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

Chris Cunningham† Kristopher Gerardi‡ Lily Shen§

September 13, 2022

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 data from three large Multiple Listing Services (MLS)s. We find that homeowners who forgo a conventional real estate agent, but list their homes on the MLS via a flat fee broker, sell for between 1 and 4 percent more before commission, but take longer to sell and are less likely to complete a sale. However, 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 find that exchanging a listing agent in the 25th percentile for one in the 75th would increase the final sales price by 5–6 percent, and a similar exchange for buying agents would lower purchase prices by 4–6 percent. The interquartile range of agent fixed effects from our model of time-on-the-market is 17–25 days. We do not find a significant trade-off between price and time-to-sell however as agents who obtain higher prices do not take longer to sell, suggesting that they are not simply setting higher reservation prices. We also show that agents who sell homes for more also appear to pay more for a home when serving as a buyer's agent, indicating that the average agent does not possess exceptional negotiating skills or that such skills are overwhelmed by principal-agent problems. Finally agents do not appear to get better at bargaining; agents do sell faster with experience, but mostly by selling for lower prices.

Key Words: Market Intermediaries, Agency Theory, Real Estate, Brokerage Labor Market, Prices, Time on the Market
JEL codes: *D01, D8, G5, L8, R31*

---

*We thank Salome Baslandze, Danny Ben-Shahar, Simon Fuchs, Veronika Penciakova, Mark Jensen, Vincent Yao, and participants at the 2022 AsRES-AREUEA Joint Conference in Tokyo, Japan for helpful comments and suggestions. We thank Stephanie Sezen for excellent research assistance. All remaining errors are our own. The views expressed in this article are those of the authors and not those of the Federal Reserve Bank of Atlanta or the Federal Reserve System. Chris Cunningham, chris.cunningham@atl.frb.org, is at the Federal Reserve Bank of Atlanta, 1000 Peachtree St., Atlanta, GA. Kristopher Gerardi, kristopher.gerardi@atl.frb.org, is also at the Federal Reserve Bank of Atlanta. Lily Shen, yannan@berkeley.edu, is at Clemson University, 145 Business Building, Clemson, SC 29634.

1 Introduction

In many types of contract negotiations, economic actors rely on a third party to help facilitate the transaction. 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, or attorneys for resolving competing claims and contract disputes. Perhaps the most frequently employed agent is for transactions in residential real estate markets. For many households, buying and selling a home is one of the most consequential financial transactions that they will participate in over their lifetime. It has both immediate and potentially far-reaching implications for their economic and financial well-being, and thus, it is unsurprising that most households rely on the help of experts. In 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, researchers have argued that information is the key motivation for buyers and sellers 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. 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. In addition, 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)s databases that provide detailed information on properties for sale in a given housing market. The information gap between real estate agents and home sellers and buyers created by the MLS has narrowed with the rise of public online real estate transaction platforms since the mid-2000s.[3] According to a recent report by the National Association of

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

Realtors (NAR), 51 percent of home buyers found the homes they purchased on an online platform other than the MLS.[4] Consistent with this trend, Hendel et al. (2009) finds that houses listed on the MLS by real estate agents do not sell at a premium relative to those sold by owners using the for-sale-by-owner (FSBO) platform. However, even with the increasing 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, unlike in many other professions, has not significantly declined with recent technological advances even as the barriers to entry into the profession remain relatively low (Hsieh and Moretti, 2003). An increasing volume of research has explored the potential value that real estate agents bring to the table using housing transaction data from small geographic areas. Benefield et al. (2019) use data from a single anonymous metropolitan statistical area (MSA) on the east coast of the U.S. and find that increased agent effort through the creation of virtual tours increases average sale prices but also increases time on the market. Turnbull and Waller (2018) use data from Central Virginia and shows that sellers' agents representing at least 5% of housing inventories in the market obtain higher prices and sell faster than other agents. Bernheim and Meer (2013) use data from neighborhoods surrounding Stanford University and document that real estate agents only create value for sellers by providing access to the MLS.[5] Turnbull and Dombrow (2007) focus on a sample of transactions in Louisiana and find no significant relationship between broker characteristics and either selling price or time on the market. Benefield et al. (2011) find that flat fee brokers affect marketing outcomes through higher selling prices and less time on the market. To date, however, there is no consensus in the literature about exactly

lia.com.

