4] Recent online real estate transaction platforms include, for example, Zillow.com, Redfin.com, and Trulia.com.

[5] According to a recent report by the National Association of Realtors (NAR), 51 percent of home buyers found the homes they purchased on an online platform other than the MLS. See the Real Estate in a Digital Age 2017 Report https://www.nar.realtor/sites/default/files/reports/2017/2017-real-estate-in-a-digital-age-03-10-2017.pdf

[6] For some examples, see Han and Hong (2016), Hendel et al. (2009), Levitt and Syverson (2008), and Rutherford et al. (2005).

There is a large debate in the asset management literature about whether fund managers are simply lucky for a short time or if they are skilled at generating high returns over prolonged periods of time.[7] To our knowledge, this question has not been addressed in the context of real estate agents, who are the most frequently utilized among all agents and are crucial to over one hundred million U.S. households. Third, does the housing market, like the financial management industry, reward high performing selling agents with increasing business? We also examine whether buyer agents who secure a low price for their client at the time of purchase are more likely to be re-hired when the new home owner ultimately decides to sell. Furthermore, we use the fact that agents often operate on both sides of the market to investigate whether they can obtain a high price when working for the seller and secure a low price when working for the buyer, which would constitute evidence consistent with significant negotiating skills. Finally, we test whether high-performing real estate agents achieve their best performance in hot markets when there are large volumes of sales and prices are growing rapidly, or in cold markets when prices are flat or falling and sale volumes are low. This question is important because it can shed light on the underlying mechanisms driving real estate agent performance and help both buyers and sellers better understand how to choose an agent in different market conditions.

Using our transactions-level MLS data, we begin by estimating standard hedonic pricing models and days-on-market (DOM) regression models. To assess the distribution of real estate agent skill, we include a full set of agent fixed effects in our models, which is possible since the MLS data contain unique identifiers for the listing agent as well as the buyer agent involved in each transaction. Similar econometric approaches have been used to estimate the value of teachers, managers, and investment banks in mergers and acquisitions (Aaronson et al., 2007; Bertrand and Schoar, 2003; Bao and Edmans, 2011). We interpret the estimates of these fixed effects as providing information on the extent to which time-invariant, agent-specific factors explain average sale prices and average DOM over and above the property characteristics and detailed geographic controls included in the specifications

A potential econometric concern in this context is the issue of assortative matching. Home buyers and sellers do not randomly select real estate agents, and agents themselves may specialize in certain segments of the market. In addition to our relatively granular geographic fixed effects, which partially address this issue, we use the repeat-sale feature of our data set and include property fixed effects in many of our specifications. The addition of property fixed effects controls for the possibility that certain types of agents may focus their activities on properties with specific, time-invariant, unobservable characteristics. Moreover, we can

[7] See Berk et al. (2020) for a review of the literature that measures mutual fund manager skill and performance.

also partially control for renovations and certain time-varying property attributes, such as additions that increase the number of bedrooms or bathrooms. These measures should alleviate concerns about assortative matching on time-varying property characteristics.

Our results suggest that there is significant heterogeneity among agents in the final transactions prices they negotiate. Using a conventional hedonic regression model and controlling for year and ZIP code fixed effects, we estimate an inter-quartile price range of between 7 and 9 percent, depending on the particular MLS, for the distribution of listing agent fixed effects. When we limit the sample to homes that have sold at least twice and include property fixed effects in the analysis, this range narrows to 5–6 percent. In addition, we find substantial heterogeneity in the price outcomes for buyer agents. The estimated inter-quartile range of the distribution of buyer agent fixed effects is between 6 and 10 percent, which narrows to 4–5 percent when property fixed effects are included.

While there is significant heterogeneity in all three cities in our sample, we find that the median listing agent obtains prices that are 1–5 percent *lower* compared to owners who sell without the assistance of a conventional agent and instead use a flat-fee broker. According to our estimates, a flat-fee seller would have needed to hire a listing agent in the top 79th to 90th percentile of the distribution to justify a 3 percent commission rate. Thus, we conclude that there are high-performing real estate agents who add significant value to the home selling process, but they constitute a minority of agents.

One caveat in interpreting these results is that individuals who sell their own homes and list on the MLS via a flat-fee broker may be different in unobservable ways compared to the average seller who hires a full-service agent. While we do not have exogenous variation in who chooses to sell their property via a flat-fee broker, we do not think these results are driven by homeowners who are exceptionally skilled at bargaining or more financially sophisticated self-selecting into flat-fee transactions. We show that when these same individuals purchased their homes, they did not appear to pay substantially less than other buyers. Furthermore, we show that these results are not driven by flat-fee sellers opting into particularly favorable local price trends, as the average flat-fee listing still commands a premium when we control for ZIP code-by-year fixed effects.

We also document significant heterogeneity in the number of days listing agents take to complete transactions. The inter-quartile range for the distribution of the fixed effects in the DOM regression specifications is between 17 and 25 days for all sales and slightly increases when we control for property fixed effects. These are economically large differences when compared to the DOM sample average of 96–122 days. In contrast to our pricing results, we find very small, and mostly statistically insignificant differences in the time that it takes the median listing agent to sell a property compared to sellers that use flat-fee brokers.

Our MLS data also contain information on property listings that fail and are withdrawn before a sale occurs. This allows us to look at the extensive margin of selling and to estimate models that compare the likelihood of a listing ending in a successful sale for a homeowner who sells their own house via a flat-fee broker with a homeowner who hires a traditional agent. We find that flat-fee listings are 8–11 percent less likely to end in a successful sale over a one-year horizon compared to listings with a traditional agent. Hence, while the average and median agent in our sample does not appear to secure prices that would justify their commission, they do appear to significantly increase the probability that a sale occurs and to slightly increase the speed at which successful sales are completed. We further show that accounting for differences in the probability of sale using a Heckman selection model does not attenuate the estimated pricing differences. Nor is agent heterogeneity a function of experience. Controlling for agent experience has a modest impact on the distributions of buying and selling agent fixed effects for transactions prices and has no effect on the distributions of agent fixed effects for DOM.

Having established substantial heterogeneity in agent outcomes, we shift the focus of the analysis to the factors that could explain why some agents perform better than others. One possibility that has been explored in the literature is the trade-off between obtaining a high selling price and selling quickly (see Anglin et al., 2003; Glower et al., 1998; Krainer, 2001; Munneke et al., 2015; Shen and Springer, 2022). We find limited evidence suggesting that listing agents focus on speed at the expense of sale price, or vice versa, as a selling strategy. Instead, it appears that agents who sell homes at a premium do not, on average, take significantly longer to sell than those who do not.

Another potential explanation for real estate agent heterogeneity is that some agents are simply better negotiators than others. To test this hypothesis, we restrict our sample to agents who represent both sellers and buyers. We then compare an agent's fixed effect when serving as a listing agent to her fixed effect when serving as a buyer agent. We find little evidence that listing agents who tend to secure high prices are in fact good at negotiating/bargaining, as these same agents are not, on average, better at securing lower prices when serving as a buying agent. Most agents that appear to sell for a premium also pay a premium when serving as a buyer agent.[8]

Still, we do find a small set of agents who consistently perform well in securing high (low) prices for their clients when selling (buying) and a small set of agents who sell their clients' properties quickly. In the remainder of the analysis we focus on these high-performing agents, which we define as agents in the top 10th percentile of the fixed effect distributions for price

[8] An alternative interpretation of this result is that it reflects the fact that buying agents have a disincentive to negotiate a lower price because a lower sales price actually reduces their commission.

and DOM. We begin by documenting that high performance is persistent and not just due to luck. Specifically, we split our sample in half along the time dimension and test whether top agents in the first half of the sample were more likely to be top agents in the second half of the sample period. We find evidence of significant persistence in high performance for the price outcomes (both buying and selling), but only weak evidence of persistently high performance for the DOM outcome.

Next, we implement a test to see whether the market rewards top agents. We regress the growth in listings between the first and second halves of the sample period on an indicator for being a high-performing agent in the first half of the sample. We find that top performers in the first half of the sample in terms of price and DOM did attract more listings in the second half suggesting that the market observes and rewards some aspects of agent skill.

We also look at individual transactions to see whether a buyer's agent that leads their clients to seemingly over-pay (perhaps by steering them to high-commission listings) are punished when it comes time to sell the home. We find that homeowners with a large positive residual associated with their purchase transaction are just as likely to re-hire that agent to list their home as homeowners whose agent helped them secure a low purchase price. This finding suggests that a buyer agent who steered their clients away from low-commission listings (the collusive enforcement behavior at the heart of the Missouri NAR lawsuit) are unlikely to be punished in the marketplace.

In a final exercise, we test whether high performing agents add more value in hot versus cold markets. In booming markets characterized by bidding wars we might expect the quality of agents to matter less than in thin markets where demand is low and competition among sellers is fiercer. This is exactly what we find as listing agents in the top decile for list price and bottom decile for buying price and DOM tend to be particularly effective in cold housing markets as defined by the National Association of Home Builders (NAHB). This effect is most consistent with hot markets being thicker, shrinking the gap between the reservation prices of buyers and sellers. However, thick markets also provide more comparable sales reducing pricing uncertainty perhaps given a skilled agent room to shift their counter-party's subjective valuation of the property.

The balance of the paper is organized as follows. In section 2, we discuss our MLS database and how we identify unique real estate agents over time within a given MLS. Section 3 presents the basic econometric framework. Section 4 discusses our main findings and provides robustness analyses. In section 5 we show the distribution of agent value-added estimates. In section 6, we identify and characterize high-performing real estate agents and present evidence that high performance is persistent and rewarded in the market. Finally, section 7 provides concluding remarks.

2 Data

Our data come from three Multiple Listing Services (MLS) datasets provided by CoreLogic. Each underlying MLS database consists of properties on the market for sale that can only be accessed by licensed real estate agents. Properties are placed into the MLS database by a listing agent. In this paper, we focus on data from three Core-Based Statistical Areas (CBSAs): Charlotte, NC, Minneapolis, MN, and Houston, TX. Our sample encompasses more than 2.3 million single-family home sales from January 2000 (or 2001 in the case of Charlotte) to December 2019. We selected these CBSAs because they are the largest metropolitan areas for which a single MLS covered at least 97 percent of all sales. This is important because some metropolitan areas, like New York City and Los Angeles, have multiple MLSs, which makes it difficult to follow agents across transactions.[9]

The information provided in our MLS data includes the address of each house, a wide range of structure characteristics, lot characteristics, transaction characteristics, key dates, and, most importantly, unique identifiers for the listing and buyer agents. The structure characteristics include the age of the building, the square footage of the living area, the number of bathrooms and bedrooms, the number of fireplaces, a flag for new construction, and a flag for buildings that were recently renovated. The lot characteristics include the size of the lot, a flag for whether there is a quality view (i.e., water view or city view), a flag for a gated community, and a flag for a waterfront lot. The transaction characteristics contain information on whether the property is distressed (i.e., foreclosure sale or short-sale), whether the property was sold-as-is, and whether it was listed by an agent who is the owner or who is related to the seller.

To standardize the data and deal with outliers, we apply a series of sample filters across our three CBSAs. A detailed discussion of each filter and its impact on the sample size is available in the Online Appendix (section A.1).

The MLS database provides critical information for our analysis, such as the name, home office, phone numbers, and email addresses of the seller's (listing) agents. Additionally, the date the sale was finalized, the final price, and the name and contact information of the agent representing the buyer are also recorded. We use this agent-specific information to track agents' performance over time and across firms, identifying them based on their unique MLS identifier. In some instances, an agent might be associated with more than one identifier, such as when they switch firms. In such cases, we create a new unique ID that links the

[9]For example, the identifiers that we use to follow agents across transactions are only unique to the specific MLS. We do have real estate agent names that we can use to link the same agent across transactions that occur in multiple MLSs. However, this strategy does not work well with common names (i.e., John Smith).

provided IDs to a single individual if they share the same first and last name and meet at least one of the following conditions: the same middle name, office name, cell phone number, office number, office email, or personal email.[10]

A homeowner can choose to sell without the help of an agent. Traditionally, this meant placing her own sign in the yard or window and perhaps advertising in a local newspaper or on an internet platform like Zillow. However, increasingly, sellers have employed a "flat-fee" broker to list their homes on the MLS for a small, one-time fee. For the most part, these flat-fee brokers do not perform the services traditionally provided by listing agents. They simply list properties on the MLS and refer all inquiries from potential buyers directly to the homeowners.

We use flat-fee brokers as a proxy for homeowners who are selling their own properties without the assistance of a traditional full-service agent—what the literature has termed "for sale by owners" or FSBOs. To identify flat-fee brokers in the MLS database, we searched within the office name and broker email address fields for the phrase "flat fee." In addition, we inspected the office name (e.g. ReMax, Century 21) of the top 10 percent of listing firms and the top selling agents in each MLS to see whether any firms include terms such as "discount", "fixed-fee", or "by-owner" on their websites. We also performed a targeted Google search for firms that advertised this service in each MLS region.[11] In the process of identifying flat-fee brokers, we came across firms or agents that appear to specialize in foreclosed or bank-owned (REO) properties as well as agents that specialize in selling newly built homes on behalf of developers. We create a separate dummy variable for brokers who specialize in new construction and we exclude transactions associated with agents who specialize in selling distressed properties, as Campbell et al. (2011) document that distressed properties are sold at steep discounts.

3 Econometric Framework

We assess real estate agent value added using two metrics. First, we estimate several hedonic models with agent fixed effects to test whether listing (or buyer) agents are able to obtain a

[10]Note that even if an agent changes her name due to marriage, we can still track her as long as she did not simultaneously change her MLS ID.

[11]Some flat-fee brokers do offer additional a la carte services such as assistance with legal documentation, advertisements for open houses, etc. In our data we do not observe whether a seller chooses to purchase any additional services from a flat-fee broker. In addition, there are a few firms that offer both flat-fee and full-service options. However, we cannot make this distinction at the transaction level. Thus, any transaction that is associated with a flat fee broker in our database is assumed to correspond to a FSBO observation in our analysis. In a few instances we found brokers with advertisements of flat-fees of 1 percent. While this is a substantial discount, we did not include these firms in our flat fee list.

premium (or discount) on the final transaction price for their clients relative to homeowners who sell their own properties without hiring an agent. Second, we explore whether listing agents can effectively reduce the marketing time for a home compared to sellers who do not use an agent.

In our primary specification with listing agent fixed effects, we will treat flat-fee broker transactions as the omitted category. Thus, the coefficient estimate on each fixed effect recovers each listing agent's price premium or discount and speed of sale relative to a flat-fee transaction. In a second specification, we drop the listing agent fixed effects and instead estimate buyer agent fixed effects. For these specifications, we compare each agent's average discount (relative to expectations) against what the average home buyer pays if she either does not hire an agent or enters a dual agency contract and shares the agent with the seller. We do not observe when an agent first signs a contract with a potential home buyer so we are unable to estimate a time-to-sale model with buyer agent fixed effects.

We begin by estimating a series of conventional hedonic regression specifications that include structure and lot characteristics and features of the sale such as whether it is an estate sale. We then estimate specifications that include indicators for flat-fee brokers, dual-agent sales, and agents selling their own homes.

We estimate two baseline models, one for house prices and one for the number of days on the market (DOM) using the following fixed-effects regression specification.

$$y_{ijrt}^{P,DOM} = X_i'\phi + \theta_t + \gamma_j + \beta_1 OwnerAgent_{it} + \beta_2 Dual_{it} + \beta_3 FlatFee_{it} + \alpha_r^{l,b} + \epsilon_{ijrt} \quad (1)$$

where i indexes the property, j indexes the ZIP code that the property is located within, r indexes the real estate agent associated with the transaction, and t indexes the year in which the transaction took place. The dependent variable, $y_{ijrt}^{P,DOM}$, is either one of two transaction outcomes: the natural log of the final sale price or the number of days on the market (DOM). X_i is a vector of structure and lot characteristics including total livable area (in logs), number of bedrooms, number of bathrooms, age of the structure (expressed as a second order polynomial), a dummy for new construction, a dummy for at least one fireplace, a dummy for properties that were recently renovated, lot size (in logs), and indicators for whether the lot has a view, is on the water, or is in a gated community. In all specifications we include year and calendar month dummies to control for time and seasonal determinants of price (θ_t). In addition, we include ZIP code fixed effects, γ_j, to control for time-invariant, neighborhood characteristics.

We also include controls for features of the particular transaction that might affect the price or timing of sale. First, we follow Rutherford et al. (2005) and Levitt and Syverson (2008) and include a dummy variable for whether the listing agent also owns the home ($OwnerAgent$). We also include an indicator for whether the buyer and seller share an agent ($Dual$). The next, and somewhat novel variable is $FlatFee_{it}$, an indicator variable for listings where a homeowner is attempting to sell the house without the help of an agent and is purchasing access to the MLS through a flat-fee broker.

Finally, we include fixed effects corresponding to listing agents, α_r^l and, in a separate specification, we include buyer agent fixed effects, α_r^b. The error term, ϵ_{ijrt}, is double-clustered at the ZIP code and year-quarter of listing levels. In some specifications, we also include property fixed effects δ_i. The inclusion of property fixed effects restricts the sample to only homes that sold at least two times.

Formally, our null hypotheses are that real estate agents do not sell for more or faster when listing their own homes, that dual-agency sales and transactions that do not occur with a buyer agent sell for a similar price as homes purchased with a dedicated buyer agent. That is $H_0^1 : \beta_1 = 0$, $H_0^2 : \beta_2 = 0$ and $H_0^3 : \beta_3 = 0$. Or, stated more plainly, our null hypothesis is that real estate agents do not significantly influence average transaction prices and time on the market.

