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

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Working Paper 2022-11a
September 2022 (Revised April 2023)

Abstract: Despite the prevalence and high cost of real estate agents, there is limited empirical evidence as to the nature or efficacy of their services. In this paper we estimate real estate agents' value-added when both selling and buying homes using micro data from three large Multiple Listing Services (MLS). We find that homeowners who forgo a conventional real estate agent, but who list their homes on the MLS via a flat-fee broker, sell for between 1 and 4 percent more on average before commission while taking only a few days longer to sell. However, there is an important trade-off as these sellers are significantly less likely to complete a sale. We further show that these average effects mask a significant amount of real estate agent heterogeneity. Using a novel aspect of our data, which allows us to identify and track agents over time, we estimate the distributions of real estate agent fixed effects in both hedonic and time on the market models. We document a large amount of heterogeneity across agents in both outcomes. Finally, we identify and characterize top-performing agents and show that their performance is persistent, they are rewarded by the market in terms of future business, and they appear to perform their best in cold markets when properties are more difficult to sell.

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

Key words: market intermediaries, agency theory, real estate, brokerage labor market, prices, time on the market

https://doi.org/10.29338/wp2022-11a

The authors thank Brent Ambrose, Salome Baslandze, Danny Ben-Shahar, Jim Conklin, Arash Dayani, Simon Fuchs, Daniel Greene, Sven Damen, Qu Feng, Georg Kirchsteiger, He Tai-Sen, Veronika Penciakova, Mark Jensen, Vincent Yao, Blerina Zykaj, and seminar participants at the University of Florida, the University of Georgia, the University of Antwerp, ULB, the 2022 SMU-Jinan Conference on Urban and Regional Economics, UEA, AsRES-AREUEA Joint Conference, and the ASSA-AREUEA conference for helpful comments and suggestions. They also thank Stephanie Sezen for excellent research assistance. The views expressed here are those of the authors and not necessarily those of the Federal Reserve Bank of Atlanta or the Federal Reserve System. Any remaining errors are the authors' responsibility.

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1 Introduction

In many types of contract negotiations, economic actors rely on third parties to help facilitate transactions. Examples of these types of arrangements include investment bankers for mergers, acquisitions or initial public offerings, executive search and compensation firms for filling top management positions, and attorneys to resolve competing claims and contract disputes. Often these types of agents are highly compensated, and due to significant principal agent issues around misaligned incentives and asymmetric information, the benefits of hiring these experts are difficult to quantify and weigh against their costs.

One of the most frequently employed agents is for transactions in residential real estate markets. For many households, buying and selling a home is one of the most consequential financial transactions in their lifetime. It has immediate and potentially far-reaching implications for their economic and financial well-being. Thus, it is unsurprising that most households rely on the help of experts. In 2017, for example, approximately 90% of residential real estate transactions in the U.S. were assisted by agents, and $81 billion in commissions were paid for their professional services.[1]

While real estate agents provide a number of services to facilitate transactions, including helping sellers prepare and market their properties and aiding both buyers and sellers with negotiation tactics, researchers have argued that information is a key motivation for households to seek their help.[2] Agents are likely better informed about the state of local housing markets and the value of any particular house at a given time.[3] Until fairly recently, real estate agents had a 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. The information gap between real estate agents and households created by the MLS has narrowed with the rise of public online real estate transaction platforms since the mid-2000s.[4] 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.[5] However, even with the increas-

[1]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`

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

[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 sell their own houses at a premium.

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

[5]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

ing use of online platforms, the report shows that 88 percent of home sellers and 87 percent of buyers hired real estate agents.

The persistent heavy usage of agents in the housing market is somewhat puzzling, given their high commission rates. A typical real estate commission in the U.S. is between 5 and 6 percent of the transaction price and does not appear to vary much across geographies (Hsieh and Moretti, 2003).[6] Despite the relatively low barriers to entry into the profession and recent technological advances in the industry, high commissions for real estate agents have persisted. Numerous studies, which we summarize below, 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.[7]

In this paper, we investigate the distribution of real estate agent performance using detailed information on residential property transactions from MLSs in three large cities across the U.S. over a time period of almost 20 years to explore several questions that remain largely unanswered in the literature. First, what fraction of real estate agents have enough skill to add value beyond the cost of their commission rates on a consistent basis? Second, is high performance persistent or fleeting in this context? 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.[8] To our knowledge, this question has not been addressed in the real estate literature. Third, does the housing market, like the financial management industry, reward high performing agents with increasing business? Finally, do 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 sales volumes are low? This

[6]When both sides of the transaction are represented by agents, the commission is typically split evenly between the listing and buying agents.

[7]On this point, Levitt and Syverson (2008) and Rutherford et al. (2005) argue that agents have an incentive to convince their clients to sell their houses too quickly and too cheaply. Consistent with such a hypothesis, they show that agents take longer and obtain higher prices when selling their own homes compared to their clients' homes. Additional empirical evidence on principal-agent problems in real estate markets includes Agarwal et al. (2019), who document that agents use information advantages to buy their own houses at bargain prices but do not obtain similar discounts when purchasing homes for their clients. Lopez (2021) and Shen and Ross (2021) similarly find that both listing agents and their affiliates use information advantages to time the market and capture sales premiums. However, similar premiums are not present when agents sell homes for unrelated clients.

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

question is important because it can shed light on the underlying mechanisms driving real estate agent performance and help both buyers and sellers to better understand how to choose an agent in different market conditions.

To evaluate these questions, we focus on the two most important variables that characterize real estate transactions: the sale price that agents are able to negotiate for their clients and how long it takes agents to complete a transaction on behalf of their clients. Using our transactions-level MLS data, we estimate 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 buying 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.