[4]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

[5]In contrast, Johnson et al. (2005) document a significant price premium for sales in Montgomery Alabama, in which listing agents do not use the MLS to market their properties.

how real estate agents add value to the process of buying and selling a home. Meanwhile, there is evidence that misaligned incentives between sellers and their agents result in market distortions that can subtract value in some instances.[6]

In this paper, we investigate the distribution of real estate agent skills using detailed information on real estate transactions from MLSs in three large cities across the U.S. to explore two 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, for those real estate agents that do possess skills, how do they create value for their clients? To evaluate the first question, we focus on the two most important variables that characterize real estate transactions: the sale price that agents are able to obtain 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 begin by estimating standard hedonic pricing models and days-on-market (DOM) regression models. To assess real estate agent skill distributions, 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.

[6]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, the same premiums are not present when agents sell homes for unrelated clients.

Furthermore, 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.[7] 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 relevant benchmark.

Our results suggest that there is significant heterogeneity across agents in the final transaction prices that they are able to negotiate. In a conventional hedonic regression, 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. Limiting the sample to homes that sell at least twice and including house fixed effects narrows this range to 5 to 6 percent. We also find substantial heterogeneity in the price outcomes for buying agents. The estimated inter-quartile range of the buying agent fixed effects distribution is between 6 and 10 percent which narrows to 4 to 5 percent when we include property fixed effects.

While there is significant heterogeneity, in all three cities in our sample we find that the median listing agent obtains prices that are 1% to 4% *lower* compared to owners that sell

[7] 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.

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% 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 own 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 do not appear to pay substantially less than other buyers. Futhermore, 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 21 days for all sales, and does not shrink when we control for house fixed effects. However, in contrast to our pricing results, we find that the median listing agent completes a transaction more quickly (by 6–10 days) compared to sales conducted via a flat-fee broker. Approximately 25% of agents in our sample sell more than two weeks quicker than FSBOs on average, while approximately 5% sell a month quicker.

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 full-service agent. We find that flat-fee listings are 6 to 11 percent less likely to end in a successful sale over a one-year horizon compared to traditional listings with a full-service 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 as well as the speed at which successful sales are completed.

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 Springer, 1996; Anglin et al., 2003; Krainer, 2001; Glower et al., 1998; Munneke et al., 2015; Shen and Springer, 2022). We find only limited evidence that listing agents focus on speed at the expense of sales price (or vice versa) as a selling strategy (as opposed to reflecting the individual circumstances of their clients). Agents that tend to sell homes at a greater premium do not, on average, take significantly longer to sell.

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 a 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.

We then investigate the role of experience. If agents secure better prices or sell faster the longer they've been in the profession, then that would be consistent with evidence that real estate agents learn on the job. We find that more experienced agents, on average, do sell properties more quickly, but sell them at lower prices.

Finally, we look at whether agents affiliated with larger brokerage firms achieve better outcomes, which would be consistent with the ability of large firms to amortize the cost of training across more agents. Larger firms may also have a greater ability to steer clients to homes that their brokerage is listing (Han and Hong, 2016). We find that agents at larger firms do sell faster in two out of three markets perhaps because they are better able to coordinate with buying agents in the same brokerage. We also find in two out of three markets that buying agents at large firms tend to pay slightly higher prices.

The balance of the paper is organized as follows. In the next section we discuss our MLS database and how we identify unique real estate agents over time, within a given MLS. Section III presents the basic econometric framework. Section IV discusses our main findings. In Section V we explore some of the factors that may determine high real estate agent performance. There is a brief conclusion.

2 Data

Our data come from the three Multiple Listing Services (MLS) data set collected and maintained by CoreLogic. Each underlying MLS consists of a database of for-sale properties 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 CBSAs: Charlotte, NC, Minneapolis, NM, 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 select these MLS because they are the largest metropolitan areas for which a single MLS covered at least 97 percent of all sales within their corresponding CBSA. This is important, because some metropolitan areas, like New York City and Los Angeles have multiple MLSs covering the region, making it difficult to follow agents across platforms.[8]

The information provided in our MLS data include the address of each house, a wide range of structure characteristics, lot characteristics, transaction characteristics, key dates

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

regarding the real estate transaction, 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.

In order to standardize the data across our three MSAs and deal with outliers, we impose a series of sample filters. First, we limit the sample to single-family detached houses, which removes around 100 to 150 thousand observations per MLS. Next, we throw out listings that occurred before CoreLogic achieved widespread of 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.[9] We exclude all homes not in the same Core Based Statistical Area (CBSA) covered by the MLS. This 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 an agent who specializes in distressed sales.[10] Between 15 and 40 thousands sales met this criterion.