We then look at the distribution and correlations of our measures of the agent selling premium, buying discount and, (for listing agents) days on the market. In a standard search model, we would expect heterogeneous buyers with a Poisson arrival rate such that a high reservation price would be associated with a longer time to sell. That is, we would expect that listing agents who routinely obtain a higher sales premium should, on average, take longer to sell a property. Obviously, a skilled listing agent will adapt their strategy based on the needs of the client: selling quickly when the owner needs to move, securing a high price when the seller is looking to maximize return on investment. Still, it is possible that some agents would come to specialize in selling quickly versus selling for a premium and perhaps market themselves as such to attract sellers based on their immediate needs. In any case, we will estimate the correlation between the distribution of listing agent selling price fixed effects and DOM fixed effects to see if there is evidence of this pattern in the data. Finally, we look for evidence of negotiating skill. If agents add value to the home buying and selling process through superior negotiation skills then we should expect to find evidence that they are proficient at securing a high price when representing a seller as the listing agent and good at securing a low price when representing a buyer. Thus, we take a subsample of agents who work on both the sell and buy side of the market and estimate the correlation between the distribution of listing agent price fixed effects and buyer agent price fixed effects.

4 Results

In this section, we present our empirical results. We begin by discussing the summary statistics of our housing transactions sample.

4.1 Descriptive Statistics

Table 1 displays summary statistics separately for the three metro areas in our sample. Average sale prices range from $242,000 to $266,000, and average DOM range from 97 to 122 days. The average number of bedrooms and bathrooms and the size of the living area are similar across the three cities.

Focusing on transaction characteristics, we see that dual agent sales comprise between 7% and 11% of our sample. Finally, about 1.2%, 1.0%, and 0.5% of transactions in our sample are listed through flat-fee brokers in Charlotte, Minneapolis, and Houston, respectively.

Table 2 displays summary statistics broken down by flat-fee and non-flat-fee transactions for each of the three cities in our sample. The average house listed through a flat-fee broker in all three markets sold for a higher price compared to the average house listed by a traditional agents. Flat-fee listings sell for between 9% and 13% more than listings with traditional agents. However, they do take longer to sell, ranging from an additional 1 to 25 days. In general, Table 2 shows that most observable property characteristics are quite similar across the two types of listings.

4.2 Benchmark Hedonic Estimates

We begin by estimating equation (1) without agent fixed effects to demonstrate that our methodology and coefficient estimates align with existing literature. We estimate separate regressions for each of our three cities. Table 3 presents these baseline regression results in columns (1), (4), and (7). Controlling for location and time using ZIP code and year and month fixed effects, we find that homes with larger lots, special views, waterfront locations, and gated communities tend to sell for more, as do homes with more habitable space and bathrooms. The signs and magnitudes of the coefficient estimates generally match previous hedonic estimates of home attributes.

In columns (2), (5), and (8) of Table 3 we include variables that capture circumstances of individual sales, including an indicator for whether the agent is selling his or her own property ("owner agent"), an indicator for whether the seller's agent is representing both the seller and buyer ("dual agent"), and a dummy for whether the owner used a flat-fee broker rather than a traditional full-service agent. We also include indicators for whether the transaction is an estate sale or if the listing agent is affiliated with a builder of new homes.[12] The estimates suggest that owner agents sell their own homes for considerably more in Houston (6 percent), consistent with the findings of Rutherford et al. (2005) and Levitt and Syverson (2008), but not in Charlotte or Minneapolis. This is consistent with Liu et al. (2020), suggesting the previously reported agent-owned premiums suffer from an omitted variable bias, which prior studies ascribed to market distortions associated with asymmetric information. The dual agent coefficient estimates vary across the three cities. In Charlotte, dual agent sales are not associated with different prices compared to transactions with separate agents. In Minneapolis, they sell for 2 percent more on average, but in Houston, they sell for 1.8 percent less.

Finally, homeowners who sell their own properties and use a flat-fee broker to access the MLS obtain prices that are between 1.1 and 4.4 percent *higher* than sellers who use traditional agents. This is a remarkable result, considering that they are also avoiding the listing agent's commission, which typically ranges from 2.5 to 3% of the final sale price. A quick, back-of-the-envelope calculation suggests that these homeowners may have saved a significant amount by not hiring a full-service agent. First, we take the average price of a flat-fee transaction in Charlotte, which is \$286k (Table 2), and assume that the owner still pays a typical buyer agent commission of 3% and a flat fee of \$400 to list on the MLS, but saves 3% on the listing agent's commission. We then calculate what the seller would have obtained with the average conventional agent by subtracting the 4.4% flat-fee premium (\$273) and assuming they paid 6% in total sale commissions. In this scenario, the homeowner who used a flat-fee broker saved \$20,008 (7%) relative to what they would have obtained from the average agent-led sale. For Minneapolis and Houston, where the flat-fee premium was smaller, the seller saved \$11,258 and \$13,229 respectively, or roughly 4% in both cases. Of course, this calculation assumes that the flat-fee coefficient estimates in Table 3 truly reflect treatment effects of selling through a flat-fee broker versus a traditional agent rather than selection effects that may be creating an upward bias in the estimates.[13] In other words, it is possible that these homeowners would have negotiated a better price had they instead used a conventional agent.

To mitigate concerns about selection bias, we introduce property fixed effects in columns (3), (6), and (9) of Table 3. This adjustment aligns the specification more closely with a repeat-sales analysis, where time-invariant property characteristics are differenced out of the

[12]These estimates are available from the authors upon request. We include the builder agent dummy variable to capture the possibility that their effective commission structure may be different than that of typical agents.

[13]Such a bias could be present if FSBOs who list their properties on the MLS through a flat-fee broker are more sophisticated or better negotiators compared to the average FSBO in the general population.

regression. However, this approach comes with a significant drawback: the sample size is substantially reduced because only properties that transact more than once remain in the sample. A unique aspect of our data is the relatively long panel of sales, allowing homes to undergo renovations and change their attributes over time. Unlike many datasets used in repeat-sales specifications, our MLS database updates property characteristics with each new listing. Therefore, even with property fixed effects included, we can still control for time-varying structural characteristics such as changes in the number of bedrooms, bathrooms, and living area.

The inclusion of property fixed effects slightly reduces the sale price premium associated with flat-fee listings for Charlotte and Houston, but slightly increases the premium in Minneapolis. Using these revised estimates in our previous calculation still indicates significant potential savings, ranging from \$11,168 to \$16,514, or between 4% and 6%.

4.3 Benchmark DOM Estimates

All else being equal, most homeowners would prefer to sell at a high price and as quickly as possible. However, there is an obvious trade-off between the listing price, reservation price, and expected time on the market (see Haurin et al. (2010) and Springer (1996) for example). In this section, we present estimates of equation (1) but switch the dependent variable from price to DOM to establish a baseline estimate of selling time. Similar to the structure of Table 3, we first estimate a baseline specification and then compare the average time of traditional agents to sales conducted with a flat-fee broker.

The specifications in columns (1), (4), and (7) of Table 4 include only parcel and structure variables along with time and ZIP code fixed effects. Across the three cities, larger houses, bigger lots, and new construction take longer to sell, as do properties with a view or waterfront location. These tend to be valuable attributes based on the results in Table 3, but preferences for these amenities may be more varied, and it may take longer for a buyer who values them to arrive or to agree on their value in the negotiation phase.

In columns (2), (5), and (8), we include the "owner agent," "dual agent," and "flat-fee broker" indicator variables. Unlike in Levitt and Syverson (2008), we find little evidence that owner-agents take longer to sell. Dual agents take between 0 and 4 days longer to sell. In Charlotte and Houston, flat-fee listings do not take longer to sell on average. In Minneapolis, homeowners selling their own properties through a flat-fee broker took 3.5 days longer (or 3.6% of the average time on the market) to sell relative to a traditional agent.

Finally, columns (3), (6), and (9) introduce property fixed effects. Absorbing unobserved, time-invariant housing attributes slightly increases the average DOM differences between flat-fee listings and traditional agent listings in both Minneapolis and Houston to approximately 6 and 4 days, respectively. However, only the Minneapolis coefficient is statistically significant, and the differences are very small when measured as a percentage of the average DOM in the two cities (97 and 111 days, respectively).

The takeaway from Tables 3 and 4 is that, on average, homeowners selling their own properties through flat-fee brokers obtain higher price premiums and do not take significantly longer to sell compared to those who use traditional agents, perhaps because they are more aggressive at negotiating.

4.4 Robustness

The specifications in Tables 3 and 4 include separate ZIP code and listing-year fixed effects (and month fixed effects to account for seasonality), and in the most saturated specification, property fixed effects. However, an additional concern is that there are unobserved factors resulting in inter-temporal, cross-sectional variation that may bias our estimates. For example, it is possible that agent skill matters less in thin markets, and flat-fee listings are more likely to appear in those markets. To account for such variation, we replicate the specification in equation (1) and include joint ZIP-by-year fixed effects.[14] These results are presented in Panel A of Table 5. For each of our three cities, we display a hedonic specification and a DOM specification with ZIP-by-year FEs. The results are largely unchanged from those reported in Tables 3 and 4.

An additional concern with the analysis thus far is selection bias. Unfortunately, we do not have an exogenous source of variation in flat-fee listings. Given that certain homeowners in our sample decide to try selling without an agent and also choose to list their properties on the MLS through a flat-fee broker, it is possible that homeowners who opt for flat-fee brokers are more financially sophisticated, possess greater knowledge about their local housing market, or are superior negotiators compared to homeowners who engage traditional agents. Consequently, the flat-fee coefficient estimates in Table 3 may merely reflect these unobserved differences, and it would be incorrect to interpret those results as evidence that the average homeowner would not obtain a higher price by hiring a full-service real estate agent.

To shed some light on this issue, we investigate whether homeowners who sold their properties themselves via a flat-fee broker obtained lower prices when they purchased their properties. Specifically, we estimate the hedonic specification in equation (1) and include an indicator variable, $FlatFeePurchaser$, which takes a value of one if the purchaser of

[14] In these specifications, we omit the property fixed effects.

the property subsequently sells the same property using a flat-fee broker. The idea behind the exercise is that if homeowners who sell via a flat-fee broker are more sophisticated and knowledgeable or better negotiators than those who hire a full-service listing agent, then we would expect to see those homeowners obtain significantly lower prices when they originally purchased their properties.

The results of this exercise are displayed in Panel B of Table 5. For each city, we report results for hedonic regression specifications with and without property fixed effects. We find limiited evidence that buyers who later sell their own properties via flat-fee brokers obtain significant discounts. In Charlotte and Houston, the coefficient for $FlatFeePurchaser$ is economically small and not statistically significantly different from zero. However, in Minneapolis, the coefficient is –1.7 percent and statistically significant at the 5% level without including property fixed effects. Adding property fixed effects slightly increases the Minneapolis coefficient (in absolute magnitude) to –0.028.

These results, combined with the finding in Table 4 that flat-fee listings take slightly longer to sell on average, suggest that selection bias is unlikely to be a first-order issue, but cannot be completely dismissed. Sellers who use flat-fee brokers (at least in Minneapolis) may have better price negotiation skills compared to the average real estate agent. However, in the next section we show that flat-fee listings are significantly less likely to end in a successful sale, which suggests that those homeowners who use flat-fee brokers may not be more significantly more knowledgeable or sophisticated.

4.5 Probability of Sale Analysis

Up until now, our analysis has exclusively focused on real estate listings that resulted in a successful sale. Conditional on selling, we have documented that homeowners using flat-fee brokers to list on the MLS tend to take a few additional days to sell compared to listings that use traditional, full-service agents. A novel aspect of our MLS database is that it also contains information on property listings that fail to sell and are ultimately withdrawn from the MLS system. This allows us to investigate whether homeowners who sell their homes through a flat-fee broker are more or less likely to sell successfully compared to homes listed by traditional agents.

In order to conduct such an analysis, we expand our sample to include all property listings in each city, regardless of whether they resulted in a successful sale. We then utilize linear probability models (LPMs) to estimate the probability of a property selling within one year of being listed.[15] Our LPM specifications include homes that were sold, remained listed on

[15] It is worth noting that the vast majority of successful sales occur within a year. However, we also increased the sale horizon to two years, but the results remained largely unchanged.

the market for over 365 days, and those that were listed but subsequently withdrawn and did not reappear in the MLS within a 365-day period.[16] We regress the dummy variable for a successful sale within one year on the same set of covariates and control variables utilized in equation (1).[17] Table 6 displays the estimation results.

The table presents two specifications for each of our three MSA samples: the first without property fixed effects and the second with them. We find that a significant fraction of listings do not result in a sale. Across our samples, between 35 and 51 percent of homes listed on the MLS do not sell within 365 days. This proportion is even lower when we restrict the sample to homes that appear on the MLS more than once (columns (2), (4), and (6)).

The main finding in Table 6 is that homeowners who list via a flat-fee broker are significantly less likely to sell their houses within a year.[18] Depending on the city and specification, they are between 7.9% and 11.1% less likely to sell compared to homeowners who hire full-service agents. These results suggest that homeowners who lack market knowledge may misjudge the value of their properties or do a poor job of marketing and eliciting buyer visits—knowledge or skills that a professional agent might possess. However, the results could also indicate that flat-fee home sellers are particularly patient or engaged in "in-home-search" (Wheaton, 1990). Such an explanation is also consistent with the DOM results discussed above. Finally, the results could also be explained by buyer agents steering their clients away from flat-fee listings, which is consistent with the model of collusive behavior presented in Levitt and Syverson (2008). For the rest of the paper, we will focus on price and DOM as our variable of interest. However, the fact that a flat-fee listing is less likely to end in a successful sale is a notable finding and suggests that there may be an important trade-off between price and probability of sale for homeowners who decide to forgo the assistance of a full-service agent.[19]

4.6 Agent Sales Volume and Experience

In the specifications above we compared flat-fee broker sales to transactions with traditional, full-service listing agents. However, that comparison may be distorted by the presence of

[16] If a property was withdrawn and subsequently relisted within the 365-day window, it is treated as a single observation. However, if a property is relisted over a year after it was withdrawn, it is considered a new observation.

[17] The only exception is that we cannot include the dummy variable for dual agent sales since it is undefined when a sale does not occur.

[18] These results are consistent with the findings of Barwick et al. (2017) and Levitt et al. (2008), who document that low commission rate listings have a lower propensity to sell due to retaliation.

[19] In the Online Appendix (section A.5), we estimate a Heckman selection model to see if the pricing results in Table 3 are sensitive to controlling for differences in the probability of sale between flat-fee brokers and full-service agents. Controlling for differences in sale probabilities has virtually no impact on the estimated flat-fee broker coefficients.

part-time agents who sell real estate as a second job or who only moonlight as agents when markets are hot and booming. Indeed, in our data, approximately between 20 and 26 percent of all sales, involved listing agents who had less than 4 sales per year. Furthermore, there are a few listing agents in our sample who engage in implausibly high numbers of transactions. These agents are likely brokers who have built up a large practice such that they can employ a team of employees that do most of the work under their name. These brokers likely employ rookie agents or agents who do not yet have a real estate license. The inclusion of these high-volume agents in our sample could be affecting the implied average performance of a conventional agent.

For these reasons we re-estimate the hedonic specifications in Table 3 and the DOM specifications in Table 4, but include two additional controls: an indicator for low volume listing agents who close four or less transactions per year and an indicator for high volume listing agents who close more than 2 sales per week (104 sales per year).[20] The results are displayed in columns (1) and (3) of Table 7. We find that high-volume agents sell for less in all three markets (column (1)) and sell more quickly (column (3)) in two markets (Charlotte and Houston). We find that low-volume listing agents also sell for less in all three of our markets. Unlike high-volume agents however, low-volume agents appear to take significantly longer to sell on average. Importantly, the inclusion of these additional controls does not significantly change the flat-fee coefficient estimates.

It is possible that the low-volume and high-volume dummies are actually capturing agents with little experience. As discussed above, the high-volume agents may simply be allocating listings to rookie agents who are trying to break into the profession. Low-volume agents could include both part-time agents as well as newer, less-experienced agents who haven't yet built a reputation. While we cannot perfectly observe agent experience in our data, we construct a proxy that is based on the number of years that an agent is active in our sample. We address the fact that our data is left-censored by dropping agents with any sales in the first two years of our sample period (since we do not know when they first began working as an agent) and assume that an agent who first appears more than two years after the beginning of our sample period is new to the profession. With this new dataset, we construct a time-varying experience variable based on the number of years an agent has been active in the MLS database at the time of a given transaction.

Columns (2) and (4) in Table 7 display results for specifications that include this measure of listing agent experience in addition to the controls for low-volume and high-volume agents.

[20]Depending on the MSA, between 2 and 8 percent of all sales in our data were completed by listing agents more than 104 sales per year. We also experimented with alternative cut-off values for high-volume agents but found little affect on the estimates.

We find that listing agents tend to sell at higher prices with each additional year of experience in Houston and Minneapolis (column (2)) and sell faster with more experience in all three markets (column (4)). Each additional year of experience lowers DOM by 0.4–1.0 days. Controlling for experience slightly has a small impact on the flat-fee coefficients in both the hedonic and DOM regressions.[21]

In summary, we find that low- and high-volume listing agents obtain lower prices on average, which is consistent with the idea that these agents are more likely to be newer to the profession or part-timers who are selling real estate as a second job. We also find more direct evidence that agents improve their performance on both the price and time-to-sale dimensions as they accumulate greater experience in the profession. Finally, we show that the inclusion of these additional controls does not erase the estimated price premium associated with flat-fee listings.