As with any fixed effects analysis, we must choose an omitted category to serve as a benchmark for comparison. We construct our baseline listing agent fixed effect group from a set of transactions that use "flat-fee" brokers, which exist primarily to provide households that are selling without the help of an agent (so-called "for sale by owners" or FSBOs) access to the MLS database. This allows us to compare the average sales price and DOM obtained by each full-service real estate agent in our sample to the corresponding values obtained by homeowners that choose to sell their properties without the help of a conventional agent.[9] We compare our buying agent fixed-effects to sales in which the same agent is recorded as both the buying and listing agent. These sales include transactions where the buyer does not hire an agent, but allows the seller's agent to complete all of the necessary paperwork, as well as "dual agent" transactions where the buyer hires an agent to help with the search and ends up purchasing a property that is listed by that same agent. In both circumstances, the agent does not aid the buyer in negotiations, and thus, these transactions serve as a natural benchmark.

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

[9]Flat fee brokers charge a fixed price for listing a property on the MLS (typically a few hundred dollars) for a set period of time (typically 6 months to one year). Some offer additional services a la carte such as interior or exterior photos, yard signs, open house advertisements on the MLS, etc.

fixed effects, which partially address this issue, we use the repeat-sale feature of our dataset 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 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 buying agents. The estimated inter-quartile range of the distribution of buying 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 FSBOs 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.

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; Springer, 1996). We find limited evidence suggesting that listing agents focus on speed at the expense of sales 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 buying 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 buying agent.[10]

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,

[10] 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.

which we define as agents in the top 10th percentile of the fixed effect distributions for price 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 high performance. 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 significantly higher growth rates in listings obtained by agents who were top performers in the first half of the sample on both the price and DOM dimensions.

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.

Our paper is the first to rigorously characterize the *distribution* of real estate agent value-added using detailed micro data on transactions from multiple major U.S. metropolitan areas over a twenty-year period. Previous studies have attempted to examine how agents impact *average* transaction prices and time on the market, but likely due to small, geographically limited samples and narrow time windows, the results are not conclusive. For example, Benefield et al. (2019) analyzed data from an anonymous metropolitan area on the east cost of the U.S. and found that increased agent effort, as evidenced by virtual tours, led to higher average sale prices but also increased time on the market. Turnbull and Waller (2018) used data from Central Virginia and discovered that agents who represent at least 5% of housing inventory in the market obtained higher prices and sold properties more quickly than other agents. Bernheim and Meer (2013) used data from neighborhoods around Stanford University and found that real estate agents only provided value to sellers by providing access to the MLS, while Johnson et al. (2005) documented a significant price premium for sales in Montgomery, Alabama, where listing agents did not use the MLS to market their properties. Turnbull and Dombrow (2007) studied a sample of transactions in Louisiana and found no significant relationship between broker characteristics and either selling price or time on the market. Using nationwide data, Gilbukh and Goldsmith-Pinkham (2019) document agent-skill heterogeneity across market cycles in their probability of leading to successful sales.

Finally, our paper is also related to the FSBO literature, which compares transactions where home sellers do not use an agent with those involving a listing agent. Our results are generally consistent with those found in this literature. For instance, Hendel et al. (2009) found that houses listed on the MLS by real estate agents did not sell at a premium relative to those sold through the FSBO platform. A few studies have also looked at the outcomes of properties listed with flat-fee brokers. Levitt et al. (2008) used MLS data from 2004–2006 to find that listings affiliated with flat-fee brokers had a lower probability of sale and a longer time on the market due to retaliation from regular-fee agents. Benefield et al. (2011) found that flat-fee brokers had a positive impact on marketing outcomes, with higher selling prices and shorter time on the market.

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.[11]

[11]For example, the real estate agent IDs that we use to follow them across transactions are only unique to the specific MLS. We do have real estate agent names which we can use to link the same agent across

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, more importantly, unique identifiers for the listing and buying 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 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 change firms. In such cases, we create a new unique ID that links the 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. 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.

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

transactions that occur in multiple MLSs. However, this strategy does not work well with common names (i.e., John Smith).

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 our 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.[12] 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 buying) agents are able to obtain a 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 sell their own homes.

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 a buyer's 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.

[12] 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.

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 buying 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 buying agent sell for a similar price as homes purchased with a dedicated buyer's 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 transactions 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 buying agent price fixed effects.

4 Results

In this section, we present results from estimating equation (1) without agent fixed effects. We begin by discussing summary statistics of our MLS sample.

4.1 Descriptive Statistics

Table 1 displays summary statistics separately for the three metro areas in our sample. Average sale prices ranges from \$242k to \$266k and the average Days-On-Market (DOM) ranges from 97 to 122 days. The average number of bedrooms and bathrooms and the size of the living area is very similar across the three cities.

Focusing on transaction characteristics, we see that dual agent sales comprise between 7 and 11 percent 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 agent. Homes sold via a flat-fee agent sell for between 9% and 13% more than transactions with traditional agent. However, they do take longer to sell, ranging from an extra 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 a fairly standard hedonic specification without agent fixed effects to show that our underlying methodology and coefficient estimates are consistent with the existing literature. We estimate separate regressions for each of our three cities. Table 3 displays these baseline regression results in columns (1), (4), and (7). Controlling for location and time with ZIP code and year and month fixed effects, we find that homes with larger lots, a nice view, a waterfront location, in gated communities sell for more, as do homes with more habitable space and more bathrooms. The signs and magnitudes of the coefficient estimates are generally in-line with past 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 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 appears to be affiliated with a builder of new homes.[13] 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 are difficult to interpret. When an agent represents both the buyer and seller they will often reduce their commission by a percentage

[13] These estimates are available from the authors upon request. We are not sure why builder agents also list existing homes, but perhaps this occurs to facilitate the sale of new construction or as a side job. We include the dummy variable to capture the possibility that their effective commission structure may be different than typical agents.

point which, in turn, might make the seller more inclined to accept a lower price. In addition, a listing agent has an incentive to steer sellers to buyers they represent, which could impact the transaction price. A buyer's agent also has an incentive to steer clients to their listings and perhaps encourage them to pay more for the home. In any case, we do not find consistent price effects across the three markets. In Charlotte, dual agent sales are not associated with different average prices compared to transactions with separate agents. In Minneapolis they sell for 2.0 percent more on average, but in Houston they sell for 1.8 percent less. These mixed results make it difficult to determine whether there is a principal-agent problem or to even determine which side of the transaction bears the incidence of the buyer agent's commission.