Finally, we eliminate extreme values from the sample. The MLS is data are input by the listing agent and can be subject to data entry errors. We went to considerable effort

[9]For example, properties located in Ashville appear on the Charlotte MLS.

[10]In order to identify flat-fee brokers, we use the brokerage name and/or conducted an internet search for agents in the top 10 % of all sales.

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. The effect of these restrictions on total sample size for each MLS are presented in Appendix Table A.1.

Critically for our analysis, the MLS database provides the name, home office, and contact phone numbers and email addresses of the listing agents. When a sale is completed, the date the sale was finalized and the final price is also recorded as well as the name and contact information of the agent representing the buyer. We use this agent-specific information to track agents' performance over time and, in some instances, across firms. Specifically, we identify agents based on their unique MLS identifier. Occasionally, an agent might be associated with more than one identifier, perhaps because she changed firms. We create a new unique ID that links the provided IDs to a single individual if they are associated with 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 if an agent changed her name because of marriage, we would still track her, as long as she didn't simultaneously change her MLS ID.

A homeowner can choose to sell their home without the help of an agent. Traditionally, this meant placing their 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.

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

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

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

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.

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 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. These are essentially For-Sale-By-Owner (FSBO) transactions in the MLS database.

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 level. In some specifications, we also include property fixed effects δ_i. The inclusion of property fixed effects means that only homes that sold at least two times during our sample period remain.

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 don't matter.

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 time-to-sell 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 the agents in our sample who work as both listing and buying agents 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 our main results. We begin by discussing summary statistics of our MLS sample. We then present estimation results from our benchmark regression specifications given in equation (1) above.

4.1 Descriptive Statistics

Table 1 displays sample summary statistics separately for the three metro areas in our sample. Average sale prices are highest in Minneapolis ($268k) and lowest in Houston ($246k). The average time to sale is lowest in Minneapolis (86.3 days) and highest in Charlotte (113 days). The average home in our sample of Minneapolis transactions is 35.4 years old, has

3.3 bedrooms, 2.4 bathrooms, and is slightly over 2000 square feet. The average home in our Charlotte and Houston samples is newer (20.2 years). The average number of bedrooms and bathrooms and the size of the living area is very similar across the three cities. Minneapolis has the largest average lot size (0.58 acres) while Houston has the highest fraction of properties located in gated communities (4 percent). New construction is much more prevalent in Charlotte and Houston compared to Minneapolis. 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 0.4% 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 brokers in all three markets sold for a higher price compared to the average house listed by a traditional, full-service agent. The largest average relative price difference occurs in Houston where flat-fee transactions obtain a price that is more than 12% higher than non-flat-fee transactions while the smallest difference occurs in Minneapolis (8%). In Charlotte and Houston, houses listed by flat-fee brokers sell between 15 and 7 days faster on average than those listed by full-service agents, whereas in Minnesota the average home listed with a Flat-Fee Broker takes slightly longer to sell (2.5 days) than the average house listed with a full-service agent. 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 MSA samples. Table 3 displays the results. In columns (1), (4), and (7) we include only structure and lot characteristics along with ZIP code and year and month fixed effects. The coefficients associated with the lot and structure variables are consistent with past work. Larger lots sell for more as do homes with a nice view, and a waterfront location. Properties located in a gated community also command a price premium. Larger homes and homes with more bathrooms sell for a premium. Controlling for house size, additional bedrooms actually subtract value in Charlotte and Houston.

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.[12] The estimates suggest that owner agents sell their own homes for considerably more in Houston (6 percent), consistent with the findings of Rutherford et al. (2005) and Levitt and Syverson (2008), but not in Charlotte or Minneapolis. This is consistent with Liu et al. (2020), suggesting the previously reported agent-owned premiums suffer from an omitted variable bias, which prior studies ascribed to market distortions associated with asymmetric information. The dual agent coefficient estimates are difficult to interpret. When an agent represents both the buyer and seller they will often reduce their commission by a percentage 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 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

[12] 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.