5 Distribution of Agent Fixed Effects

The positive coefficient estimates associated with the flat-fee listing dummy suggest that many homeowners could retain significantly more of their housing equity by selling their own homes without the services of the average real estate agent. However, there is likely a lot of heterogeneity in ability across real estate agents. In this section, we characterize the distribution of this ability.

Our strategy for measuring real estate agent skill is to estimate the hedonic and DOM regression specifications in equation (1) with a full set of listing agent fixed effects. We then recover the fixed effect estimates for both models and characterize the distributions, using flat-fee listings in our sample as a benchmark (i.e. the omitted group). This way, we are able to compare the difference in price and DOM obtained by each listing agent in our sample to the average price and DOM obtained by our sample of homeowners who sell without an agent using flat-fee brokers to access the MLS. Similarly, we estimate buyer agent fixed effect specifications and compare the distribution of buyer agent price and DOM outcomes to the benchmark of dual agent sales. We estimate specifications with and without property fixed effects.[22]

We present moments from the distribution of estimated agent fixed effects in Table 8 and plots of the entire distributions in Figures 1 and 2. Panel A in Table 8 summarizes the

[21] We also attempted to control for capacity constraints by including the total number of new listings that an agent had in the previous three months. This variable had little impact on the results.

[22] We group together agents with less than 30 total listings in our sample and assign them a separate fixed effect. We also estimated specifications in which we dropped those agents altogether and found similar results.

distribution of listing agent and buyer agent fixed effects in the hedonic models for each of our three cities in the sample, showing statistics for specifications with and without property fixed effects.[23] The first notable observation is the considerable heterogeneity in the prices that agents obtain for their clients. In specifications with property fixed effects, exchanging a 5th percentile agent for a 95th percentile agent would increase the sale price by between 15 percent (Minneapolis) and 21 percent (Charlotte), with the interquartile range between 5 and 6 percent. Note that the omitted category is flat-fee. Thus, setting aside the additional time and effort involved in selling a property, a homeowner would need to hire a listing agent whose average sale premium was at least three percent to justify forgoing the flat-fee option. According to the estimates in Panel A, such listing agents fall between the 75th and 90th percentiles of the distributions in all three cities. For instance, in Minneapolis, only 1 out of 10 agents appears to earn more after fees compared to a flat-fee listing. Moreover, the median listing agent in all three cities obtains a *lower* price (ignoring fees) compared to the average seller who lists through a flat-fee broker.

There is also significant heterogeneity among buyer agents. The interquartile range of the buyer agent fixed effects ranges from 4 to 5 percent. In Charlotte, when property fixed effects are included, a buyer agent in the 5th percentile of the distribution obtains a price that is 17 percent lower than an agent in the 95th percentile. Similar levels of heterogeneity are observed in the distributions for Minneapolis and Houston.

It is worth highlighting that including property fixed effects in the hedonic regressions substantially reduces the amount of price dispersion observed for both seller and buyer agents. One possible explanation for this pattern is that the inclusion of property fixed effects helps mitigate the bias that arises from potential assortative matching. Specifically, it's possible that some of the dispersion we observe is due to real estate agents specializing in certain market segments based on unobserved and uncontrolled factors. By including property fixed effects, we account for assortative matching based on time-invariant variables, which reduces the amount of price dispersion across agents.

Panel B of Table 8 displays the distribution of listing agent fixed effects based on the DOM regressions. These distributions also exhibit significant heterogeneity across agents. Focusing on the specifications that control for property fixed effects, we find that the median agent sells homes 2.5 to 7.5 days faster compared to a seller who lists through a flat-fee broker. These are small differences relative to the average DOM in our three cities (97–122 days). The interquartile range for the DOM distribution is large, exceeding 30 days for the Charlotte sample, 20 days for Minneapolis, and 26 days for Houston. Unlike the hedonic

[23]Table A.4 in the Online Appendix displays information about the fraction of statistically significant fixed effect coefficients for each of the specifications in Table 8.

fixed effect distributions in Panel A, the dispersion in the DOM fixed effect distributions is not as sensitive to the inclusion of property fixed effects, which suggests that assortative matching on time-invariant unobserved property characteristics is not as significant for the DOM outcome.

In Figures 1 and 2, we present kernel density estimates of the real estate agent fixed effect distributions summarized in Panels A and B of Table 8. The distributions of listing agent fixed effects from the hedonic models, without property fixed effects (solid black line) in the left side of Figure 1, show that the mass of the distribution is shifted well to the left of zero, and a substantial majority of agents have an average sale premium that is lower than the typical 3 percent agent commission. However, controlling for time-invariant, unobserved property characteristics (grey dashed line) significantly tightens up the distributions and shifts them to the right. This suggests that some of the price premium reflects differences in the unobserved quality of the homes listed by traditional agents compared to those listed through flat-fee brokers. The distributions of listing agent fixed effects from the DOM models in Figure 2 also display significant heterogeneity.

The kernel density estimates of the buyer agent fixed effect distributions are presented on the right side of Figure 1. Controlling for property fixed effects also reduces the dispersion in buyer agent outcomes. Comparing the buyer agent density estimates with and without property fixed effects suggests that house quality may have obscured the negotiating ability of some buyer agents in Charlotte, while it made some buyer agents appear more effective in Minneapolis and Houston.

Lastly, in Figure 2, which displays the kernel density plots of the estimated listing agent fixed effects from the DOM regressions for each city in our sample, we can clearly observe that including property fixed effects does not have as significant of an impact.

5.1 Estimating the Trade-off Between Price and DOM

Figure 3 depicts scatter plots of the estimates of listing agent fixed effects from the hedonic regression (vertical axis) against the estimates of listing agent fixed effects from the DOM regression (horizontal axis) for each of the three cities in our sample. The plots on the left side of the figure correspond to listing agent fixed effects estimated without housing fixed effects, and the plots on the right show listing agent fixed effects when we include property effects.

The purpose of the figure is to determine if there is a trade-off between selling for a high price and selling quickly. If agents consistently urge their clients to accept low bids, they may sell more quickly, but at a lower price on average (See Levitt and Syverson, 2008 and Anglin et al., 2003). Conversely, listing agents may wait for high bids or offer only modest price concessions during negotiations. The plots without property fixed effects show a slightly downward-sloping relationship, suggesting that agents who take longer to sell also sell for less on average. However, this relationship may be due to unobserved heterogeneity, as agents who list lower-quality homes will tend to take longer to sell. Indeed, when we control for property fixed effects in the plots on the right side of the figure, the negative relationship disappears, and we find virtually no correlation between the price and DOM fixed effects.

A second motivation in constructing Figure 3 is to determine how many agents provide their clients with both a higher price and a shorter time to sell compared to the typical homeowner who sells their property using a flat-fee broker. In the plots, these listing agents are located in the northwest quadrant, which we shade in green. Conversely, most homeowners do not want to take a long time to sell for a low price, and thus, we shade the southeast quadrant in red to denote the worst performing agents. Again, recalling that the omitted category is flat-fee listings, it is striking that the mass of agent fixed effects is clustered near the origin of the plots.

5.2 Evidence on Negotiating Skill

One skill that distinguishes top real estate agents is their ability to negotiate effectively and secure better prices for their clients. To examine this issue, we focus on a sample of agents who serve as both listing and buyer agents in our data set. Figure 4 presents a scatter plot of our estimates of an agent's fixed effect when serving as a listing agent versus their fixed effect when serving as a buyer agent. A good negotiator should be able to secure high prices when selling a property and low prices when buying, resulting in placement in the lower right quadrant of the scatter plot (shaded in green). Conversely, weak negotiators should cluster in the top left quadrant (shaded in red), buying high and selling low.

In the absence of property fixed effects, we observe a positive upward sloping line. This suggests that agents who sell homes at a premium on average also tend to buy homes at a premium when they serve as a buyer agent. However, this effect becomes significantly more muted when we include property fixed effects. The plots indicate that only a few agents are located in the bottom right quadrant, indicating that they are skilled negotiators who obtain high prices when selling and low prices when buying, on average. Thus, while real estate agents may have many skills, the ability to negotiate favorable pricing terms appears to be relatively uncommon.

6 Top-Performing Agents

In the previous section we estimated the distribution of agent value-added to the two most important outcomes in the home buying and selling process: the final sale price and the amount of time a property takes to sell. We documented that most traditional agents do not achieve superior outcomes compared to homeowners who sell their own properties using a flat-fee broker. However, it is apparent in Table 8 and Figures 1 and 2 that there is a small fraction of agents who do achieve significantly better outcomes. In this section we will focus on these top-performing agents.

We begin by explaining how we define high performance and providing summary statistics of the top-performing agents in our sample. Then we test for persistence in high performance and whether the market recognizes and rewards high performance in the form of additional listings. Finally, we investigate whether top-performing agents are more valuable in hot versus cold markets.

6.1 Defining and Characterizing Top-Performing Agents

We define a top-performing agent as one whose estimated fixed effect is better than 90 percent of all agent fixed effects for a given outcome. We do this separately for our three outcomes of interest. Thus, listing agents who are in the top decile of the price fixed effects distribution are top-performing on the price dimension since they are trying to obtain a high price for their clients. In contrast, buyer agents in the bottom decile of the price distribution are top-performing since they are trying to obtain low prices. Finally, seller agents who are in the bottom 10th percentile of the DOM distribution are considered top-performing since, all-else equal, they are trying to sell as quickly as possible.

In Table 9 we provide summary statistics, by city, for the top-performing agents as well as for the rest of the agents in our sample.[24] The table displays the average number of listings, the number of years active in the sample period, the average number of listings in a given year conditional on being active (i.e. having at least one sale), and the average size of the property that was sold. Following Ambrose et al. (2021), we identify the race of individual agents using the Bayesian Improved First Name Surname Geocoding (BIFSG) method developed in Voicu (2018). Additionally, we utilize the data from Tang et al. (2011), as suggested by Goldsmith-Pinkham and Shue (2023), to determine the gender of each individual agent.

Regarding the price outcome, top-performing listing agents have more listings across the

[24]The top agents in Table 9 are identified from fixed effects regressions that include property fixed effects. In the following sections where we further investigate top agents, we show results for top performers identified both with and without property fixed effects.

sample period in two of the three cities (Charlotte and Houston). In contrast, in all three cities, the top-performing buyer agents have fewer listings, on average, suggesting that they may allocate more effort to each client at the expense of lower volume.[25] Surprisingly, we find that across all three measured outcomes and across all three cities, the top agents, on average, have slightly shorter tenures.

Turning to the demographic variables, we find that the top-performing listing and buyer agents on the price dimension are less likely to be female. However, women are slightly more likely to be among the fastest selling agents. These findings are roughly consistent with evidence from the experimental labor literature on gender wage negotiation and tolerance for risk (Dittrich et al., 2014 and Maitra et al., 2021).

Unlike gender, there does not appear to be any clear patterns for the race and ethnicity indicators. One takeaway from the table is the fact that minority individuals are significantly under-represented in the real estate agent occupation.[26] But in terms of the likelihood of being among the top-performing agents, in some markets and in some tasks, Black, Hispanic and Asian agents are disproportionately likely to be at the top, while in other markets they are less likely. For example, minority listing agents in Houston and buyer agents in Charlotte are more likely to be top agents than their share of the real estate agent sector would predict. However, in Charlotte, minority listing agents are less likely to be top performers on the price dimension relative to their market shares.

6.2 Is High Performance Persistent?

In this section, we implement a simple test to determine if high performance is persistent or simply a result of luck. Specifically, we split the sample in half and assess whether top-performing agents in the first half of the sample period (2000-2009) were more likely to remain top-performing agents in the second half of the sample period (2010-2019).

The test consists of two steps. In the first step we re-estimate the fixed effects regressions detailed in equation (1), but include interaction terms between an indicator variable for listings that occur in the second half of the sample period and the agent fixed effects. We extract the two sets of fixed effect estimates and identify top-performing agents in each half of the sample using the same definition underlying Table 9. In the second step we regress an indicator for being a top-performing agent in the second half on an indicator for being

[25] We are unable to directly test whether there is a tradeoff between effort and volume because we do not observe the number of buyers that an agent represents at a given point in time.

[26] This is a fairly well-known issue. See for example, "Selling Houses While Black", NYT Coleman, Collette, January 12, 2023. https://www.nytimes.com/2023/01/12/realestate/black-real-estate-agents-discrimination.html

a top-performer in the first half of the sample.[27] If high performance is persistent, then we should expect to obtain a positive coefficient estimate between 0 and 1, where 1 would correspond to a scenario of perfect persistence.

The estimates are presented in Table 10, which contains three panels corresponding to each of the cities in our sample. Within each panel, we show the persistence of top-performing status when the underlying agent fixed effects are estimated with and without property fixed effects. Columns (1) and (2) present the estimates for the persistence of being a top-performing listing agent based on selling price. Without controlling for underlying property fixed effects, a top agent in the first half of the sample was 32% (Houston) to 47% (Charlotte) more likely to be a top-performing agent in the second half of the sample compared to an agent who was not a top performer in the first half. The persistence estimates fall to 8–13% when agent fixed effects are estimated while also controlling for property fixed effects. A similar pattern holds for top-performing buyer agents. The top 10th percentile of agents who secured low prices for their clients in the first half of the sample were 17% (Houston) and 29% (Charlotte) more likely to be top-performing agents in the second half of the sample (column (3)). Controlling for property fixed effects (column (4)) also significantly lowers the persistence estimates for the top-performing buying agents.

Finally, columns (5) and (6) test for persistence in high performance for the DOM outcome. In the absence of property fixed effects, we find that top-performing agents in the first half of the sample are between 5% and 12% more likely to be a top performer in the second half of sample. However, the estimates decline significantly when agent effects are estimated while controlling for unobserved property characteristics (column (6)). For the Charlotte and Minneapolis samples, persistence in high performance goes to zero.

Overall, we find evidence that high performance is moderately persistent on the pricing dimension but is not persistent on the DOM dimension. These results suggest that only a small subset of agents consistently obtain higher average prices over an extended period of time.

6.3 Does the Market Reward Top-Performing Agents?

We have established that only a small fraction of real estate agents consistently deliver favorable price outcomes for their clients. A pertinent question is whether these agents are rewarded by the market with increased business. In this section, we conduct a test to investigate whether the top-performing agents in the first half of our sample period attract

[27] To be included in the sample, an agent has to be active and have at least one listing/buying contract in both halves of the sample. In addition an agent must have at least 30 sales over the entire 20-year sample period.

additional listings in the second half of the sample. As we do not observe when a home buyer signs a contract with a buyer agent, we focus exclusively on top listing agents. Although we observe all listings, even those that fail, we only observe buyer agents when they engage in successful transactions. To test whether the top-performing listing agents draw more clients, we first calculate the percentage growth in the number of listings across the two halves of the sample period.[28] We then use the growth rate in listings as the dependent variable in a specification similar to the one presented in Table 10 above and regress growth in listings on an indicator for being a top-performing agent in the first half of the sample.

The results of this exercise are displayed in Table 11. In column (1), the top-performing indicator is determined based on a hedonic regression of sales from 2000 through 2009 without property fixed effects, while the top-performing dummy in column (2) is derived from a specification that includes property fixed effects. Columns (3) and (4) display results for the DOM outcome. The results suggest that the market does recognize and reward top-performing agents as we find that the best agents in the first half of the sample period attract considerably more clients in the second half. In column (1) we find that agents who extract the highest prices for their clients gained between 50–60% more listings compared to other surviving agents.[29] This result is not driven by some listing agents simply selling unobservably better houses as it is robust to the inclusion of property fixed effects.

The results in columns (3) and (4) in Table 11, which correspond to the DOM outcome are even stronger. The estimates in column (3) suggest that the fastest-selling agents attract 157–177% more listings compared to other surviving agents. The effect is slightly attenuated, but remains quantitatively large and statistically significant when we control for property fixed effects in column (4).

We cannot directly measure whether a buyer's agent that negotiates a good price on their clients behalf attracts more buyers in the future as buyer agent contracts that do not end with a successful purchase are not observed in the data. We could observe whether the number of future purchases the buyer closes grows over time as in Table 11, but there may be some tension between bargaining and the probability of sale. Instead, we construct a different, but arguably better metric, which measures the likelihood that a buyer agent is hired to serve as the listing agent for the subsequent sale of the same property.

In our MLS data, depending on the city, of properties that sold at least twice in our sample period, between 18% and 23% had the same individual employed as the buyer agent

[28] Specifically, we calculate the growth rate in listings as $ln(\frac{listings_{2009-2019}}{listings_{2000-2009}})$.

[29] Note that this specification includes all agents that had 30 or more sales in the entire sample period and at least one sale in both halves of the sample. If weaker agents subsequently leave the profession and stop listing homes for sale that would lower their listing growth measure. Thus, this specification can be thought of as nesting the intensive and extensive margin of agent listings growth.

for the initial purchase of the property and the listing agent for the subsequent sale of the home.[30] Thus, a buyer agent who serves their client well, may have a good chance of ultimately selling the home in the future as the listing agent. We test this conjecture directly. First, we recover the price residual, $\hat{e}_{it}$ from a fully saturated hedonic regression specification that controls for property characteristics, unique features of the sale (estate, etc.), year and month fixed effects and then either zip code or zip code-by-year fixed effects. We also control for duration of time that the seller was in the home (as a quadratic). We then include this lagged residual in a model that predicts whether a seller hires their former buyer agent to be their listing agent when they choose to sell.

If the market for real estate agents rewards price negotiation, we would expect a negative coefficient on this lagged residual, $\hat{e}_{it-1}$. That is, home buyers that seemingly underpay for their homes–controlling for observables–should be more likely to reward their agent with future work. However, that is not what we find. In Table 12 we present the coefficient estimates associated with the lagged price residual in a regression predicting whether the buyer agent was hired to subsequently sell the home. Across all three markets, and despite a relatively saturated specification, the coefficient estimates are positive rather than negative. Home buyers that appear to overpay for their homes are more likely to go back to their original buyer agent. Stated differently, while the top-performing listing agents appear to be rewarded with additional business, buyer agents who negotiate lower prices do not appear to be rewarded with future business from the same homeowner. This result could be driven by the inability of homeowners to determine whether their agents are able to negotiate lower prices than other agents selling similar properties.