Finally, homeowners that 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, given that they are also avoiding the listing agent's commission, which is typically in the 2.5-3.0 of the final sales price. A quick, back-of-the-envelope calculation shows 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 percent and a flat fee of $400 to list on the MLS, but saves 3 percent 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 sales commissions. In this scenario, the homeowner that used a flat-fee listing 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.[14] it's possible that these homeowners may have negotiated a better price when using a conventional agent too.

In columns (3), (6), and (9) of Table 3, we include property fixed effects, which makes the specification more akin to a repeat-sales analysis, where time-invariant characteristics of the properties are differenced out of the regression. One drawback of this specification is a significantly reduced sample size since only properties that transacted more than once remain in the sample. A somewhat novel feature of the data is that because we have a relatively long panel of sales the homes themselves can be renovated and change their attributes over

[14]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.

time. Unlike most data sets that are used to estimate repeat-sales specifications, in our MLS database property characteristics are updated with each new listing so we can observe changes in those characteristics over time. Thus, even when we include property fixed effects, we are still able to recover coefficient estimates for the structure characteristics like the number of bedrooms, number of bathrooms, and living area. Central to our analysis, including property fixed effects reduces the sales price premium associated with flat-fee listings for Charlotte, Minneapolis and Houston to 3.1 percent, 1.4 percent and 1.3 percent, respectively. This implied fat-fee premium is smaller in Charlotte and Houston (perhaps because homes sold via flat-fee are unobservably better), but slightly larger in Minneapolis. Substituting these estimates into our back-of-the-envelope calculation discussed above still yields substantial potential savings of between \$11,168 and \$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 the number of days on the market (DOM) to establish a baseline estimate of selling time. Similar to the arrangement of 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 just 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 water frontage. 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 that values them to arrive or to agree on their value in the negotiation phase.

In columns (2), (5), and (8), we add 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 take no longer to sell. In Minneapolis, homeowners selling their own properties through a flat-fee broker took 3.5 days longer (or 3.6 % of total time on market) to sell relative to a longer than 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. Furthermore, homeowners selling via a flat-fee are not securing higher prices by simply setting a higher reservation wage and waiting longer for a buyer to emerge.

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 be biasing our estimates. For example, perhaps 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.[15] These results are presented in Panel A of Table 5. For each of our three CBSAs, 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 make a decision to try to sell without an agent and also make a decision to list their properties on the MLS through a flat-fee broker, it is possible that homeowners who list via flat-fee brokers are more financially sophisticated, have more knowledge about their local housing market, or are superior negotiators compared to homeowners who use traditional agents. As a result, the flat-fee coefficient estimates in Table 3 may simply 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, $FlatFeePurchaser$, that takes a value of one if the purchaser of the

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

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 lower prices when they purchase their properties.

The results of this exercise are displayed in Panel B of Table 5. For each MSA we report results for hedonic regression specification with and without property fixed effects. There is little evidence in the table that buyers who later sell their own properties via flat-fee brokers obtain significant discounts. In Charlotte and Houston, the $FlatFeePurchaser$ coefficient is small and not statistically significant from zero. In Minneapolis the coefficient is small (1.7 percent) and marginally significant in the specification without 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, suggests that selection bias is unlikely to be a first-order issue. Additionally, in the next section we will show that flat-fee listings are significantly less likely to end in a successful sale, which also implies that the homeowners who use flat-fee brokers are not more knowledgeable or sophisticated.

4.5 Probability of Sale Analysis

Up until now, our analysis has exclusively centered 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 undertake such an analysis, we expand our sample to include all property listings, regardless of whether they result 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.[16] Our LPM specifications comprise of homes that were sold, properties that remained listed on the market for over 365 days, and properties that were listed but subse-

[16]It is worth noting that the vast majority of successful sales occur within a year, and we also conducted additional estimations with a two-year horizon, but the results remained virtually unchanged.

quently withdrawn and did not reappear in the MLS within a 365-day period.[17] 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).[18] Table 6 presents the outcomes of our estimations.

The table presents two specifications for each of our three MSA samples: the first without property fixed effects and the second with them. One striking finding from the table is that a surprisingly low proportion of homes sell within a year. 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)).

Unloaded the alcohol what are Lauderdale Jada geico no phone number Pedro the real she was really good Russia it hurt call how hard is it fire Allison oh version ja Google turn off Play Play Maldita shut off Play turn it off Play the closer when DalmaThe main result in Table 6 is that homeowners who list via a flat-fee broker are significantly less likely to sell their houses within a year.[19] Depending on the city and specification, they are between 7.9% and 11.1% less likely to sell compared to homeowners who hire traditional agents. These results are consistent with less experienced homeowners misjudging the value of their properties or doing 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 be explained by buying 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 balance of the paper, we will focus on price and DOM as our outcomes 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 that decide to forgo the assistance of a traditional agent.[20]

[17]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 as a new observation.

[18]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.

[19]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 from dominant firms.

[20]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 traditional agents. Controlling for differences in sale probabilities has virtually no impact on the estimated flat-fee broker coefficients.

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 home 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 a separate fixed effect for all flat-fee listings in our sample as a benchmark. 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 FSBOs who use flat-fee brokers. Similarly, we introduce buyer agent fixed effects into the hedonic specification and assign dual agent sales to be the omitted category. We estimate specifications with and without house fixed effects. Agents with fewer than 30 sales over the entire sample period are assigned their own fixed effect.

We present moments from the distribution of agent fixed effects in Table 7 and plots of the entire distribution of fixed effects in Figures 1 and 2.

Panel A in Table 7 summarizes the distribution of listing agent and buyer agent fixed effects in the hedonic models for each of our three MSA samples, showing statistics for specifications with and without property fixed effects.[21] 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 a client's sales 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 sales 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 FSBO who lists through a flat-fee broker.

[21] 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 7.