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 buyers 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 1.0 and 4.3 percent *higher* than sellers who use full service agents. This is a remarkable result, especially since they are also avoiding the listing agent's commission, which is typically in the 2.5-3.0 percent range. 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. Then, if we assume that the owner obtains a 4.3 percent premium by selling the property without a full-service agent, the homeowner would save $19,740. For Minneapolis and Houston, the seller would save $19,494 and $21,489 respectively. 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 full-service agent rather than selection effects that may be creating an upward bias in the estimates.[13]

In columns (3), (6), and (9) of Table 3, we include house 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 time. Unlike most datasets 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

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

like the number of bedrooms, number of bathrooms, and living area. Interestingly, the sign of the coefficient associated with the number of bedrooms flips becoming positive and statistically significant while the magnitude of the living area coefficient shrinks, consistent with the idea that home buyers do value an additional bedroom and that homes with a lot of bedrooms relative to their size are unobservably less attractive. Central to our analysis, including property fixed effects reduces the sales price premium associated with flat-fee listings for Charlotte, Minneapolis and Houston to 3.0 percent, 1.4 percent and 1.4 percent, respectively. This suggests that homeowners who choose to sell their properties themselves have unobservably more desirable homes. Substituting these estimates into our back-of-the-envelope calculation discussed above still yields substantial potential savings of between $16,245 and $20,551 however.

4.3 Benchmark DOM Estimates

All else equal, a homeowner would prefer to sell at the highest price and would prefer to sell as rapidly as possible. However, there is an obvious trade-off between the listing price and expected time on the market, which has been well-documented in the literature. (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 days on the market in order to compare average time to sale between our sample of FSBOs who list with a flat-fee broker and sellers who hire traditional full-service agents.

In Table 4 we present the results of this exercise. We estimate the same set of specifications as we did in Table 3. The specifications in columns (1), (4), (7) 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. Based on the results in Table 3, these tend to be valuable attributes, 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 variables that capture circumstances of individual sales, including an indicator for whether the agent is selling her own property ("owner agent"), an indicator for whether the agent is representing both sides of the transaction ("dual agent"), and an indicator for whether the owner is listing with a flat-fee broker and selling without the help of a traditional, full-service agent. The results for owner agents and dual agents are mixed. Owner agents sell slightly more quickly in Minneapolis and Houston, although only the Houston coefficient is statistically significant. In Minneapolis, owner agents tend to take longer to sell, which is consistent with previous work (Levitt and Syverson (2008)), however, the coefficients are not statistically significant. We see small, mostly insignificant differences in DOM for dual agent transactions. There is some evidence that flat-fee listings take longer to sell. In Houston, homeowners selling their own properties through a flat-fee broker took approximately 5 days longer to sell on average, while those in Minneapolis took about 6.4 days longer.

Finally, columns (3), (6), and (9) introduce property fixed effects. Absorbing unobserved, time-invariant housing attributes increases the average DOM differences between flat-fee listings and traditional full-service agent listings in both Minneapolis and Houston to approximately 8 and 7 days respectively.

The takeaway from Tables 3 and 4 is that on average, homeowners selling their own properties through flat-fee brokers obtain higher sales prices but take longer to sell compared to those who use full-service agents. This finding is consistent with earlier studies that document a general trade-off between higher sale prices and longer marketing time (Levitt and Syverson, 2008 and Anglin et al., 2003). We now turn our focus to models with agent fixed effects that allow us to look at the entire distribution of agent quality.

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.[14] These results are presented in Panel A of Table 5. For each of our three MSAs, 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. Homeowners make a decision to try to sell without an agent and they 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 full-service agents. The flat-fee coefficient estimates in Table 3 may simply reflect these unobserved differences, and it would be wrong to interpret those results as evidence that the average homeowner would not get 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 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.

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

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 marginally significant with a value of -0.031 (column (4)).

These results, combined with the finding in Table 4 that flat-fee listings take significantly 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

Thus far, we have focused exclusively on listings that have ended in a successful sale. Conditional on selling, we have documented that homeowners using flat-fee brokers to list on the MLS tend to take approximately one additional week 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 properties 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.

To conduct such an analysis, we expand our sample, including listings regardless of whether they result in a successful sale. We then estimate linear probability models (LPMs) where the dependent variable is an indicator for whether a property sells within one year of being listed.[15] The LPM specifications include homes that sell, properties that are listed and remain on the market for more than 365 days, and homes that are listed and withdrawn and

[15]The vast majority of successful sales occur within a year. We have also estimated our models using a two-year horizon, but the results were virtually identical.

do not re-appear in the MLS within 365 days.[16] The dummy variable for a successful sale with one year is regressed on the same set of covariates and control variables as in equation (1).[17] The results are presented in Table 6.