6.4 Are Top-Performing Agents More Effective in Hot or Cold Markets?

We now explore whether top-performing agents achieve better outcomes in booming markets, where there are many buyers and bidding wars, or in slower markets where sale volumes are low, and prices are stagnant or falling. This is an important question because it can help us understand the underlying factors that drive agent performance.[31]

We interact the top-performing agent dummies constructed in section 6.1 with the National Association of Home Buyers (NAHB's) Housing Market Index (HMI), which is a

[30] We only consider properties that were held by the same owner for at least one year in order to eliminate flippers.

[31] In a different context, Sun et al. (2018) studied fund manager skill persistence and found that mediocre managers had a difficult time mimicking skilled ones when the stock market was down.

commonly used measure of real estate market strength.[32] This index combines transaction prices, number of sales, and buyer traffic measures and is publicly available. We interact the HMI index with the top-performer dummy in our baseline hedonic and DOM regressions presented in Tables 3 and 4. The results are displayed in Table 13 for all three cities in our sample for specifications with (Panel B) and without (Panel A) property fixed effects. Columns (1), (4), and (7) present the hedonic coefficient estimates for top-performing listing agents. Columns (2), (5), and (8) show hedonic results for the top-performing buyer agents and columns (3), (6) and (9) present the coefficient estimates for the listing agents who sell the quickest.

While top listing agents (by construction) sell for more, the coefficient associated with the HMI interaction term is negative and statistically significant in columns (1), (4), and (7), indicating that they obtain significantly higher prices in cold as opposed to hot markets. In columns (2), (5), and (8), the interaction term coefficients are positive, indicating that in cold markets, top-performing buyer agents are able to secure lower prices for their clients, while in hot markets they secure higher prices. Thus, the evidence in Table 13 suggests that top-performing listing agents obtain better price outcomes for their clients in cold markets when it is difficult to sell while top-performing buyer agents also obtain better outcomes in cold markets when it is more favorable to buy. Why do top listing agents perform better in difficult conditions for sellers while top buyer agents seem to perform worse when conditions are more difficult for buyers? One possible explanation is that in hot markets, homes for sale are more likely to attract multiple offers (Ngai and Tenreyro, 2014). In that environment, potential buyers are bidding against one another until the winning buyer offers a price higher than the reservation price of the next-most interested party. In other words, hot markets are also thick markets, which, in turn, may reduce the ability of skillful agents to negotiate. Thick markets also provide comparable recent sales, which could help anchor price negotiations and limit the ability of high-skilled agents to anchor or frame the scope of negotiations.

Finally, in columns (3), (6), and (9) we find that the fastest-selling listing agents, while still faster than other agents (by construction), are relatively slower in hot markets. This finding is consistent with the idea that when markets are booming, agent skill matters less.

In Panel B, we estimate the same specifications but control for property fixed effects. The results for top-performing buyer agents for the price outcome and top-performing seller agents for the DOM outcome are similar to those reported in the specifications without property fixed effects in Panel A. However, the results for top-performing seller agents for the price outcome become significantly weaker as only the interaction term coefficient in Minneapolis remains negative and statistically significant.

[32] The HMI time-series is presented in Figure A.2 in the Online Appendix.

The fact that the top-performing listing agents add more value in cold markets compared to hot markets is consistent with a few underlying mechanisms. One possibility is that the top agents have good negotiating skills. Cold markets are characterized by fewer offers, and for any given offer, the available surplus to be split between buyers and sellers (i.e., the difference between a seller's reservation price and a buyer's willingness to pay) is likely greater compared to the difference in hot markets. Thus, in cold markets, having a skilled negotiator is likely more valuable. Another possible mechanism is marketing. In thin markets, agents need to work harder to attract buyers, and so an agent with excellent marketing skills may be especially valuable in generating interest and ultimately offers. Irrespective of the exact mechanism, however, the listing agent results in Table 13 complement the persistence results presented above in section 6.2. If the top-performing agents were simply lucky as opposed to skilled, we would not expect to see significant differences in their performance in hot versus cold markets.

7 Conclusion

Individuals and firms faced with making large, infrequent financial transactions under imperfect information often seek the advice of experts and are willing to pay high costs for their services. In this paper, we focus on real estate agents who are hired by the vast majority of households to aid in the process of buying and selling residential properties. We find little evidence that the average listing agent secures a price premium for their clients that justifies their commission. The average prices of homes sold by traditional agents in our sample are below those obtained by homeowners who sell their own properties using flat-fee brokers, even after controlling for location and property fixed effects. However, we do find evidence that the average traditional listing agent is more likely to successfully sell a property.

These average effects mask significant heterogeneity across agents. Using the unique real estate agent identifiers in our sample of MLS transactions, we include a full set of listing and buying agent fixed effects in otherwise standard hedonic and days-on-market (DOM) regression models. Controlling for property fixed effects, we find an inter-quartile price range of 5-6 percent for the distribution of listing agent fixed effects and a similar range for the distribution of buying agent fixed effects. According to our estimated distributions, a homeowner selling their own house via a flat-fee broker would have needed to hire a listing agent in the top 79th to 90th percentile of the price distribution to justify a three percent commission. Thus, we conclude that high-performing agents who add significant value to the home selling process constitute a small minority of agents. We suspect that weak agents persist in the market because the same information asymmetries that lead one to hire an agent in the first place also make it difficult to evaluate them. The most striking evidence for this is that buyer's agents who appear to secure a low price for their clients are *less* likely to be hired to sell the home when that same client chooses to sell it.

Still some real estate agents appear to be exceptional, repeatedly selling homes for more than other agents or more quickly than other agents. Yet it is unclear where their competitive advantage lies. The correlation between listing agent sale price fixed effects and DOM fixed effects is close to zero, implying that listing agents who obtain high prices don't simply set higher reservation prices and wait longer on average or (conversely) that fast-selling agents regularly set low listing prices. Nor does the unobserved skill appear to be bargaining, as most agents who sell homes at a premium do not appear, on average, to secure much of a discount for their clients when serving as a buyer agent.

Nevertheless, we do identify high-performing agents. These agents are not just lucky. Past success is predictive of future performance. Furthermore, despite the preponderance of low-skilled agents in the market, top-performing listing agents do attract more clients over time, which suggests that the market for agents is at least somewhat efficient at identifying exceptional agents. Finally, we show that the best listing agents appear to be most useful in down cycles when markets are thinner, and the gap between the seller's and buyer's reservation prices is likely wider but also when recent sales that might anchor negotiations are fewer. Discovering the specific tools these agents employ that make them more effective and the exact market conditions that foster high performance is a fruitful avenue for future work.

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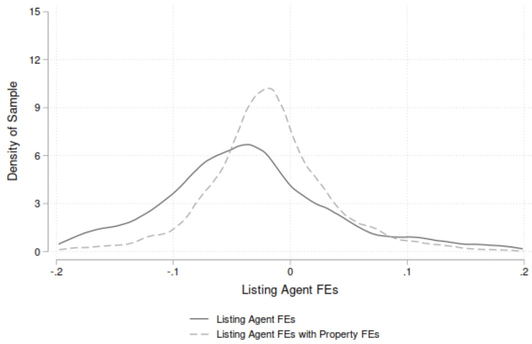
Figure 1: Kernel Density Estimates of Real Estate Agent Fixed Effects: Sale Prices

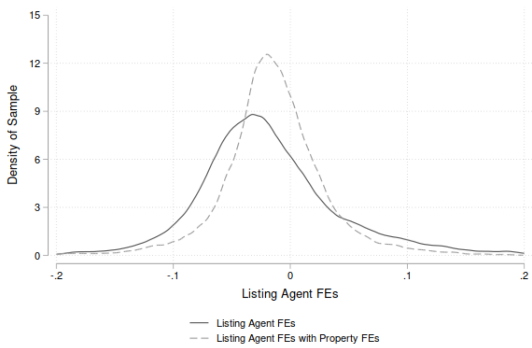
Panel A: Charlotte



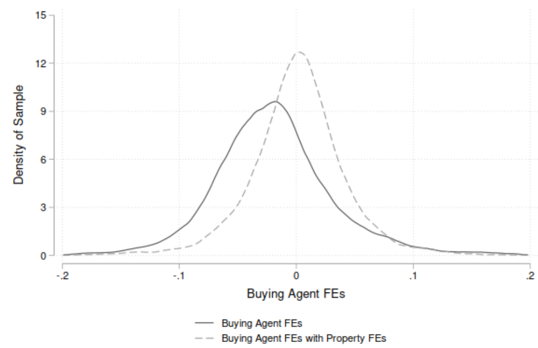
Listing Agent

Buying Agent

Panel B: Minneapolis

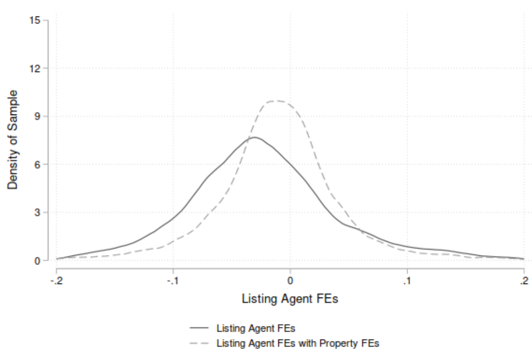


Listing Agent

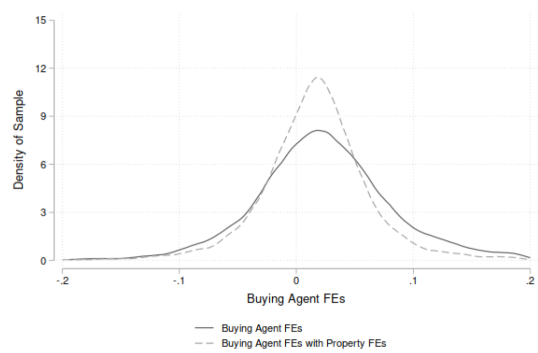


Buying Agent

Panel C: Houston



Listing Agent



Buying Agent

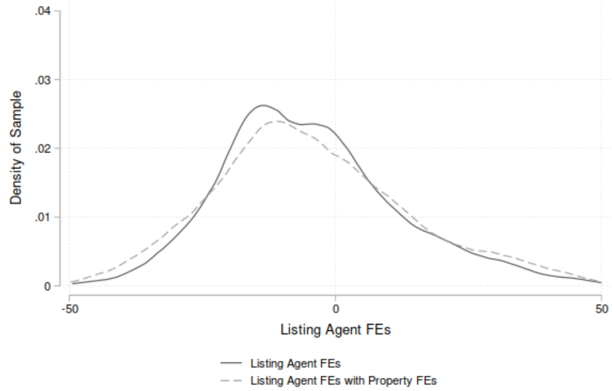
Notes: This figure displays kernel density estimates for the listing agent and buying agent fixed effects ($\alpha_r^{l,b}$ from the following hedonic regression model:

$$y_{ijrt}^{Price} = X_{ir}'\phi + \theta_t + \gamma_j + \alpha_r^{l,b} + \eta_i + \epsilon_{ijrt} \tag{2}$$

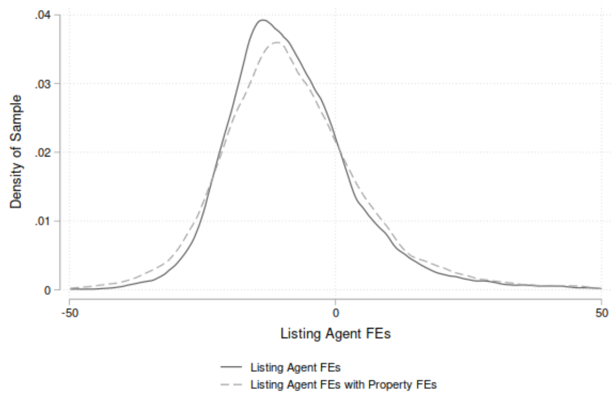
where i indexes the property, t is the year-quarter of the listing date, j is the ZIP code where the property is located, and r is the agent. The dashed density estimates include property fixed effects, η_i. The omitted category in the listing agent fixed effects models is flat-fee brokers, while the omitted category in the buying agent models is dual agent transactions. The underlying data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive).

Figure 2: Kernel Density Estimates of Agent Fixed Effects: Days-on-Market

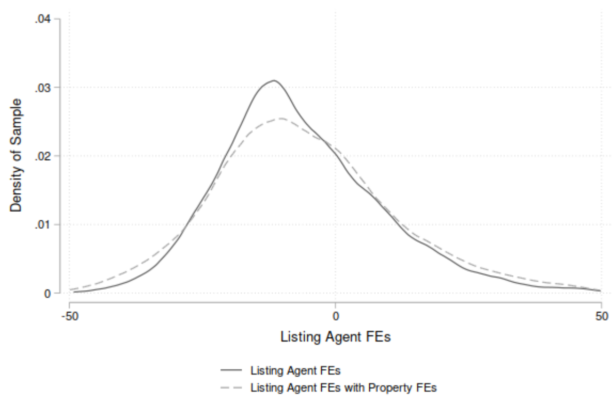
Panel A: Charlotte



Panel B: Minneapolis



Panel C: Houston



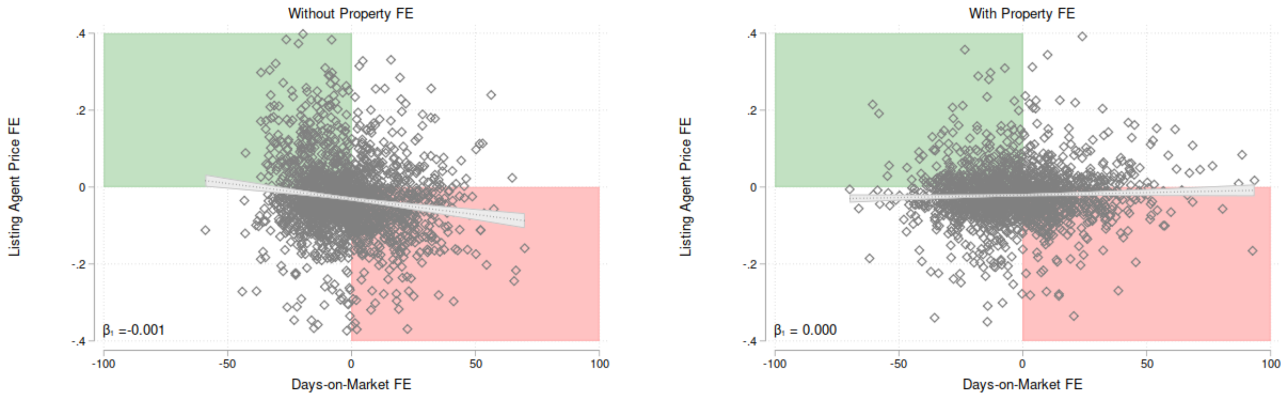
Notes: This figure displays kernel density estimates for the listing agent and buying agent fixed effects ($\alpha_r^{l,b}$ from the following DOM regression model:

$$y_{ijrt}^{DOM} = X'_{ir}\phi + \theta_t + \gamma_j + \alpha_r^{l,b} + \eta_i + \epsilon_{ijrt} \tag{3}$$

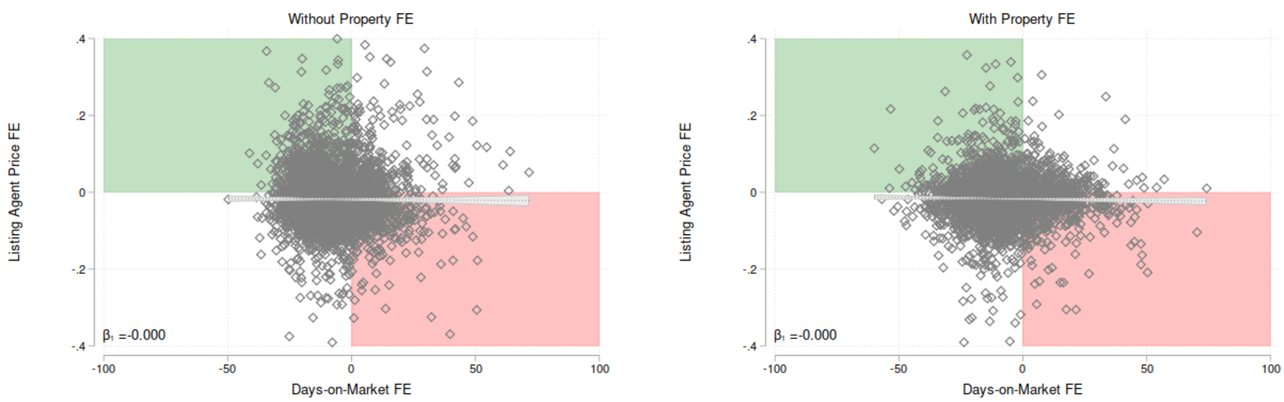
where i indexes the property, t is the year-quarter of the listing date, j is the ZIP code where the property is located, and r is the real estate agent. The dashed density estimates include property fixed effects, η_i. The omitted category is flat-fee brokers. The underlying data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive).