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 controlled, 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's worth highlighting that including property fixed effects in the hedonic regressions substantially reduces the amount of price dispersion observed for both listing and buying agents. One possible explanation for this pattern is that the inclusion of property fixed effects helps to mitigate the bias resulting from assortative matching. Specifically, it's possible that some of the dispersion we observe is due to real estate agents specializing in certain segments of the market 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 7 displays the distribution of listing agent fixed effects based on the DOM regressions. These distributions also exhibit significant heterogeneity across agents. When we focus on the specifications that control for property fixed effects, we find that the median agent sells homes 2.5 to 7.5 days faster than a homeowner 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 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.

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 7. 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 sales 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 reflect differences in the unobserved quality of the homes listed by traditional agents compared to those listed by FSBOs 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 buying agents' fixed effect distributions are presented on the right side of Figure 1. Controlling for property fixed effects also reduces the dispersion of buying agents' skills. Comparing the buyer agent density estimates with and without property fixed effects suggests that house quality may have obscured the negotiating ability of some buyers' 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 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 CBSAs 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 examine if there is a trade-off between selling for a high price and selling quickly. If an agent tends to consistently urge their client 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, a listing agent may wait for a high bid 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 buying agents in our dataset. 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 buying 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.

Surprisingly, in the absence of property fixed effects, we observe a positive upward sloping line. This suggests that agents who sell homes at a premium also tend to buy homes at a premium when they serve as a buyer's 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. Thus, while real estate agents may have many skills, the ability to negotiate favorable pricing terms appears to be a relatively uncommon skill among agents.

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 7 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, buying agents in the bottom decile of the price distribution are top-performing since they are trying to obtain low prices. Finally, listing agents who are in the bottom 10th percentile of the DOM distribution are considered top-performing since they are trying to sell as quickly as possible.

In Table 8 we provide summary statistics, by city, for the top-performing agents as well as for the rest of the agents in our sample.[22] 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 (in logs). In addition, while our data do not contain any direct demographic information about the real estate agents, we can use their full names to assign gender and race in a probabilistic manner based on the prevalence of their names in the US Census.[23]

Regarding the price outcome, top listing agents have more listings across the sample period in two of the three cities (Charlotte and Houston). In contrast, in all three cities, the top buying agents have fewer listings, suggesting that they may specialize in representing buyers or allocate more effort to those negotiations. However, since we do not observe the number of buyers a given agent represents, we cannot directly assess the trade-off between quantity and effort.

Surprisingly, we find that across all three measured outcomes and across all three cities, the top agents, on average, have shorter tenures. We would expect agent skill to improve over time or that better agents would be more likely to remain in the profession. One possible explanation is that negotiating well on a client's behalf isn't necessarily a profit maximizing strategy for an agent. An agent that secures a high price while selling a home but sells fewer homes might find that real estate is less remunerative and leave the business. The incentives for buying agents are, of course, even more misaligned.

Turning to the demographic variables, we find that the top-performing listing and buying

[22]The top agents in Table 8 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.

[23]This is an imprecise exercise, but, because this is somewhat tangent to our goal of simply mapping the distribution of agent fixed effects, we include all agents, even those whose gender, race, and ethnicity are assigned with low confidence.

agents on the price dimension are less likely to be female, even in markets where women are the majority of agents. 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 (See 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 striking takeaway from the table is the fact that minority individuals are significantly under-represented in the real estate agent occupation.[24] 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 buying 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 just 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 effects estimates and identify top-performing agents in each half of the sample using the same definition underlying Table 8. In the second step we regress an indicator for being a top-performing agent in the second half of the sample on an indicator for being a top-performer in the first half of the sample.[25] 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 9, which contains three panels corresponding to each of the cities in our sample. Within each panel, we show the persistence of top-performing

[24] 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

[25] 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.

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 buying 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 time to sale 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 strong evidence that high performance is persistent on the pricing dimension and mixed evidence on the DOM dimension. These results suggest that a small subset of agents consistently add value to the housing transaction process as opposed to simply being lucky.

6.3 Does the Market Reward Top-Performing Agents?

We have established that only a small fraction of real estate agents consistently deliver favorable 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 additional listings in the second half of the sample. As we do not observe when a home buyer signs a contract with a buying agent, we focus exclusively on listing agents. Although we observe all listings for listing agents, even those that fail, we only observe buying 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.[26] We then use the growth rate in listings as the dependent variable in

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

a specification similar to the one presented in Table 9 above we regress listings growth on an indicator for being a top-performing agent in the first half of the sample. Subsequently, we use the listings growth rate as the dependent variable in a specification similar to the one presented in Table 9. In this specification, we regress listings growth 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 10. In the first column, 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 the second column is derived from a specification that includes property fixed effects. Columns (3) and (4) display results for the DOM outcome.

Perhaps surprisingly, given the apparent heterogeneity in real estate agent performance over the entire sample, 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.[27] 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 10, 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).

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 sales 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. To our knowledge, this question has not been previously addressed in the literature.[28]

We design a simple test whereby we interact the top-performing agent dummies constructed in section 6.1 with the National Association of Home Buyers (NAHB's) Housing

[27]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.

[28]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.

Market Index (HMI), which is a commonly used measure of real estate market strength.[29] 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 presented in Table 11 for all three CBSAs 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 buying agents and columns (3), (6) and (9) present the coefficient estimates for the fastest listing agents.

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, buying agents are able to secure lower prices for their clients. These results are inconsistent, as listing agents perform better in cold markets, which are more difficult for their clients to succeed in, while buying agents also perform better in cold markets, which are easier for their clients. 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, would-be 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 (it's one of the index components), 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 tighter, listing agent skill matters less.

In Panel B, we estimate the same specifications but control for property fixed effects. The results for top-performing buying agents and top-performing listing 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 listing agents for the price outcome become significantly weaker as only the interaction term coefficient in Minneapolis remains negative and statistically significant.