The table displays two specifications for each of our three MSA samples. The first specification does not include property fixed effects, while the second does include them. The first thing to note from the table is that a surprisingly small fraction of homes is sold within a year. Between 38 and 47 percent of homes listed in the MLS do not sell within 365 days. Even fewer listings end in a successful sale when we limit the sample to homes that appear on the MLS more than once (columns (2), (4), and (6)).

The main result in Table 6 is that homeowners who list via a flat-fee broker are significantly less likely to sell their home within a year, consistent with findings of Barwick et al. (2015) who document low commission rate listings have lower propensity to sell. Depending on the city and specification, they are between 6.2% and 10.6% less likely compared to homeowners who hire traditional agents. These results are consistent with less experienced homeowners misjudging the value of their home 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 an important 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.

[16]If a property is listed, withdrawn and re-listed within the 365-day window, it is treated as a single observation. If it is re-listed more than a year after it was withdrawn, then we treat it as a new observation.

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

5 Distribution of Agent Fixed Effects

The positive coefficient estimates associated with the flat-fee listing dummy suggests 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 attempt to characterize the distribution of this ability and in particular, determine if there are highly skilled agents who can consistently obtain higher prices and sell faster than the average FSBO in our sample.

Our strategy for measuring real estate agent skill is to estimate the hedonic and DOM regressions given by 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. In 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.

Aside from the addition of agent fixed effects, the hedonic regression specifications are identical to those shown in Table 3 except that the flat-fee broker dummy is excluded. Instead, we group all flat-fee listings together, assign them a single fixed effect, and leave them out of the regression so that they become the benchmark against which we measure all of the listing agent fixed effects. Similarly, we introduce buyer agent fixed effects into the hedonic specification and assign dual agent sales to be the omitted category. We also include listing agent fixed effects in the DOM regressions where the omitted category is again flat-fee listings. We estimate specifications with and without house fixed effects. The full set of coefficient estimates are available from the authors upon request. We present moments from the distribution of the agent fixed effects in Table 7 and show plots of the entire distribution of the fixed effects in Figures 1 and 2.

Table 7, Panel A summarizes the distribution of listing agent and buyer agent fixed effects in the hedonic models for each of our three MSA samples. We show statistics for specifications with and without property fixed effects. The first thing to note is the considerable amount of heterogeneity in the prices that agents obtain for their clients. Focusing on the 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 (Minneapolis) and 20 percent (Charlotte). The interquartile range is 6 percent for Charlotte and Houston and 5 percent for Minneapolis. Recall 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 displayed in Panel A, these listing agents fall between the 75th and 90th percentiles of the distributions in all three cities. In Minneapolis, only 1 out of 10 agents appears to earn more after-fees compared to a flat-fee listing. Furthermore, the median listing agent in all three MSAs obtains a *lower* price (ignoring fees) compared to the average FSBO who lists through a flat-fee broker.

There is also significant heterogeneity among buying agents. The interquartile range of the buying agent fixed effects is between 4 and 6 percent. In Charlotte, controlling for property fixed effects, a buying agent in the 5th percentile of the distribution obtains a price that is 17 percent lower than an agent in the 95th percentile. In Charlotte, the median buying agent obtains a slightly lower price compared to the average dual agent transaction but obtains a slightly higher price in Houston.

Controlling for property fixed effects in the hedonic regressions significantly decreases the amount of agent dispersion. This pattern is especially dramatic in the Charlotte MSA where the interquartile range falls significantly (from 10 percent 6 to percent).

Panel B of Table 7 displays the distribution of listing agent fixed effects from the DOM regressions. There is also a significant amount of heterogeneity in these distributions. Focusing on the specifications with property fixed effects, the median agent sells 6 to 9.4 days more quickly than a homeowner that lists through a flat-fee broker. The interquartile range is more than 25 days for the Charlotte sample, 16 days for Minneapolis, and 21 days for

Houston. The dispersion in the DOM fixed effect distributions is not as sensitive to the inclusion of property fixed effects as the hedonic distributions in Panel A.