Figure 3: Listing Agent Fixed Effects Scatter Plots: Price vs. DOM

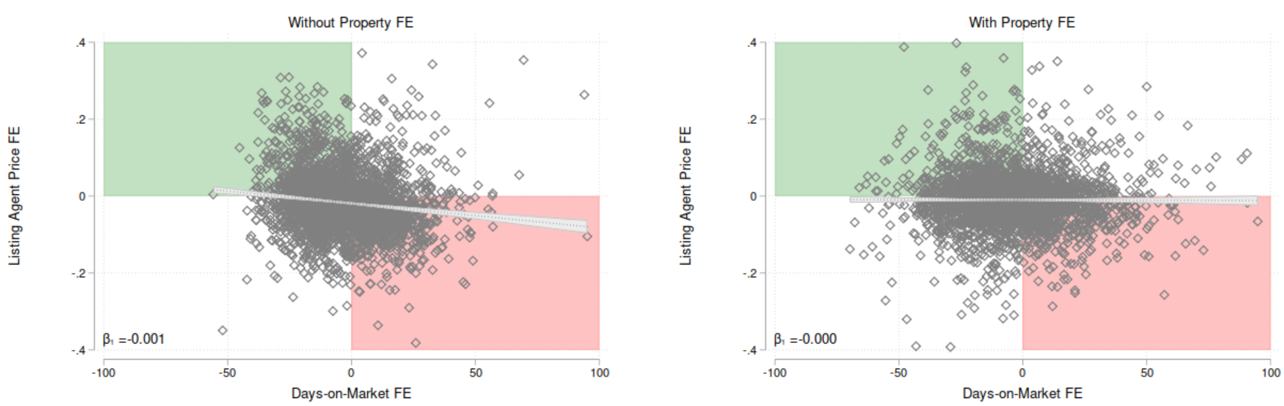
Panel A: Charlotte, NC



Panel B: Minneapolis, MN



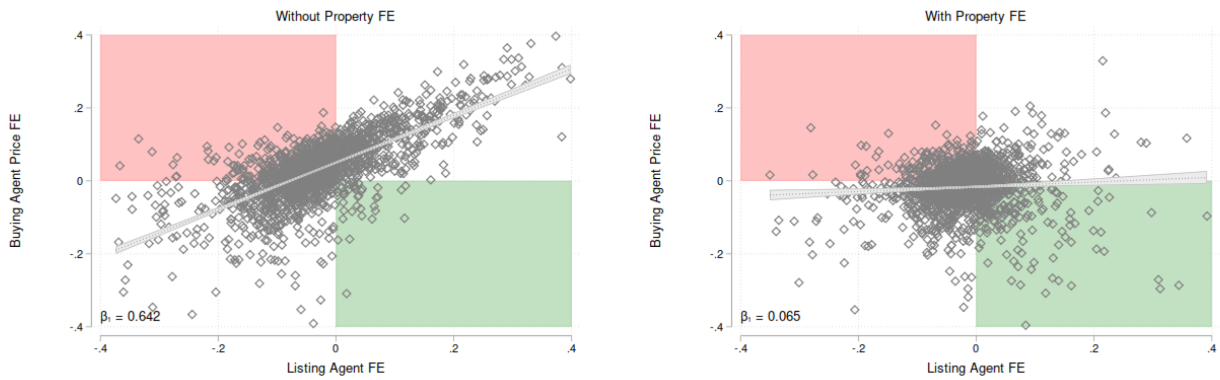
Panel C: Houston, TX



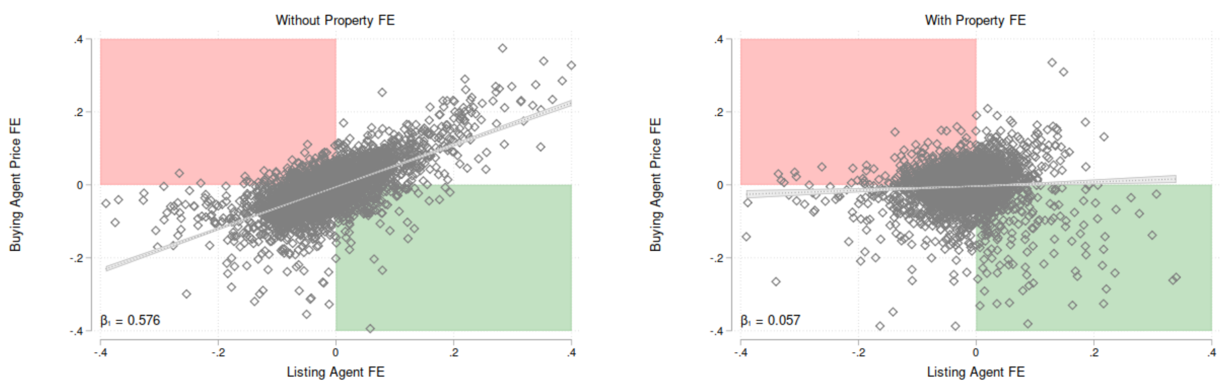
Notes: This figure displays scatter plots of listing agent price fixed effects vs. listing agent DOM fixed effects. Plots on the right side of each panel are derived from specifications that include property fixed effects. In each plot a linear regression is fit through the points. The underlying data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive).

Figure 4: Agent's Listing vs. Buying Price Effect

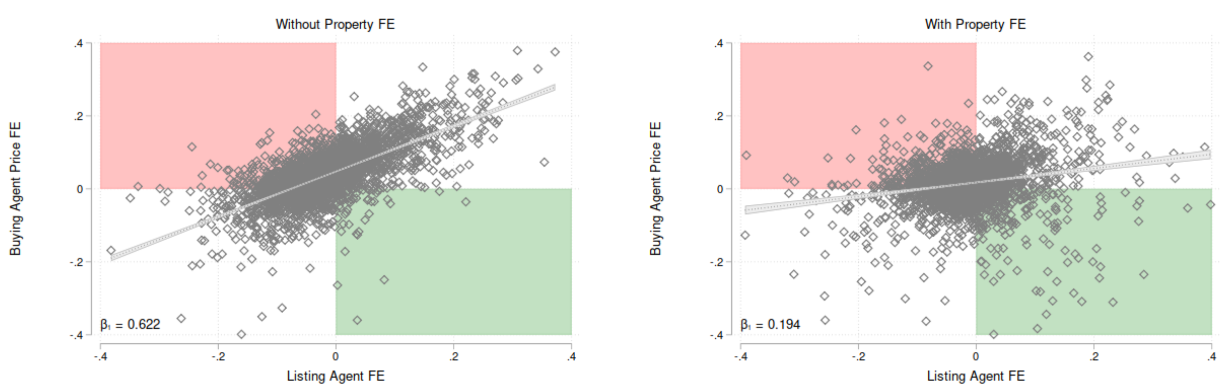
Panel A: Charlotte, NC



Panel B: Minneapolis, MN



Panel C: Houston, TX



Notes: This figure displays scatter plots of listing agent price fixed effects vs. buying agent price fixed effects. The underlying sample includes only agents that work as both listing agents and buying agents. Each point corresponds to an agent's estimated price fixed effect when they worked as a listing agent and the same agent's estimated price fixed effect when they worked as a buying agent. Plots on the right side of each panel are derived from specifications that include property fixed effects. In each plot a linear regression is fit through the points. The underlying data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive).

Table 1: Descriptive Statistics by Metropolitan Area

	Charlotte		**Minneapolis**		**Houston**	
	Mean	Sd	Mean	Sd	Mean	Sd
Sale Price (Thousands $)	257	202	266	170	242	215
DOM (# of Days on Market)	122	104	96.6	77.2	111	91.1
Living Area (100s Square Feet)	22.6	9.85	20.2	8.67	23.8	9.43
# Bathrooms	3.55	0.813	3.25	0.911	3.52	0.730
# Bedrooms	2.80	0.967	2.33	0.929	2.32	0.718
Building Age (Years)	20.1	21.9	35.5	30.7	20.7	19.5
Lot Size (Acres)	0.467	0.71	0.578	1.15	0.480	0.942
Housing Market Index (HMI)	51.9	18.4	53.6	17.3	50.9	18.6
Fireplace (d)	.	.	0.574	.	0.908	.
New Construction (d)	0.187	.	0.047	.	0.165	.
Renovated (d)	0.017	.	0.030	.	0.028	.
View (d)	0.027	.	0.029	.	0.033	.
Gated (d)	0.014	.	0.001	.	0.040	.
Waterfront (d)	0.022	.	0.085	.	0.016	.
Owner Agent Transaction (d)	0.000	.	0.001	.	0.001	.
Dual Agent Transaction (d)	0.107	.	0.075	.	0.068	.
Flat Fee Broker (d)	0.012	.	0.011	.	0.005	.
# Transactions	358,905		735,865		1,010,844	

Notes: This table reports summary statistics from a pooled sample of residential property listings in the Charlotte, Houston, and Minneapolis metro areas that ended in a successful sale. The data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive). The label (d) denotes dummy variables.

Table 2: Descriptive Statistics by Fee Group

Panel A: Charlotte

	Flat-Fee		**Non Flat-Fee**	
	Mean	Sd	Mean	Sd
Sale Price (Thousands $)	286	167	257	202
DOM (# of Days on Market)	98.0	72.2	122.5	104
Living Area (100s Square Feet)	24.0	9.48	22.6	9.85
# Bathrooms	2.90	0.887	3.55	0.813
# Bedrooms	3.65	0.81	2.8	0.968
Building Age (Years)	21.5	19.9	20.1	22.0
Lot Size (Acres)	0.45	0.62	0.468	0.71
Fireplace (d)	.	.	.	.
New Construction (d)	0.000	.	0.189	.
Renovated (d)	0.033	.	0.017	.
View (d)	0.033	.	0.027	.
Gated (d)	0.015	.	0.014	.
Waterfront (d)	0.028	.	0.022	.
Owner Agent Transaction (d)	0.000	.	0.000	.
Dual Agent Transaction (d)	0.037	.	0.108	.
# Transactions	4,381		354,524	

Panel B: Minneapolis

	Flat-Fee		**Non Flat-Fee**	
	Mean	Sd	Mean	Sd
Sale Price (Thousands $)	289	141	265	170
DOM (# of Days on Market)	95.3	73	96.6	77.3
Living Area (100s Square Feet)	21.1	8.17	20.2	8.67
# Bathrooms	3.34	0.891	2.35	0.935
# Bedrooms	2.42	0.891	3.26	0.913
Building Age (Years)	38.5	29.7	35.5	30.7
Lot Size (Acres)	0.508	0.99	0.579	1.14
Fireplace (d)	0.656	.	0.573	.
New Construction (d)	0.000	.	0.048	.
Renovated (d)	0.050	.	0.030	.
View (d)	0.043	.	0.029	.
Gated (d)	0.002	.	0.001	.
Waterfront (d)	0.111	.	0.085	.
Owner Agent Transaction (d)	0.001	.	0.001	.
Dual Agent Transaction (d)	0.020	.	0.076	.
# Transactions	7,895		727,970	

Panel C: Houston

	Flat-Fee		**Non Flat-Fee**	
	Mean	Sd	Mean	Sd
Sale Price (Thousands $)	274	213	242	215
DOM (# of Days on Market)	102	78	111	91.1
Living Area (100s Square Feet)	24.3	8.98	23.8	9.43
# Bathrooms	3.56	0.738	3.52	0.730
# Bedrooms	2.34	0.694	2.32	0.718
Building Age (Years)	26	20.9	20.7	19.5
Lot Size (Acres)	0.403	0.7	0.480	0.944
Fireplace (d)	0.883	.	0.908	.
New Construction (d)	0.000	.	0.166	.
Renovated (d)	0.062	.	0.028	.
View (d)	0.036	.	0.033	.
Gated (d)	0.046	.	0.040	.
Waterfront (d)	0.020	.	0.016	.
Owner Agent Transaction (d)	0.000	.	0.001	.
Dual Agent Transaction (d)	0.017	.	0.068	.
# Transactions	4,704		1,006,140	

Notes: This table reports summary statistics from a sample of residential property listings in the Charlotte (Panel A), Minneapolis (Panel B), and Houston (Panel C) MSAs that ended in a successful sale. The data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive). The label (d) denotes dummy variables.

Table 3: Baseline Hedonic Regressions

Dependent Var: Ln(Price)	Charlotte			Minneapolis			Houston		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ln(Living Area)	0.912***	0.912***	0.536***	0.539***	0.539***	0.185***	0.838***	0.838***	0.353***
	(0.026)	(0.026)	(0.052)	(0.023)	(0.023)	(0.017)	(0.022)	(0.022)	(0.037)
# Bedrooms	-0.055***	-0.055***	0.022***	0.021***	0.021***	0.035***	-0.054***	-0.054***	0.023***
	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
# Bathrooms	0.063***	0.063***	0.058***	0.062***	0.062***	0.084***	0.124***	0.124***	0.105***
	(0.006)	(0.006)	(0.014)	(0.006)	(0.006)	(0.009)	(0.007)	(0.007)	(0.012)
New Construction (d)	0.057***	0.062***	0.077***	0.145***	0.143***	0.077***	0.040***	0.046***	0.024**
	(0.010)	(0.010)	(0.011)	(0.007)	(0.007)	(0.007)	(0.008)	(0.009)	(0.009)
Renovated (d)	0.082***	0.080***	0.156***	0.024***	0.024***	0.087***	0.071***	0.071***	0.115***
	(0.011)	(0.011)	(0.018)	(0.004)	(0.004)	(0.007)	(0.005)	(0.005)	(0.008)
Building Age	-0.007***	-0.007***	-0.016***	-0.006***	-0.006***	-0.012***	-0.010***	-0.009***	-0.019***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Building Age2	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fireplace	.	.	.	0.054***	0.054***	0.022***	0.042***	0.041***	0.019***
	.	.	.	(0.006)	(0.006)	(0.003)	(0.006)	(0.006)	(0.005)
Ln(Lot Size)	0.100***	0.100***		0.084***	0.084***		0.093***	0.093***	
	(0.006)	(0.006)		(0.003)	(0.003)		(0.005)	(0.005)	
View (d)	0.105***	0.105***		0.097***	0.097***		0.112***	0.113***	
	(0.013)	(0.013)		(0.013)	(0.013)		(0.011)	(0.011)	
Gated (d)	0.165***	0.166***		0.074**	0.074**		0.043**	0.043**	
	(0.022)	(0.022)		(0.025)	(0.025)		(0.013)	(0.013)	
Waterfront (d)	0.287***	0.287***		0.106***	0.106***		0.200***	0.200***	
	(0.043)	(0.043)		(0.012)	(0.012)		(0.029)	(0.029)	
Owner Agent (d)		0.028	0.119		0.009	0.074**		0.056***	0.052***
		(0.046)	(0.066)		(0.013)	(0.025)		(0.011)	(0.015)
Dual Agent (d)		-0.004	0.012*		0.020***	0.006		-0.018***	-0.007*
		(0.005)	(0.005)		(0.003)	(0.004)		(0.004)	(0.003)
Flat-Fee Broker (d)		0.044***	0.031***		0.011*	0.014**		0.021**	0.013*
		(0.007)	(0.006)		(0.005)	(0.004)		(0.007)	(0.006)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
ZIP Code FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Structure Vars	Y	Y	Y	Y	Y	Y	Y	Y	Y
Parcel Char.	Y	Y	N	Y	Y	N	Y	Y	N
Agent Char.	N	Y	Y	N	Y	Y	N	Y	Y
Property FE	N	N	Y	N	N	Y	N	N	Y
Listing Agent FE	N	N	N	N	N	N	N	N	N
Buying Agent FE	N	N	N	N	N	N	N	N	N
# Observations	358,905	358,905	190,989	735,728	735,728	426,590	1,010,844	1,010,844	518,884
Adjusted R2	0.842	0.843	0.939	0.792	0.792	0.907	0.861	0.862	0.949
Mean Ln(Price)	12.25	12.25	12.27	12.36	12.36	12.32	12.18	12.18	12.24

Note: This table presents results from the hedonic regressions specified in equation 1. The dependent variable is the logarithm of the sale price. The first column of each MSA controls for property and parcel characteristics. The second column controls for transaction and agent characteristics. The last column of each MSA includes property fixed effects and thus, restricts the sample to properties that sold multiple times during the sample period. The underlying data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive). Robust standard errors are double-clustered at the ZIP code and year-quarter levels (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table 4: Days on the Market Regressions