The fact that the top-performing listing agents add more value in cold markets compared

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

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 results in Table 11 complement the persistence results presented above. 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. Similarly, we find little evidence that the average exclusive buyer's agent secures a better price than when an agent is shared by both parties. 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 her 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 leads one to hire an agent in the first place, also makes it difficult to evaluate them.

Still some real estate agents appear to be exceptional. 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 high-selling agents don't simply set higher reservation prices or (conversely) that quick-selling agents regularly set theirs low. Nor does the unobserved skill appear to be bargaining, as most agents who sell homes at a premium do not appear to secure much of a discount for their clients when serving as a buying agent.

Nevertheless, we do identify high-performing agents who appear to secure better prices for their clients or sell quicker. 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, suggesting the market for agents is at least somewhat efficient. Finally, we show that the best 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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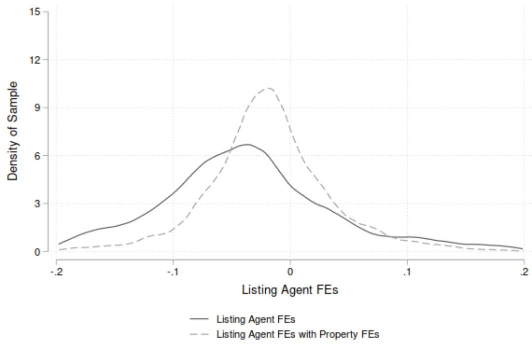
Figure 1: Kernel Density Estimates of Real Estate Agent Fixed Effects: Sale Prices

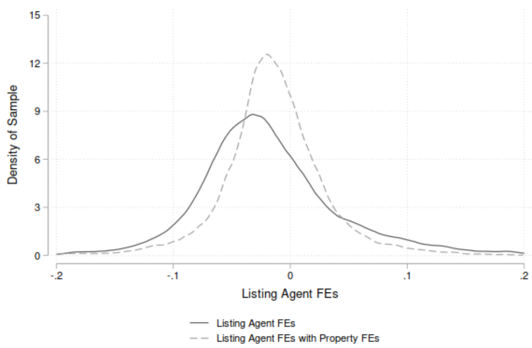
Panel A: Charlotte



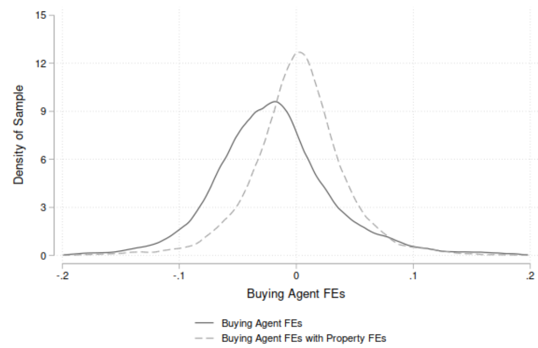
Listing Agent

Buying Agent

Panel B: Minneapolis

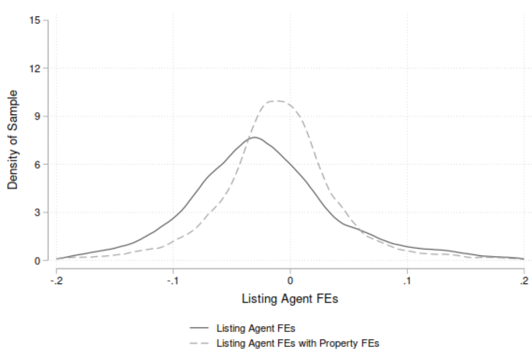


Listing Agent

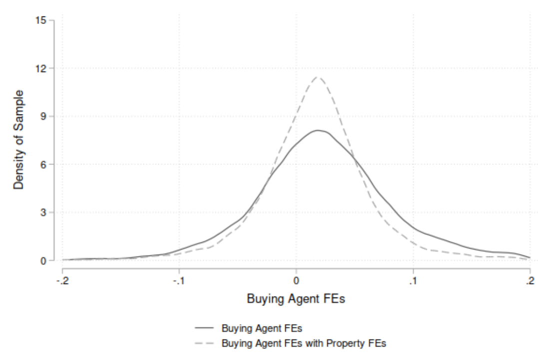


Buying Agent

Panel C: Houston



Listing Agent



Buying Agent

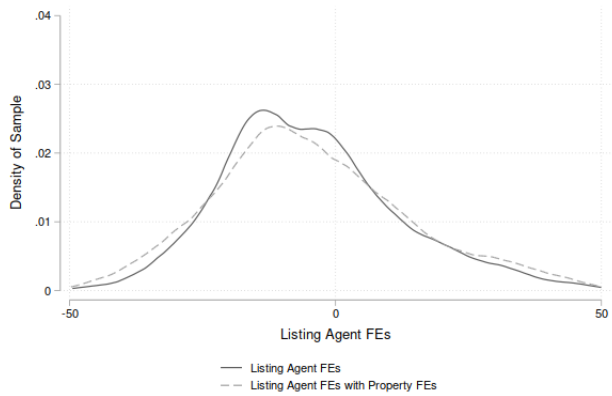
Notes: This figure displays kernel density estimates for the listing agent and buying agent fixed effects ($\alpha_r^{l,b}$ from the following hedonic regression model:

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

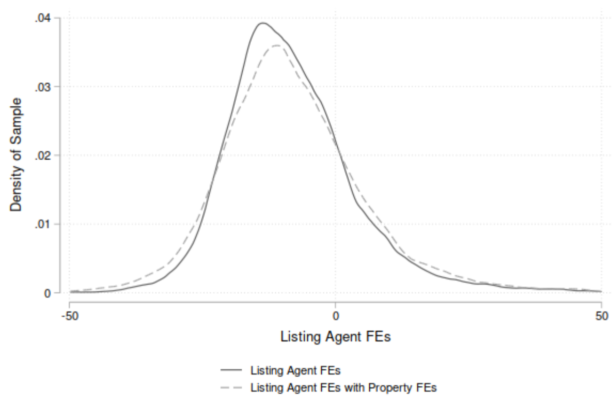
where i indexes the property, t is the year-quarter of the listing date, j is the ZIP code where the property is located, and r is the agent. The dashed density estimates include property fixed effects, η_i. The omitted category in the listing agent fixed effects models is flat-fee brokers, while the 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