In Figures 1 and 2 we plot the corresponding kernel density estimates of the real estate agent fixed effect distributions summarized in Panel A and Panel B of Table 7. Focusing on the distributions of listing agent fixed effects from the hedonic models on the left side of Figure 1 without property fixed effects (solid black line) it is clear that the mass of the distribution is shifted well to the left of 0 and a substantial majority of agents have an average sales premium that is lower than the typical 3 percent agent commission. Controlling for time-invariant unobserved property characteristics (grey dashed line) significantly tightens up the distributions and shifts them to the right, which suggests that at least some of the price premium reflects differences in the quality of the homes listed by full-service agents compared to those listed by FSBOs through flat-fee brokers.

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 lowers the dispersion of buying agents' skill. Comparing the buyer agent density estimates with and without house fixed effects suggests that house quality may have obscured some buyers agent's negotiating ability in Charlotte but made some buyer agents look more efficacious in Minneapolis and Houston.

Finally, in Figure 2, which displays the kernel density plots of the estimated listing agent fixed effects from the DOM regressions for each MSA sample, we can clearly see that including house fixed effects does not have nearly as much of an effect.

5.1 Estimating the Trade-off Between Price and DOM

Figure 3 presents 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 MSAs 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 are for listing agent fixed effects when we include property effects.

The purpose of the figure is to see if there is a trade-off between selling for a high price and selling quickly. If an agent tends to consistently push her client to accept low bids, she may, on average, sell more quickly but at a lower price (See Levitt and Syverson, 2008 and Anglin et al., 2003). Or, conversely, a listing agent may tend to hold out and wait for a high bid, or offer only modest price concessions, in negotiation. The plots without property fixed effects show a (slightly) downward sloping relationship, which suggests that agents who take longer to sell, also sell for less on average. However, this relationship may occur 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 a slight positive relationship emerges.

A second motivation in constructing Figure 3 is to see how many agents provide their respective clients with both a higher price and a lower time to sell compared to the typical homeowner who sells her own 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 are clustered near the origin of the plots.

5.2 Evidence on Negotiating Skill

One characteristic that top real estate agents might possess is the ability to effectively negotiate better prices for their clients, whether representing the buyer or the seller. We revisit this issue by focusing on a sample of agents who act as both listing and buying agents in our data. Specifically, in Figure 4 we plot our estimates of an agent's fixed effect when serving as a listing agent versus their fixed fixed effect when serving as a buying agent. A good negotiator should secure high prices as a listing agent and low prices as a buying agent, and should thus land in the lower right quadrant of the scatter plot (shaded in green), buying low and selling high. In contrast, agents who are weak negotiators should cluster in the top left quadrant (shaded in red), buying high and selling low. When we do not include house fixed effects, we find, perhaps surprisingly, a positive upward sloping line. Agents that tend to sell homes at a premium also appear to buy homes at a premium when they serve as a buyer's agent. This effect becomes significantly more muted when we include property fixed effects, however. The plots show that there are only a few agents in the bottom right quadrant who obtain high prices when selling and low prices when buying. Whatever other skills real estate agents may bring to the table, the ability to bargain and negotiate favorable pricing terms appears to be a skill possessed by relatively few agents.

6 Determinants of Agent Skill

We have documented a large amount of heterogeneity in the prices that agents are able to obtain for their clients on both sides of real estate transactions as well as in the time that it takes for listing agents to complete a sale. A natural question is what exactly explains this large amount of heterogeneity? In this section we will focus on two potential determinants: experience and firm size.

In many professions, skills that improve productivity and efficiency are learned on the job. Thus, we might expect that real estate agents learn how to become better negotiators and how to market properties more effectively over time.

We construct a measure of agent experience at the time of a given transaction based on the number of months since an agent's first sale.[18] This requires us to drop agents that were active at the very beginning of our sample as we cannot observe their entry into the market.

[18] In addition, we have experimented with an alternative measure that counts the number of transactions an agent has participated in up to the current transaction. However, we are more concerned about introducing reverse causality bias with this measure as highly skilled agents are likely to attract more clients over time. The results using this alternative measure are consistent with our preferred measure based on time in the profession.

Thus, we exclude agents who completed a sale within the first two years of our sample. Our supposition is that agents who only appear more than two years into the sample are likely new to the profession so that the first sale we observe is in fact their first sale.[19]

In addition to experience, we investigate whether real estate agents who work for larger firms perform differently. We measure firm size based on the total number of listings the firm handled in the sample period. A buying agent who shows a home to a client generates some probability of sale, which also benefits the listing agent of the property. However, assuming the commission is split, the buying agent is unlikely to internalize the potential gain to the listing agent. A large brokerage house that extracts fees from their agents is more likely to internalize such gains and may have mechanisms for steering buying agents to their listing agent colleagues.[20] A larger firm may also be better at facilitating information sharing about possible matches between clients. Larger firms with more financial resources and the ability to amortize training costs across more agents may have more rigorous training programs. Finally, larger firms may have grown in size because they have a dominant set of selling strategies.