Dependent Var: DOM	Charlotte			Minneapolis			Houston		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ln(Living Area)	22.774***	22.779***	23.421**	22.809***	22.759***	5.018*	40.002***	39.927***	15.008
	(2.751)	(2.800)	(8.797)	(1.420)	(1.411)	(1.938)	(1.899)	(1.899)	(8.155)
# Bedrooms	-3.419***	-3.352***	2.271	-2.764***	-2.741***	0.545	-3.529***	-3.327***	0.382
	(0.844)	(0.829)	(1.549)	(0.391)	(0.389)	(0.627)	(0.431)	(0.420)	(1.346)
# Bathrooms	7.718***	7.691***	2.775	3.535***	3.525***	1.671	6.137***	6.203***	6.641***
	(0.827)	(0.798)	(2.130)	(0.337)	(0.337)	(0.915)	(0.629)	(0.601)	(1.937)
New Construction (d)	54.711***	57.431***	47.651***	27.385***	27.126***	29.332***	46.119***	53.828***	52.374***
	(2.672)	(2.850)	(3.353)	(2.152)	(2.148)	(2.779)	(3.085)	(3.277)	(4.517)
Renovated (d)	-1.473	-1.382	1.774	-2.997**	-3.014**	-2.107	0.394	0.401	1.085
	(1.359)	(1.347)	(3.221)	(0.979)	(0.981)	(1.370)	(0.647)	(0.645)	(1.392)
Building Age	0.300***	0.298***	-0.238	-0.728***	-0.725***	-1.108***	0.271***	0.269***	-0.592*
	(0.076)	(0.075)	(0.275)	(0.048)	(0.048)	(0.122)	(0.051)	(0.050)	(0.268)
Building Age2	0.000	0.000	0.003	0.006***	0.006***	0.007***	-0.000	-0.000	0.006**
	(0.001)	(0.001)	(0.003)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Fireplace	.	.	.	0.575	0.572	-0.305	-2.651**	-3.138***	2.261
	.	.	.	(0.393)	(0.392)	(1.398)	(0.884)	(0.818)	(1.827)
Ln(Lot Size)	7.968***	7.738***		4.648***	4.634***		8.631***	8.597***	
	(0.774)	(0.763)		(0.325)	(0.325)		(1.829)	(1.831)	
View (d)	6.076***	6.005***		10.077***	10.031***		6.555***	6.471***	
	(1.504)	(1.501)		(1.260)	(1.258)		(1.130)	(1.107)	
Gated (d)	33.115***	33.071***		9.227*	9.210*		8.475***	8.098***	
	(4.392)	(4.396)		(4.074)	(4.067)		(1.187)	(1.142)	
Waterfront (d)	16.891***	16.816***		7.022***	6.975***		8.109***	8.173***	
	(2.431)	(2.446)		(0.827)	(0.827)		(2.342)	(2.327)	
Owner Agent (d)		13.354	27.459		4.947	4.596		-5.683*	-3.117
		(13.103)	(32.930)		(4.473)	(7.921)		(2.731)	(7.122)
Dual Agent (d)		1.771	0.321		2.873***	0.692		4.161***	2.537*
		(1.001)	(1.368)		(0.594)	(0.856)		(0.790)	(1.037)
Flat-Fee Broker (d)		-0.818	2.117		3.535**	5.988***		1.731	3.678
		(1.524)	(3.097)		(1.323)	(1.677)		(1.406)	(2.393)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
ZIP Code FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Structure Vars	Y	Y	Y	Y	Y	Y	Y	Y	Y
Parcel Char.	Y	Y	N	Y	Y	N	Y	Y	N
Agent Char.	N	Y	Y	N	Y	Y	N	Y	Y
Property FE	N	N	Y	N	N	Y	N	N	Y
Listing Agent FE	N	N	N	N	N	N	N	N	N
Buying Agent FE	N	N	N	N	N	N	N	N	N
# Observations	358,905	358,905	190,989	735,728	735,728	426,590	1,010,844	1,010,844	518,884
Adjusted R2	0.125	0.126	0.165	0.135	0.135	0.166	0.125	0.127	0.162
Mean DOM	122.34	122.34	115.66	96.59	96.59	92.97	110.78	110.78	105.87

Note: This table presents results from the DOM regressions specified in equation 1. The dependent variable is the number of days on the market measured from the initial listing date to the closing date. The first column of each MSA controls for property and parcel characteristics. The second column controls for transaction and agent characteristics. The last column of each MSA includes property fixed effects and thus, restricts the sample to properties that sold multiple times during the smaple period. The underlying data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive). Robust standard errors are double-clustered at the ZIP code and year-quarter levels (*** p<0.01, ** p<0.05, * p<0.1).

Table 5: Robustness Exercises

Panel A: Zip Code-by-Year Fixed Effects

	Charlotte		Minneapolis		Houston	
	(1) Ln(Price)	(2) DOM	(3) Ln(Price)	(4) DOM	(5) Ln(Price)	(6) DOM
Flat-Fee Broker (d)	0.039***	-0.479	0.017**	4.097**	0.017*	2.218
	(0.007)	(1.574)	(0.005)	(1.321)	(0.007)	(1.425)
ZIP Code-by-Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Structure Vars	Y	Y	Y	Y	Y	Y
Parcel Char.	Y	Y	Y	Y	Y	Y
Agent Char.	Y	Y	Y	Y	Y	Y
Property FE	N	N	N	N	N	N
Listing Agent FE	N	N	N	N	N	N
Buying Agent FE	N	N	N	N	N	N
# Observations	358,899	358,899	735,715	735,715	1,010,830	1,010,830
Adjusted R2	0.852	0.134	0.804	0.144	0.870	0.141
Mean Dep. Var.	12.25	122.34	12.36	96.59	12.18	110.78

Panel B: Flat-Fee Purchasers

Dependent Variable: Ln(Price)	Charlotte		Minneapolis		Houston	
	(1)	(2)	(3)	(4)	(5)	(6)
Flat-Fee Purchaser (d)	0.008	-0.013	-0.017**	-0.028***	-0.005	-0.015
	(0.007)	(0.007)	(0.005)	(0.008)	(0.007)	(0.008)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Zip FE	Y	Y	Y	Y	Y	Y
Zip-by-Year	N	N	N	N	N	N
Structure	Y	Y	Y	Y	Y	Y
Parcel Char.	Y	Y	Y	Y	Y	Y
Agent Char.	Y	Y	Y	Y	Y	Y
Property FE	N	Y	N	Y	N	Y
Listing Agent FE	N	N	N	N	N	N
Buying Agent FE	N	N	N	N	N	N
# Observations	354,524	186,696	727,834	418,683	1,006,140	514,404
Adjusted R2	0.843	0.939	0.792	0.907	0.862	0.949
Mean Ln(Price)	12.24	12.27	12.36	12.32	12.18	12.23

Note: This table presents results from two robustness exercises. Panel A displays results for both hedonic and DOM regression specifications that include ZIP Code-by-year fixed effects and thus control for time-varying, local shocks that may affect housing markets. Panel B displays results from hedonic regressions that test whether home buyers who subsequently sell their own properties using Flat-Fee Brokers obtain price discounts. "Flat-Fee Purchaser" is a dummy variable that takes a value of one if the home buyer associated with the transaction uses a flat fee broker to sell the property at a later date. The underlying data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive). Robust standard errors are double-clustered at the ZIP code and year-quarter levels (*** p<0.01, ** p<0.05, * p<0.1).

Table 6: Probability of Sale Regressions

Dependent Var: Prob(Sale occurs $\leq$ 1 year)	**Charlotte**		**Minneapolis**		**Houston**	
	(1)	(2)	(3)	(4)	(5)	(6)
Flat-Fee Broker (d)	-0.092***	-0.111***	-0.099***	-0.106***	-0.079***	-0.097***
	(0.009)	(0.012)	(0.010)	(0.011)	(0.008)	(0.010)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
ZIP Code FE	Y	Y	Y	Y	Y	Y
Structure Vars	Y	N	Y	N	Y	N
Parcel Char.	Y	Y	Y	Y	Y	Y
Agent Char.	Y	Y	Y	Y	Y	Y
Property FE	N	Y	N	Y	N	Y
Listing Agent FE	N	N	N	N	N	N
Buying Agent FE	N	N	N	N	N	N
# Observations	548,050	396,213	1,060,426	789,246	1,518,736	1,061,224
Adjusted R^2	0.121	0.138	0.419	0.380	0.088	0.101
Mean Dep. Var.	0.64	0.59	0.49	0.45	0.65	0.60

Note: This table presents results for a linear probability model of the likelihood that a listing ends in a successful sale within one year. The dependent variable is an indicator for whether a property was sold within one year of being listed. The underlying data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive). Robust standard errors are double-clustered at the ZIP code and year-quarter levels. Standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 7: The Effect of Sales Volume and Experience on Agent Performance

Panel A: Charlotte

	(1)	(2)	(3)	(4)
Dependent Var:	Ln(Price)		DOM	
Flat Fee Brokerage (d)	0.042***	0.054***	2.205	-1.799
	(0.007)	(0.009)	(1.710)	(2.007)
High volume (d)	-0.034***	-0.011*	-7.555***	-10.890***
	(0.004)	(0.005)	(1.529)	(1.870)
Low volume (d)	-0.013***	0.008*	10.416***	9.086***
	(0.002)	(0.004)	(0.765)	(1.004)
Experience		0.001		-0.975***
		(0.001)		(0.194)
Observations	358,905	173,781	358,905	173,781
Adjusted R-squared	0.843	0.835	0.141	0.141
mean dep. var.	12.32	12.32	122.34	113.58

Panel B: Houston

	(3)	(4)	(5)	(6)
Dependent Var:	Ln(Price)		DOM	
Flat Fee Brokerage (d)	0.020**	0.036***	5.961***	4.561**
	(0.007)	(0.007)	(1.354)	(1.669)
High volume (d)	-0.011***	-0.006	-1.841*	-3.210**
	(0.003)	(0.003)	(0.900)	(1.102)
Low volume (d)	-0.022***	-0.020***	11.071***	10.438***
	(0.002)	(0.002)	(0.599)	(0.798)
Experience		0.001***		-0.418***
		(0.000)		(0.111)
Observations	1,010,844	463,489	1,010,844	463,489
Adjusted R-squared	0.862	0.846	0.127	0.145
mean dep. var.	12.18	12.26	110.78	106.63

Panel C: Minneapolis

	(3)	(4)	(5)	(6)
Dependent Var:	Ln(Price)		DOM	
Flat Fee Brokerage (d)	0.010*	0.018**	3.570**	4.227*
	(0.005)	(0.006)	(1.252)	(1.702)
High volume (d)	-0.022***	-0.009	see	0.107
	(0.005)	(0.005)	(1.157)	(1.539)
Low volume (d)	-0.021***	-0.021***	5.068***	3.002***
	(0.002)	(0.002)	(1.330)	(0.357)
Experience		0.001**		-0.745***
		(0.000)		(0.132)
Observations	735,728	293,023	735,728	293,023
Adjusted R-squared	0.792	0.805	0.137	0.134
mean dep. var.	12.36	12.41	96.59	95.02

Note: Columns 1 and 2 examine ln(sale) price while columns 3 and 4 look at Days on Market (DOM) and include additional listing agent attributes but are otherwise the same as the specifications in 3 and 4 without property fixed effects. Columns 2 and 4 limit the analysis to new agents (those with no sales in the first 2 years) and controls for their experience (duration in years) at the time of sale. Columns 4 and 6 also control for the agent's new listings in the past 3 months to control for constraints on agent's time and effort. All specifications control for property characteristics, calendar time and zip code fixed effects. The underlying data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive). Robust standard errors are double-clustered at the ZIP code and year-quarter levels. Standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 8: Distribution of Agent Fixed Effects

Panel A: Hedonic Regressions

	Property FE	N	Percentile of Distribution 5th	25th	50th	75th	90th	95th	Adj R2
Charlotte									
Listing Agent	No	2,618	-0.26	-0.09	-0.05	0.	0.06	0.12	0.87
	Yes	2,613	-0.13	-0.05	-0.02	0.01	0.05	0.08	0.93
Buying Agent	No	2,878	-0.11	-0.03	0.02	0.07	0.12	0.16	0.85
	Yes	2,878	-0.11	-0.04	-0.01	0.01	0.04	0.06	0.92
Minneapolis									
Listing Agent	No	5,858	-0.11	-0.06	-0.03	0.01	0.06	0.11	0.82
	Yes	5,853	-0.09	-0.04	-0.02	0.01	0.04	0.06	0.9
Buying Agent	No	6,358	-0.1	-0.05	-0.02	0.01	0.04	0.07	0.8
	Yes	6,358	-0.07	-0.02	0.	0.02	0.05	0.07	0.89
Houston									
Listing Agent	No	6,775	-0.14	-0.06	-0.03	0.01	0.06	0.11	0.88
	Yes	6,768	-0.1	-0.04	-0.01	0.02	0.05	0.08	0.93
Buying Agent	No	7,909	-0.07	-0.01	0.02	0.06	0.1	0.14	0.87
	Yes	7,909	-0.06	-0.01	0.02	0.04	0.07	0.09	0.92

Panel B: DOM Regressions

	Property FE	N	Percentile of Distribution 5th	25th	50th	75th	90th	95th	Adj R2
Charlotte									
Listing Agent	No	2,618	-33.17	-17.18	-5.85	7.55	23.69	33.78	0.16
	Yes	2,613	-38.62	-16.96	-2.6	13.38	34.83	52.74	0.18
Minneapolis									
Listing Agent	No	5,858	-26.3	-15.64	-7.56	1.73	11.87	19.79	0.16
	Yes	5,853	-32.14	-17.11	-7.54	3.25	15.44	25.15	0.18
Houston									
Listing Agent	No	6,775	-30.24	-15.7	-5.74	6.58	20.34	29.54	0.16
	Yes	6,768	-34.22	-15.73	-3.82	10.47	26.08	40.	0.18

Note: This table presents the distribution of the estimated agent fixed effects by MSA following (Equation 1), except that specifications that include listing agent fixed effects do not include a flat-fee dummy (the omitted category) and specifications that include buying agent fixed effects omit the dual agent dummy. The dependent variable in Panel A is Ln(Price) and the dependent variable in Panel B is the number of days on the market. The underlying data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive).

Table 9: Select Summary Statistics of Top-Performing Real Estate Agents

Panel A: Listing Agent Price

	Charlotte		Minneapolis		Houston	
	Top Performer	Rest	Top Performer	Rest	Top Performer	Rest
Avg Number of Listings	124.7	100.2	76.4	96.1	130.5	106.5
Years Active	9.9	12.2	11.5	13.4	10.7	12.3
Avg Listings Per Year	14.8	9.1	7.1	7.3	13.9	9.2
Avg Sized Property (100s ft^2)	21.7	20.9	20.1	18.3	24.1	21.5
Share Female	0.510	0.593	0.455	0.456	0.560	0.664
Share Black	0.000	0.005	0.000	0.000	0.004	0.002
Share Hispanic	0.011	0.013	0.004	0.004	0.056	0.044
Share Asian	0.000	0.003	0.002	0.003	0.013	0.006

Panel B: Buying Agent Price

	Charlotte		Minneapolis		Houston	
	Top Performer	Rest	Top Performer	Rest	Top Performer	Rest
Avg Number of Listings	60.5	67.9	58.1	76.4	59.6	70.5
Years Active	11.8	12.4	12.7	13.2	12.4	13.2
Avg Listings Per Year	5.6	6.0	4.9	6.1	5.2	5.5
Avg Sized Property (100s ft^2)	18.9	21.7	17.5	18.5	20.9	23.1
Share Female	0.400	0.640	0.407	0.489	0.562	0.689
Share Black	0.023	0.010	0.002	0.006	0.009	0.010
Share Hispanic	0.050	0.030	0.008	0.018	0.158	0.102
Share Asian	0.027	0.013	0.060	0.015	0.076	0.030

Panel C: Listing Agent DOM

	Charlotte		Minneapolis		Houston	
	Top Performer	Rest	Top Performer	Rest	Top Performer	Rest
Avg Number of Listings	70.4	106.5	75.5	96.1	66.6	115.2
Years Active	10.9	12.0	12.3	13.3	10.2	12.3
Avg Listings Per Year	6.8	10.0	6.6	7.3	7.4	10.1
Avg Sized Property (100s ft^2)	22.3	20.8	19.0	18.5	21.5	21.8
Share Female	0.618	0.580	0.508	0.449	0.672	0.649
Share Black	0.004	0.005	0.000	0.000	0.002	0.002
Share Hispanic	0.021	0.012	0.004	0.004	0.037	0.046
Share Asian	0.000	0.003	0.000	0.003	0.007	0.007

Note: This table presents summary statistics of real estate agent characteristics for the population of agents and those in the top 10th percentile of agent fixed effects in selling a home (high) buying a home (low) and selling a home quickly (DOM).

Table 10: Evidence of Persistence Among Top Performing Agents

Panel A: Charlotte

Dependent Var:	Listing Agent Price		Buying Agent Price		Listing Agent DOM	
Top Agent 2010-2019 (d)	(1)	(2)	(3)	(4)	(5)	(6)
Top Agent 2000-2009 (d)	0.468***	0.082***	0.290***	0.183***	0.055*	-0.011
	(0.020)	(0.023)	(0.021)	(0.022)	(0.023)	(0.023)
Property FEs	N	Y	N	Y	N	Y
Observations	1,923	1,835	2,153	2,044	1,923	1,835
Adjusted R^2	0.218	0.006	0.084	0.033	0.003	-0.000

Panel B: Minneapolis

Dependent Var:	Listing Agent Price		Buying Agent Price		Listing Agent DOM	
Top Agent 2010-2019 (d)	(1)	(2)	(3)	(4)	(5)	(6)
Top Agent 2000-2009 (d)	0.421***	0.086***	0.188***	0.175***	0.046**	0.001
	(0.013)	(0.015)	(0.014)	(0.014)	(0.015)	(0.015)
Property FEs	N	Y	N	Y	N	Y
Observations	4,526	4,354	4,895	4,718	4,526	4,354
Adjusted R^2	0.177	0.007	0.035	0.031	0.002	-0.000

Panel C: Houston

Dependent Var:	Listing Agent Price		Buying Agent Price		Listing Agent DOM	
Top Agent 2010-2019 (d)	(1)	(2)	(3)	(4)	(5)	(6)
Top Agent 2000-2009 (d)	0.318***	0.131***	0.173***	0.070***	0.117***	0.034*
	(0.013)	(0.012)	(0.013)	(0.011)	(0.014)	(0.014)
Property FEs	N	Y	N	Y	N	Y
Observations	5,143	5,000	6,178	6,058	5,143	4,878
Adjusted R^2	0.101	0.021	0.030	0.006	0.014	0.001

Note: This table regresses a dummy for being in the top 10th percentile of agents based on selling price, purchase price and selling time between 2009 and 2019 on whether the agent was in the top 10th percentile in the period before that.