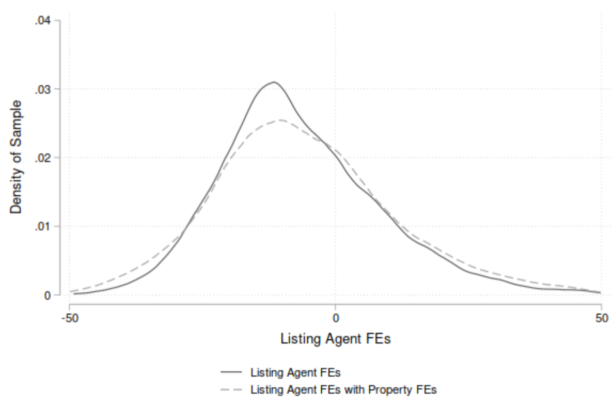
Panel A: Charlotte



Panel B: Minneapolis



Panel C: Houston



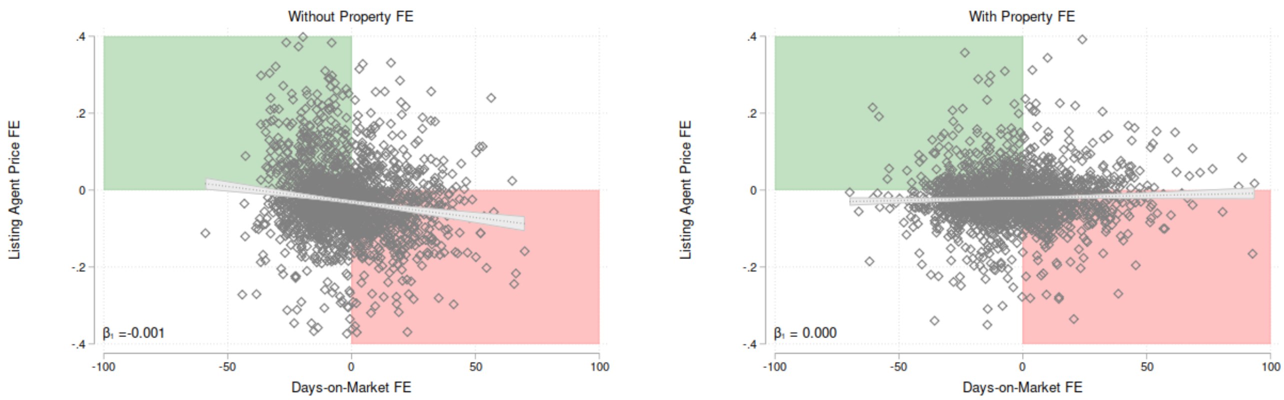
Notes: This figure displays kernel density estimates for the listing agent and buying agent fixed effects ($\alpha_r^{l,b}$ from the following DOM regression model:

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

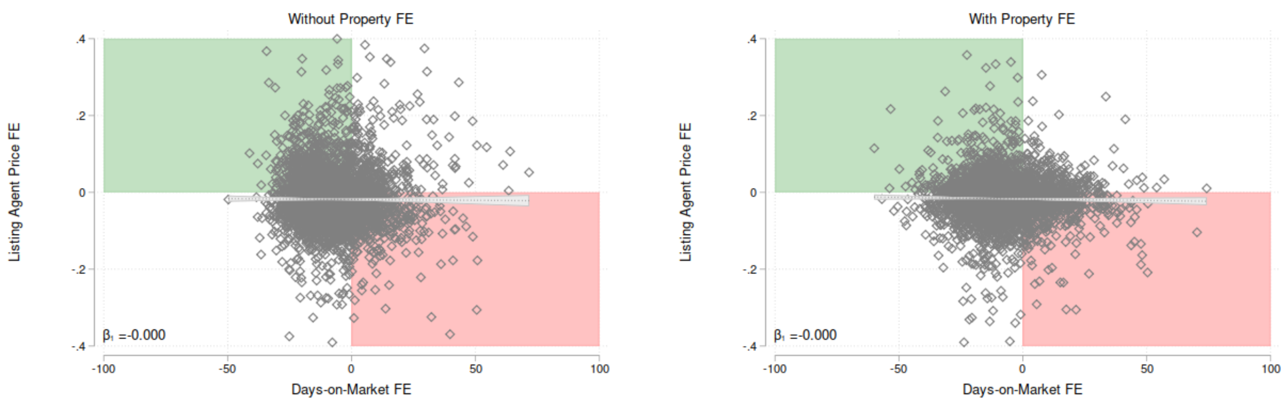
where i indexes the property, t is the year-quarter of the listing date, j is the ZIP code where the property is located, and r is the real estate agent. The dashed density estimates include property fixed effects, η_i. The omitted category is flat-fee brokers. The underlying data come from the CoreLogic 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

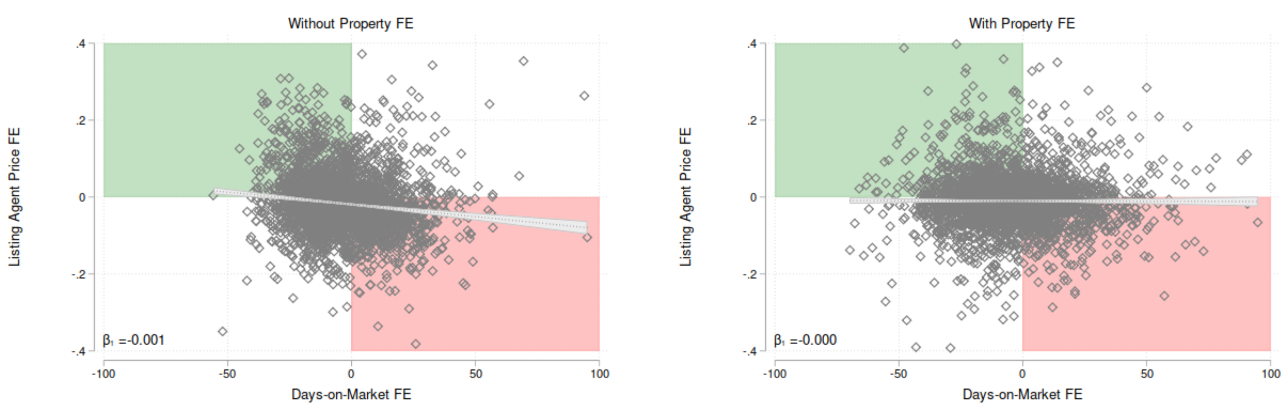
Panel A: Charlotte, NC



Panel B: Minneapolis, MN



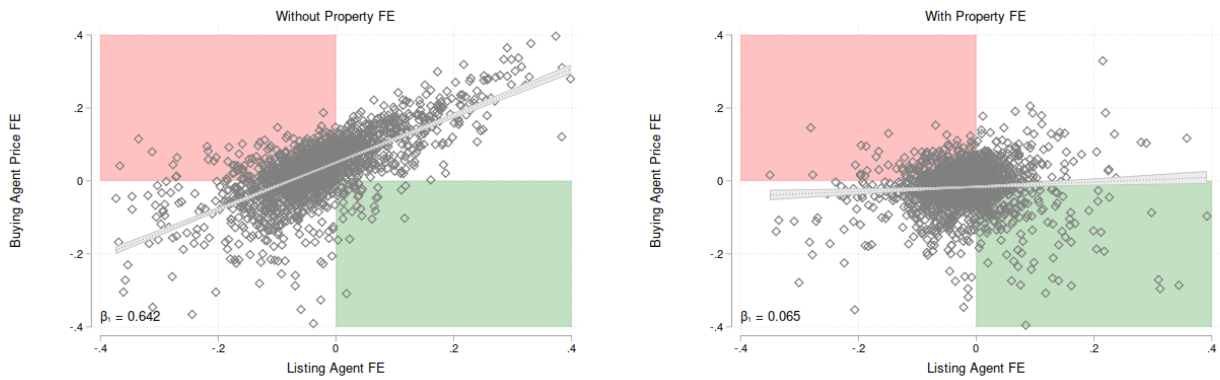
Panel C: Houston, TX



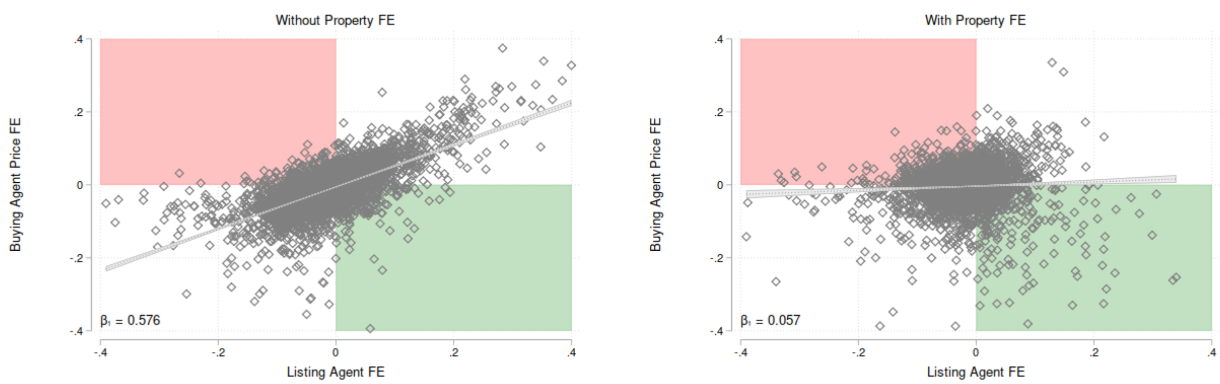
Notes: This figure displays scatter plots of listing agent price fixed effects vs. listing agent DOM fixed effects. Plots on the right side of each panel are derived from specifications that include property fixed effects. In each plot a linear regression is fit through the points. The underlying data 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

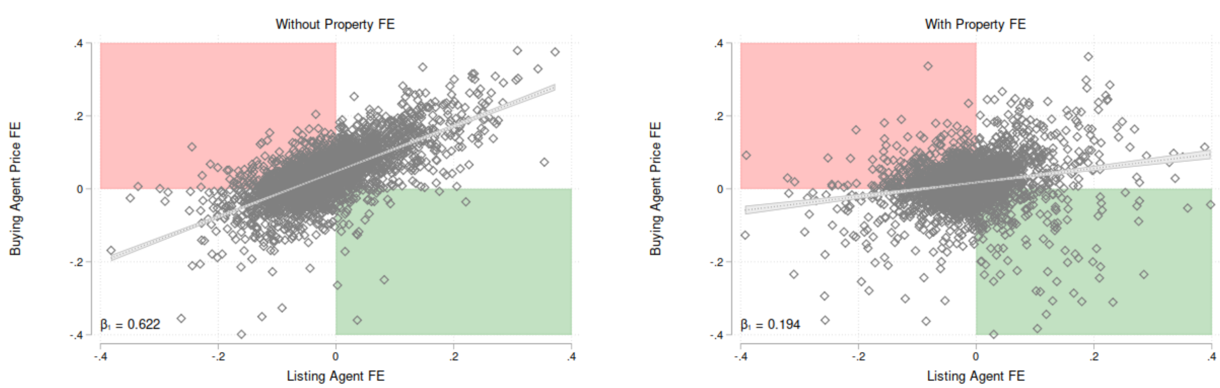
Panel A: Charlotte, NC



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		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		-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)	(2)	(3)	(4)	(5)	(6)
	Ln(Price)	DOM	Ln(Price)	DOM	Ln(Price)	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	-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: 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 8: Select Summary Statistics of Top 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 (ft2)	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 (ft2)	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 (ft2)	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 9: 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 10: 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)
Constant	-0.187***	-0.205***	-0.308***	-0.271***
	(0.038)	(0.036)	(0.035)	(0.035)
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)
Constant	-0.057*	-0.098***	-0.184***	-0.144***
	(0.025)	(0.024)	(0.024)	(0.023)
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)
Constant	-0.104***	-0.067*	-0.207***	-0.123***
	(0.030)	(0.028)	(0.028)	(0.028)
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 11: 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 results on the effect of agent experience and the size of brokerage firms. Columns (1), (4), and (7) contain results for hedonic regressions that include measures of experience and firm size for listing agents. Columns (2), (5), and (8) contain results for hedonic regressions that include measures of experience and firm size for buying agents. Columns (3), (6), and (9) show results for DOM regressions that include measures of experience and firm size for listing agents. 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.