Table 11: Evidence that the Market Rewards Top Performing Agents

Panel A: Charlotte

Dependent Var: $ln(\frac{listings_{10-19}}{listings_{00-09}})$	Listing Agent Price		Listing Agent DOM	
	(1)	(2)	(3)	(4)
Top Agent 2000-2009	0.492***	0.507***	1.770***	1.194***
	(0.113)	(0.107)	(0.113)	(0.108)
Property FEs	N	Y	N	Y
Observations	1,881	1,796	1,881	1,796
Adjusted R^2	0.009	0.012	0.116	0.063

Panel B: Minneapolis

Dependent Var: $ln(\frac{listings_{10-19}}{listings_{00-09}})$	Listing Agent Price		Listing Agent DOM	
	(1)	(2)	(3)	(4)
Top Agent 2000-2009	0.605***	0.944***	1.660***	1.407***
	(0.077)	(0.069)	(0.070)	(0.069)
Property FEs	N	Y	N	Y
Observations	3,818	3,677	3,818	3,677
Adjusted R^2	0.016	0.049	0.127	0.103

Panel C: Houston

Dependent Var: $ln(\frac{listings_{10-19}}{listings_{00-09}})$	Listing Agent Price		Listing Agent DOM	
	(1)	(2)	(3)	(4)
Top Agent 2000-2009	0.677***	0.480***	1.573***	1.055***
	(0.092)	(0.084)	(0.086)	(0.085)
Property FEs	N	Y	N	Y
Observations	3,016	2,855	3,016	2,855
Adjusted R^2	0.017	0.011	0.101	0.051

Note: This table regresses the percentage growth in the number of listing for selling agents between 2009 and 2019 relative to their total number of listings between 2000 and 2009 on whether the agent was in the top 10th percentile in the first half of the sample.

Table 12: Do Aggressive Buying Agent's Get Rehired to Sell the Same Home in the Future?

Dependent Var: p(selling agent is former buying agent)	**Charlotte**		**Minneapolis**		**Houston**	
	(1)	(2)	(3)	(4)	(5)	(6)
Residual from original purchase price hedonic $\hat{e}_{it-1}$	0.056***	0.059***	0.030***	0.035***	0.028***	0.035***
	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)
Zip Code FE	Y	Y	Y	Y	Y	Y
Zip Code x County FE	N	Y	N	Y	N	Y
Price Residual SD	0.25	0.25	0.22	0.22	0.22	0.22
Share Former Buyer Agent	0.22	0.22	0.23	0.23	0.18	0.18
Observations	69,770	69,693	198,187	197,948	205,160	204,892
Adjusted R^2	0.091	0.093	0.099	0.103	0.101	0.105

Note: This table regresses a dummy for whether the listing agent formerly served as the buying agent for all homes both bought and sold in our data excluding estate sales and listings by owner-agents. The first stage hedonic (results available upon request) and the same-agent specifications above include controls for property characteristics, time and zip or zip x year fixed effects (as in Tables 3 and 6 Panel A, respectively). Errors are clustered at the zip-quarter level.

Table 13: Top Agent Performance Across Hot and Cold Markets

Panel A: Full Sample

	Charlotte			Minneapolis			Houston		
	Listing Agent Price (1)	Buyer Agent Price (2)	Listing Agent DOM (3)	Listing Agent Price (4)	Buyer Agent Price (5)	Listing Agent DOM (6)	Listing Agent Price (7)	Buyer Agent Price (8)	Listing Agent DOM (9)
Top Performer x HMI	-0.131***	0.258***	0.106***	-0.227***	0.409***	0.092***	-0.122***	0.158***	0.038*
	(0.029)	(0.035)	(0.031)	(0.023)	(0.057)	(0.019)	(0.019)	(0.020)	(0.016)
HMI	0.070**	0.039	0.057*	0.133***	0.089**	0.099***	0.070***	0.051**	0.059***
	(0.022)	(0.024)	(0.023)	(0.028)	(0.027)	(0.028)	(0.017)	(0.017)	(0.016)
Top Performer (d)	0.295***	-0.315***	-0.086***	0.294***	-0.330***	-0.057***	0.244***	-0.210***	-0.009
	(0.021)	(0.023)	(0.015)	(0.016)	(0.038)	(0.011)	(0.014)	(0.013)	(0.011)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Zip FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Structure	Y	Y	Y	Y	Y	Y	Y	Y	Y
Parcel Char.	N	N	N	N	N	N	N	N	N
Agent Char.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Property FE	N	N	N	N	N	N	N	N	N
Listing Agent FE	N	N	N	N	N	N	N	N	N
Buying Agent FE	N	N	N	N	N	N	N	N	N
Mean Ln Price/DOM	12.24	12.27	12.24	12.36	12.36	12.36	12.18	12.2	12.18
Mean HMI	0.52	0.52	0.52	0.54	0.53	0.54	0.51	0.51	0.51
Mean Top Performer	0.08	0.06	0.06	0.1	0.06	0.06	0.08	0.05	0.07
Observations	354,322	304,212	354,322	727,792	680,144	727,792	1,006,129	881,338	1,005,930
Adjusted R^2	0.851	0.850	0.845	0.803	0.799	0.793	0.867	0.868	0.862

Panel B: Repeat-Sales Sample

	Charlotte			Minneapolis			Houston		
	Listing Agent Price (1)	Buyer Agent Price (2)	Listing Agent DOM (3)	Listing Agent Price (4)	Buyer Agent Price (5)	Listing Agent DOM (6)	Listing Agent Price (7)	Buyer Agent Price (8)	Listing Agent DOM (9)
Top Performer x HMI	0.042	0.187***	0.230***	-0.154***	0.408***	0.124***	-0.016	0.036	0.031*
	(0.025)	(0.033)	(0.032)	(0.022)	(0.083)	(0.020)	(0.020)	(0.025)	(0.013)
HMI	0.057*	0.049**	0.045	0.155***	0.127***	0.136***	0.053**	0.046**	0.049**
	(0.024)	(0.017)	(0.025)	(0.025)	(0.022)	(0.024)	(0.016)	(0.016)	(0.016)
Top Performer (d)	0.079***	-0.221***	-0.189***	0.167***	-0.314***	-0.093***	0.082***	-0.117***	-0.021**
	(0.016)	(0.020)	(0.025)	(0.017)	(0.055)	(0.014)	(0.011)	(0.014)	(0.007)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Zip FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Structure	Y	Y	Y	Y	Y	Y	Y	Y	Y
Parcel Char.	N	N	N	N	N	N	N	N	N
Agent Char.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Property FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Listing Agent FE	N	N	N	N	N	N	N	N	N
Buying Agent FE	N	N	N	N	N	N	N	N	N
Mean Ln Price/DOM	12.27	12.3	12.27	12.32	12.32	12.32	12.23	12.26	12.23
Mean HMI	0.51	0.51	0.51	0.53	0.53	0.53	0.50	0.50	0.50
Mean Top Performer	0.08	0.05	0.07	0.06	0.06	0.06	0.08	0.05	0.06
Observations	186,536	150,148	186,536	418,639	371,554	418,639	514,388	426,508	514,388
Adjusted R^2	0.941	0.945	0.941	0.909	0.913	0.907	0.950	0.953	0.949

Note: This table presents the coefficient estimates for the top performer dummies interacted with a measure of national housing market activity. While top agents are (by construction) selling for more, buying for less and selling faster, they perform these tasks less well in strong markets, perhaps because thick markets reduce the negotion space. All specifications include property fixed effects. The underlying data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive). Robust standard errors are double-clustered at the ZIP code and year-quarter levels (*** p<0.01, ** p<0.05, * p<0.1).

The Good, the Bad and the Ordinary: Estimating Agent Value-Added Using Real Estate Transactions

Supplementary Online Appendix

This appendix supplements the empirical analysis in Cunningham, Gerardi, and Shen (2023). Below is a list of the sections contained in this appendix.

Table of Contents

A.1 Sample Filters

In order to standardize the data across our three MSAs and deal with outliers, we impose a series of sample filters. Table A.1 below shows how the number of observations in our sample is affected by each filter. We begin with approximately 790 thousand sales in Charlotte, 1.4 million sales in Minneapolis, and 1.5 million sales in Houston. The first restriction limits the sample to single-family detached houses, which removes around 100 to 150 thousand observations per MLS. The second restriction eliminates listings that occurred before CoreLogic achieved widespread coverage of each MLS (January 2000 for Minneapolis and Houston and April 2001 for Charlotte). We also eliminate listings after December 31, 2019 to avoid the housing market disruptions associated with the COVID-19 pandemic. This removes an additional 40 to 90 thousand observations per MLS. While most homes on a given MLS are physically located in that metropolitan area, there are some located outside. Homes in rural communities surrounding the metro area or cities attractive to second home buyers, for example, can also appear. We exclude all homes not in the same Core Based Statistical Area (CBSA) covered by the MLS, which removes a further 50 to 130 thousand observations. In addition, we exclude distressed property sales conducted via an auction, a foreclosure, by a bank (Real-Estate-Owned (REO)), or by a real estate agent who specializes in distressed sales. Between 15 and 40 thousand sales met this criterion.

Finally, we eliminate extreme values from the sample. The MLS data are input by the listing agent and can be subject to data entry errors. We went to considerable effort to clean and fix obvious errors, but some entries are hard to explain. In addition, some truly exceptional homes appear in the data that we worry may skew or bias our results. Thus, we impose the following restrictions to eliminate outliers: We exclude homes that have more than 8000 square feet or less than 500 square feet of livable space; homes with less than one full bathroom or more than 10 bathrooms or bedrooms. We exclude homes that were on parcels larger than 10 acres. We also exclude homes that sold for less than 20 thousand dollars or more than 4 million dollars. This removes an additional 30 to 250 thousand observations. We also exclude any ZIP codes within the CBSA that had fewer than 100 sales over the sample period. Very few (remaining sales) were lost to this restriction.

Table A.1: Observation Counts for each Sample Restriction

	Charlotte	**Minneapolis**	**Houston**
Original Sample	788,341	1,389,903	1,453,141
Keep Single Family Housing	695,764	1,282,529	1,310,146
Keep Sample Years	629,535	1,121,967	1,173,755
Drop Distressed Sales	577,410	998,475	1,053,368
Drop Extreme Values	562,077	956,943	1,039,096
Keep Observations Within Designated CBSAs	359,572	736,716	1,012,026
Drop Zipcodes with Less Than 100 Listings	359,048	735,950	1,011,052
Drop New Construction Sold with Flat-Fee Agent	358,905	735,865	1,010,844

Notes: This table displays the number of remaining observations after applying each sample filter. The underlying data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive).

A.2 Flat-Fee Agents

We list the flat fee brokers in our sample along with their corresponding number of observations in the final sample in each MSA in Table A.2.

Table A.2: Listings of Flat-Fee Agencies

Charlotte	
Flat-Fee Brokers	\# Listings
ASSIST 2 SELL	1
BANG REALTY-NORTH CAROLINA	1
CAROLINA REALTY SOLUTIONS	1,664
CAROLINAS CHOICE REAL ESTATE	3
CAROLINAS CHOICE REALTY, INC.	7
CAROLINAS CHOICE, REALTORS	3
CAROLINAS CHOICE, REALTORS INC	15
CLICKIT REALTY	381
DANE WARREN REAL ESTATE	894
DON ANTHONY REALTY, LLC	662
DON ANTHONY REALTY, LLC.	11
FLAT FEE REALTY LLC	1
FLAT FEE REALTY, LLC	1
HERITAGE HOME REALTY	195
HERITAGE HOME REALTY, LLC	44
HERITAGE HOMES LLC	9
OWNERS.COM	7
PLANB CAROLINAS LLC	1
S AND B PROPERTIES OF NC INC	10
SELECT PREMIUM PROPERTIES INC	167
SELLERS RESOURCE GROUP	112
SMART CHOICE REALTY	21
SMART CHOICE REALTY COMPANY INC	9
UNITED BROKERS LTD	162
Total	4,381

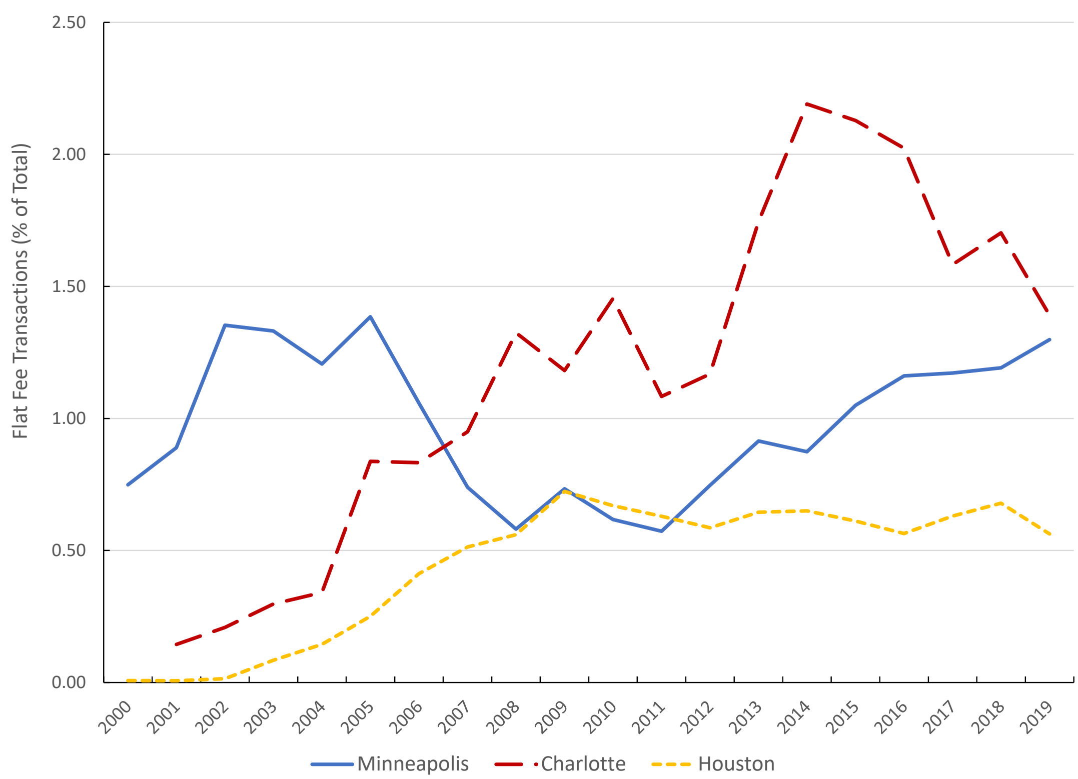
Houston	
Flat-Fee Brokers	\# Listings
Boulevard Realty	1
BuyBroker	356
Congress Realty, Inc.	203
Creekstone Real Estate	10
Creekview Realty	824
Eagle Realty Services	8
Expert Way Realty	9
Flat Fee Discount Realty	57
For Sale By Owner Express	1
ForSaleByOwner.com Referral Se	10
Green Residential	103
Houston Realty Team	13
Listing Results, LLC	1,043
MLS4Public, LLC	37
My Castle Realty	1,510
National Realty Advisors	13
Nex Companies, LLC	1
Owners.com	168
Real Estate FSBO, Inc.	2
Savvy Way Realty, INC.	2
Texas Flat Fee, REALTORS	27
Texas Real Estate Group	74
USRealty.com, LLP	16
VIP Realty	67
Vip Premier Realty Client Side	137
Vip Realty	12
Total	4,704

Minneapolis	
Flat-Fee Brokers	\# Listings
123 Realty	42
Beycome of Minnesota	4
BuySelf, Inc	879
Congress Realty	11
Congress Realty, Inc.	2
CreekStone Realty, LLC	7
For Sale By Owner of MN, Inc	30
For Sale By Owner, Inc	1
Home Avenue - Agent	843
Home Avenue - FSBO	3,807
Home Avenue, Inc.	6
HomeAvenue - Agent	376
HomeAvenue - FSBO	460
Homelister, Inc.	1
ICA FSBO	3
JL Realty	18
Next Generation Realty LLC	10
Owners.com	17
POP Realty MN	77
Pro Flat Fee Realty	82
Pro Flat Fee Realty LLC	182
Real Estate Corners, Inc	246
Realtor Menu Inc.	1
Save For Sale By Owner, Inc	3
Savvy Avenue, LLC	364
Smart Choice Realty	11
Success Realty	224
Success Realty Minnesota, LLC	171
TheMLSonline.com, Inc.	16
dofsbo.com Real Estate	1
Total	7,895

A.3 Flat Fee Transaction Trends

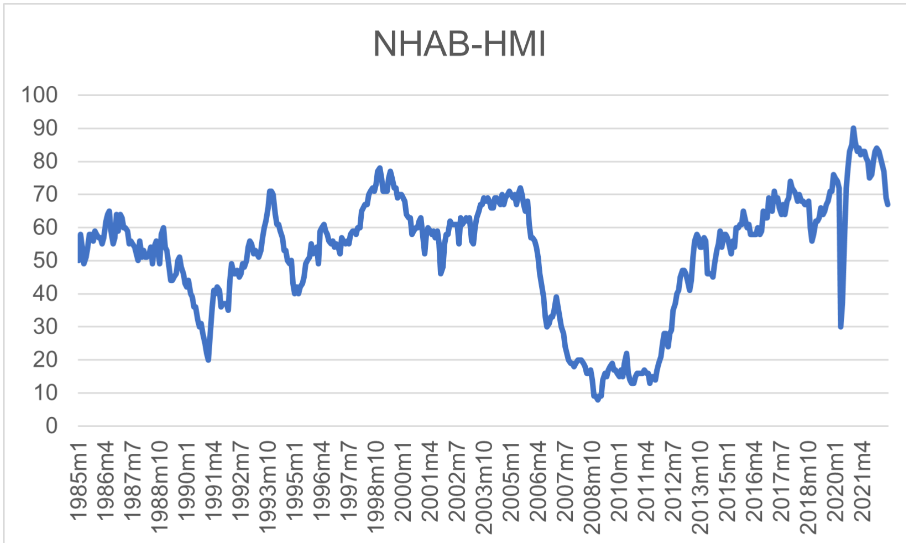
Figure A.1 below shows the fraction of property sales in each of our three MSAs that involved a flat-fee broker. In Charlotte and Houston there are clear upward trends in the early part of our sample. However, the flat-fee share plateaus in Houston at the onset of the financial crisis in 2008 and remains flat through the end of the sample period. In contrast, the flat-fee share continues to rise in Charlotte until peaking in 2014 at over 2% and then declining back to 1.5% by the end of 2019. The dynamics are different in Minneapolis as there is no clear trend over time. The underlying data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive).