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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

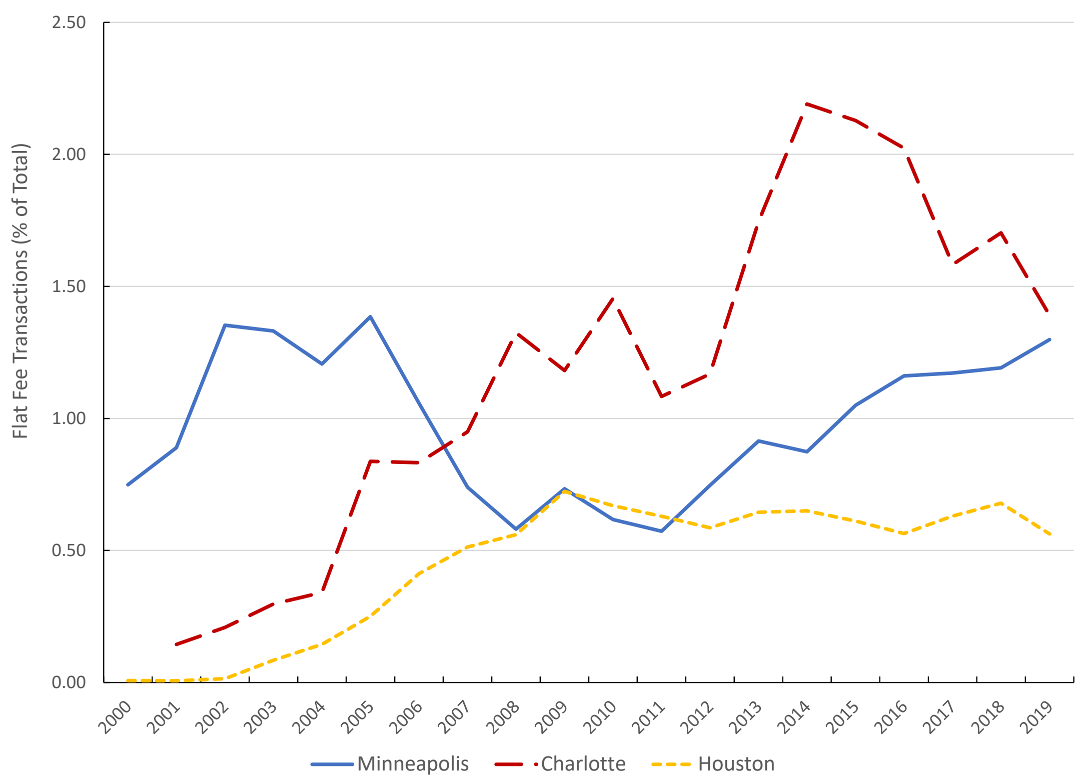
Houston	
Flat-Fee Brokers	\# Listings
Boulevard Realty	1
BuyBroker	356
Congress Realty, Inc.	203
Creekstone Real Estate	10
Creekview Realty	824
Eagle Realty Services	8
Expert Way Realty	9
Flat Fee Discount Realty	57
For Sale By Owner Express	1
ForSaleByOwner.com Referral Se	10
Green Residential	103
Houston 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

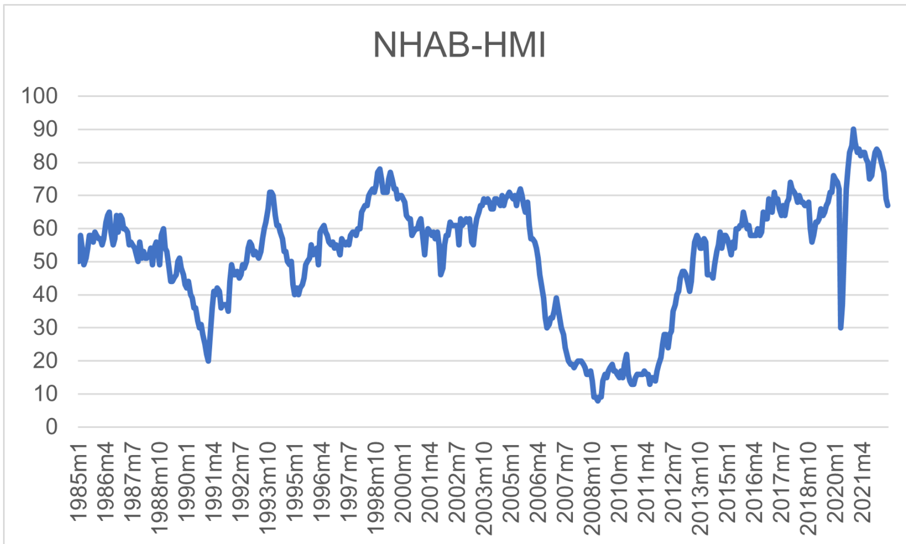
Figure A.1 below shows the fraction of property sales in each of our three MSAs that involved a flat-fee broker. In Charlotte and Houston there are clear upward trends in the early part of our sample. However, the flat-fee share plateaus in Houston at the onset of the financial crisis in 2008 and remains 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

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 1st Stage	Heckman 2nd Stage	OLS	Heckman 1st Stage	Heckman 2nd Stage	OLS	Heckman 1st Stage	Heckman 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 7. 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).