Figure A.1: Flat Fee Transactions Over Time



A.4 Housing Market Index

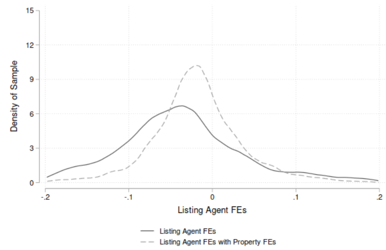
Figure A.2: National Association of Home Builders/Wells Fargo, Housing Market Index



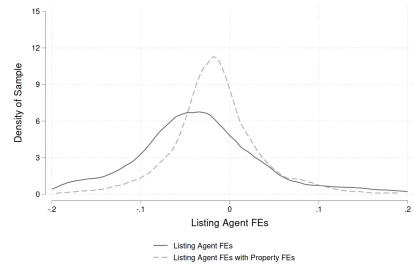
Notes: This figure displays the Housing Market Index (HMI) a monthly national housing market index prepared by the National Association of Home Builders based on survey members response to question about expected sales of new homes and buyer traffic.
https://www.nahb.org/news-and-economics/housing-economics/indices/housing-market-index

Figure A.3: Kernel Density Estimates of Real Estate Agent Fixed Effects on Listing Agent's Sales Price: 30 vs 50 sample restriction

Panel A: Charlotte

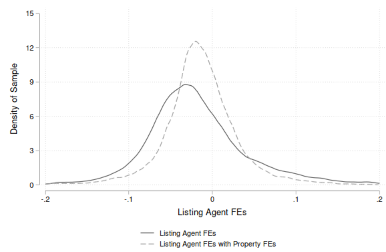


Agents w/ sales>30

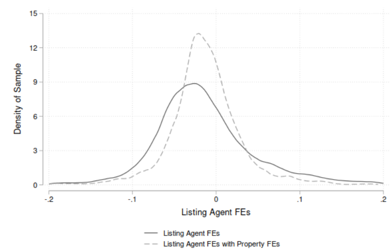


Agents w/ sales>50

Panel B: Minneapolis

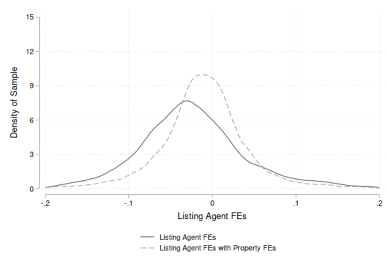


Agents w/ sales>30

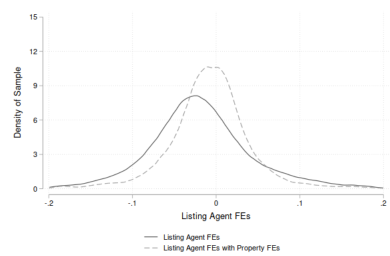


Agents w/ sales>50

Panel C: Houston



Agents w/ sales>30



Agents w/ sales>50

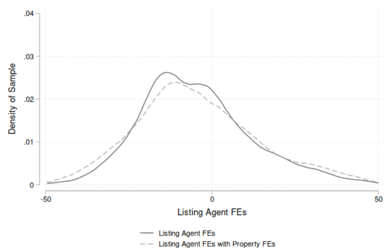
Notes: This figure displays kernel density estimates for the listing agent and buying agent fixed effects ($\alpha_r^{l,b}$ from the following hedonic regression model:

$$y_{ijrt}^{Price} = X_{ir}'\phi + \theta_t + \gamma_j + \alpha_r^{l,b} + \eta_i + \epsilon_{ijrt} \tag{4}$$

where i indexes the property, t is the year-quarter of the listing date, j is the ZIP code where the property is located, and r is the agent. The dashed density estimates include property fixed effects, η_i. The omitted category in the listing agent fixed effects models is flat-fee brokers, while the omitted category in the buying agent models is dual agent transactions. The underlying data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive).

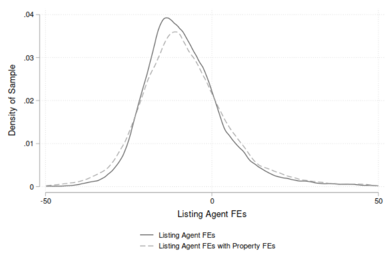
Figure A.4: Kernel Density Estimates of Real Estate Agent Fixed Effects on Listing Agent's DOM: 30 vs 50 sample restriction

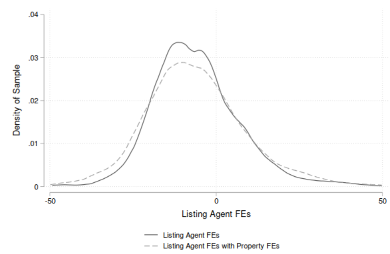
Panel A: Charlotte



Agents w/ sales>30 Agents w/ sales>50

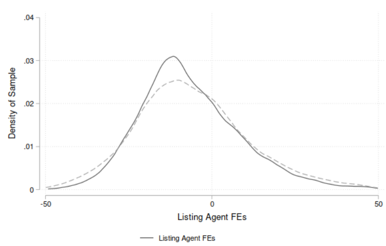
Panel B: Minneapolis

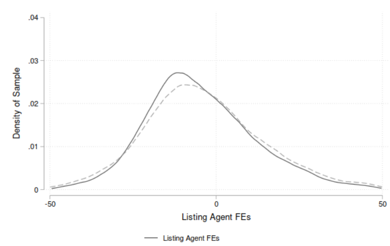




Agents w/ sales>30 Agents w/ sales>50

Panel C: Houston





Agents w/ sales>30 Agents w/ sales>50

Notes: This figure displays kernel density estimates for the listing agent and buying agent fixed effects ($\alpha_r^{l,b}$ from the following hedonic regression model:

$$y_{ijrt}^{Price} = X_{ir}'\phi + \theta_t + \gamma_j + \alpha_r^{l,b} + \eta_i + \epsilon_{ijrt} \tag{5}$$

where i indexes the property, t is the year-quarter of the listing date, j is the ZIP code where the property is located, and r is the agent. The dashed density estimates include property fixed effects, η_i. The omitted category in the listing agent fixed effects models is flat-fee brokers, while the omitted category in the buying agent models is dual agent transactions. The underlying data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive).

Figure A.5: Kernel Density Estimates of Real Estate Agent Fixed Effects on Buying Agent's Sales Price: 30 vs 50 sample restriction

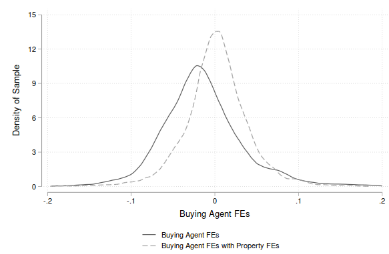
Panel A: Charlotte

Agents w/ sales>30

Agents w/ sales>50

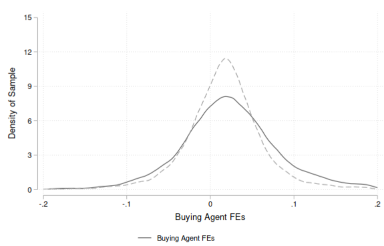
Panel B: Minneapolis

Agents w/ sales>30

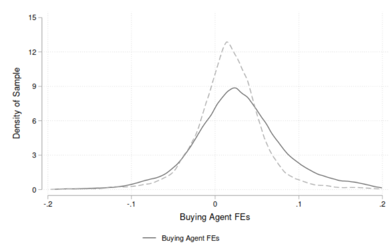


Agents w/ sales>50

Panel C: Houston



Agents w/ sales>30



Agents w/ sales>50

Notes: This figure displays kernel density estimates for the listing agent and buying agent fixed effects ($\alpha_r^{l,b}$ from the following hedonic regression model:

$$y_{ijrt}^{Price} = X_{ir}'\phi + \theta_t + \gamma_j + \alpha_r^{l,b} + \eta_i + \epsilon_{ijrt} \tag{6}$$

where i indexes the property, t is the year-quarter of the listing date, j is the ZIP code where the property is located, and r is the agent. The dashed density estimates include property fixed effects, η_i. The omitted category in the listing agent fixed effects models is flat-fee brokers, while the omitted category in the buying agent models is dual agent transactions. The underlying data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive).

A.5 Heckman Selection Model

In the main text we show properties that were listed with flat-fee brokers sell at higher prices but have a lower probability of actually being sold. This might imply a selection bias in the hedonic regressions that could explain the higher flat-fee prices. Thus, we conduct a robustness test below in Table A.3, where we implement a Heckman selection model to control for differences in the probability of sale between flat-fee brokers and traditional agents. The model estimates two equations - a selection equation that models the probability of a listing ending in a successful sale and a pricing equation that models the transaction price as a function of property and agent characteristics.

The results in Table A.3 show that controlling for differences in the likelihood of sale in the pricing equation, has virtually no effect on the flat-fee coefficients (columns (3), (6), and (9)) compared to the baseline hedonic model (columns (1), (4), and (7)), which did not control for selection.[1]

[1] The OLS specifications in Table A.3 do not include the same time and geographic fixed effects as the specifications in Table 3 due to the fact that we are unable to get the Heckman models to converge when we include those fixed effects.

Table A.3: Heckman Selection Model

	Charlotte			Minneapolis			Houston		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	Heckman		OLS	Heckman		OLS	Heckman	
		1st Stage	2nd Stage		1st Stage	2nd Stage		1st Stage	2nd Stage
Ln(Living Area)	1.173***	0.184***	1.174***	0.704***	-0.382***	0.704***	1.118***	0.155***	1.118***
	(0.037)	(0.030)	(0.037)	(0.022)	(0.020)	(0.022)	(0.042)	(0.018)	(0.042)
# Bedrooms	-0.080***	-0.022	-0.080***	-0.018***	0.052***	-0.017**	-0.156***	-0.051***	-0.156***
	(0.009)	(0.012)	(0.009)	(0.005)	(0.010)	(0.005)	(0.016)	(0.006)	(0.016)
# Bathrooms	0.112***	0.056***	0.112***	0.118***	-0.095***	0.116***	0.237***	0.052***	0.237***
	(0.012)	(0.010)	(0.012)	(0.007)	(0.009)	(0.007)	(0.016)	(0.008)	(0.016)
New Construction (d)	0.113***	0.561***	0.113***	0.164***	0.125***	0.162***	0.113***	0.433***	0.114***
	(0.022)	(0.026)	(0.022)	(0.011)	(0.032)	(0.011)	(0.023)	(0.026)	(0.023)
Renovated (d)	0.024	-0.063	0.024	-0.019**	-0.361***	-0.021**	0.075***	-0.022	0.075***
	(0.016)	(0.043)	(0.016)	(0.007)	(0.016)	(0.007)	(0.008)	(0.018)	(0.008)
Building Age	0.006**	0.013***	0.006**	0.000	0.008***	0.000	-0.006**	0.008***	-0.006**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Building Age2	-0.000*	-0.000***	-0.000*	0.000	-0.000***	0.000	0.000***	-0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Lot Size)	-0.012	-0.006	-0.011	0.032***	0.081***	0.036***	-0.009	0.058***	-0.009
	(0.018)	(0.012)	(0.018)	(0.007)	(0.008)	(0.007)	(0.010)	(0.009)	(0.010)
View (d)	0.131***	0.006	0.131***	0.103***	-0.221***	0.101***	0.128*	0.176***	0.128*
	(0.021)	(0.022)	(0.021)	(0.015)	(0.017)	(0.015)	(0.057)	(0.032)	(0.057)
Gated (d)	0.160***	0.114*	0.161***	0.109***	-0.411***	0.105***	0.144***	-0.001	0.144***
	(0.041)	(0.054)	(0.041)	(0.027)	(0.075)	(0.027)	(0.017)	(0.018)	(0.017)
Waterfront (d)	0.266***	0.122***	0.267***	0.093***	0.088***	0.098***	0.255***	0.095***	0.256***
	(0.058)	(0.026)	(0.058)	(0.015)	(0.016)	(0.016)	(0.055)	(0.027)	(0.055)
Owner Agent (d)	0.111	0.749*	0.113	0.021	0.154*	0.033*	0.157***	0.236**	0.158***
	(0.062)	(0.339)	(0.062)	(0.014)	(0.063)	(0.014)	(0.024)	(0.075)	(0.024)
Dual Agent (d)	-0.099***	2.926***	-0.101***	0.012*	2.362***	-0.005	-0.121***	3.341***	-0.122***
	(0.012)	(0.054)	(0.012)	(0.006)	(0.033)	(0.006)	(0.007)	(0.064)	(0.007)
Flat-Fee Broker	0.096***	-0.205***	0.096***	0.083***	-0.157***	0.088***	0.084***	-0.367***	0.084***
	(0.011)	(0.059)	(0.011)	(0.009)	(0.020)	(0.009)	(0.011)	(0.047)	(0.011)
Year FE	N	N	N	N	N	N	N	N	N
Month FE	N	N	N	N	N	N	N	N	N
ZIP Code FE	N	N	N	N	N	N	N	N	N
Structure Vars	Y	Y	Y	Y	Y	Y	Y	Y	Y
Parcel Char.	Y	Y	Y	Y	Y	N	Y	Y	N
Agent Char.	Y	Y	Y	N	Y	Y	N	Y	Y
Property FE	N	N	N	N	N	N	N	N	N
Listing Agent FE	N	N	N	N	N	N	N	N	N
Buying Agent FE	N	N	N	N	N	N	N	N	N
# Observations	361,736	548,290	548,290	742,530	1,060,724	1,060,724	1,021,430	1,519,367	1,519,367
Adjusted R^2	0.684			0.604			0.658		
Mean Ln(Price)	12.25	12.25	12.25	12.36	12.36	12.36	12.18	12.18	12.18

A.6 Statistical Significance of Agent FE

In this section, we present the distribution of agent FEs based on their sign and statistical significance. Specifically, we examine the number and percentage of agent FEs that are positive and statistically significant ($p<0.05$), negative and statistically significant, and statistically insignificant.

Table A.4 reveals that both the number of positive and negative FEs decrease compared to Table 8. This suggests that even a smaller number of agents can consistently provide positive value-added. However, the majority of agents do not have a statistically significant impact on transactions or have a negative and significant impact before fees.

Table A.4 suggests that most agents in our sample are not consistently selling homes for a premium or buying homes for a discount, despite charging a 3% commission. Our findings remain consistent with controlling for the statistical power of our estimated agent FE coefficient estimates.

Table A.4: Statistical Significance of Agent Fixed Effects

Panel A: DOM Agent Price Fixed Effects

	Property FE	Total # of Agent	Significantly>0 (%)	Significantly>0 (#)	Significantly<0 (%)	Significantly<0 (#)	Statistically Insignificant (%)	Statistically Insignificant (#)
Clarlotte								
Listing	No	2618	10.7%	281	40.8%	1068	48.5%	1269
	Yes	2613	5.5%	144	15.3%	399	79.2%	2070
Buying	No	2878	26.2%	753	13.3%	382	60.6%	1743
	Yes	2878	4.2%	122	16.1%	462	79.7%	2294
Minneapolis								
Listing	No	5858	13.0%	760	29.8%	1746	57.2%	3352
	Yes	5853	4.0%	236	11.4%	670	84.5%	4947
Buying	No	6358	8.1%	513	23.3%	1,482	68.6%	4363
	Yes	6358	3.7%	237	3.3%	208	93.0%	5913
Houston								
Listing	No	6775	11.3%	768	27.9%	1890	60.8%	4117
	Yes	6768	5.7%	384	10.1%	685	84.2%	5699
Buying	No	7909	26.7%	2109	6.6%	522	66.7%	5278
	Yes	7909	8.6%	680	2.2%	173	89.2%	7056

Panel B: DOM Agent Fixed Effects

	Property FE	Total # of Agent	Significantly>0 (%)	Significantly>0 (#)	Significantly<0 (%)	Significantly<0 (#)	Statistically Insignificant (%)	Statistically Insignificant (#)
Clarlotte								
	No	2878	5.7%	148	13.9%	365	90.3%	2365
	Yes	2878	4.7%	122	17.6%	462	87.8%	2294
Minneapolis								
	No	5858	5.9%	348	23.9%	1398	70.2%	4112
	Yes	5853	2.1%	124	8.0%	468	89.8%	5261
Houston								
	No	6775	10.0%	680	18.8%	1275	71.1%	4820
	Yes	6768	4.1%	277	4.9%	330	90.9%	6161

This table displays the percentage and count of agents categorized by the sign and statistical significance of their fixed effects coefficients from the estimation of equation (1). The listing agent fixed effects specifications use flat-fee transactions as the omitted category while the buying agent fixed effects specifications use dual agent transactions as the omitted category. We assume that fixed effects are statistically significant at the 5 percent level for the 1-tailed tests and 10 percent for the statistically insignificant test in the right-most columns. The underlying data comes from the CoreLogic Multiple Listing Service Database and covering listings posted between January 2000 and December 2019 (inclusive).