We present the results on the effect of agent experience and firm size on the average sale price and DOM for each of the three MSAs in our sample in Table 8. Columns (1), (4), and (7) display hedonic results for listing agent experience and firm size while columns (2), (5), and (8) show hedonic results for buying agent experience and firm size. Finally, columns (3), (6), and (9) display DOM results for listing agent experience and firm size. All of the specifications include structure and agent characteristics as well as property fixed effects. There is a statistically significant, negative relationship between years of experience and transaction price for listing agents across all three MLSs. The negative relationship is strongest in Charlotte where a one standard deviation increase in experience (4.8 years) is

[19] This measure is, of course, imperfect. For example, we would mischaracterize experienced agents who relocate and change markets; however, given the fact that real estate markets are segmented by location, we treat potential relocating agents in our sample as new agents before their first successful transaction in the new market.

[20] Han and Hong (2016) look into in-house transactions and provide strong evidence that such mechanisms exist.

associated with a 1.0% decline in price. This is perhaps surprising at first, as we might expect to see agents obtain higher prices over time as they become better negotiators. However, Turnbull and Waller (2018) and Bian et al. (2015) have documented that as a listing agent's experience and reputation increase, her effort per listing declines, resulting in lower sale prices. In contrast, we find little effect of firm size on price for listing agents.

For buying agents, there is no robust relationship between experience and price. However, buying agents at larger firms do appear to pay slightly more than other agents in Minneapolis. This result is consistent with the idea that larger firms have more mechanisms to reward buying agents for favoring their colleagues' listings, even if that leads to their clients paying slightly higher prices.

Finally, the results for the DOM specifications suggest that selling time decreases with experience in all three MLSs, consistent with Rutherford and Yavas (2012) who document that time on the market decreases in years of experience of the listing agent. In Charlotte, for example, a one standard deviation increase in experience reduces average DOM by approximately 7.1 days. This result has some implications for how we should interpret the negative effect of experience on price discussed above. If an agent's interests were perfectly aligned with her clients, then we should expect a positive relationship between experience and selling price. However, this is likely not the case. A real estate agent who accepts a low bid on behalf of her client will earn a slightly smaller commission, yes, but can then quickly shift to recruiting more clients and selling more homes. However, it may take time for a agent to build her reputation and a client base that is big enough to benefit from such a strategy. A key element could be convincing their clients to accept a lower bid than they might otherwise want to. Of course, we might expect this pattern to emerge for buying agents as well. A buying agent's interest is likely to purchase a home as quickly as possible, perhaps by encouraging the client to pay more for one of the first homes they see, or to accept a relatively high price in negotiations. However, we do not observe timelines for buying agents. One reason that we do not see a correlation between experience and price for buying agents might be that many buyers face a loan-to-value constraint and are unable to increase the size of the mortgage they can obtain. The underwriting process also includes an appraisal from a third party that may inhibit the buyer's ability to over-pay. A seller with positive equity is under no such constraint.[21] Finally, at least before the negotiation phase, a buying agent's incentives may be more closely aligned with the client to find a home for sale that will maximize their expected surplus, whereas a listing agent has to convince their client to accept a given offer rather than hold out for more.

7 Conclusion

Individuals and firms faced with making large, infrequent financial transactions under imperfect information will often seek the advice of experts and 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 typical 3 percent sales commission. The average price of a home sold by a full-service real estate agents in our sample is well below the price obtained by a homeowner who sells her own property using a flat-fee broker, even controlling for location and property fixed effects. Similarly, we find that the average buying agent does not secure a price discount relative to the average home buyer who does not hire an agent. However, we do find evidence that the average full-service listing agent is more likely to successfully sell a property and, conditional on selling achieves a sale more quickly than a homeowner selling via a flat-fee broker.

We show that these average effects mask significant heterogeneity across agents, however. 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 4–5 percent for the distribution of listing agent fixed effects and

[21] Engelhardt (2003) shows that homeowners are reluctant to realize a nominal loss on their home.

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 3 percent commission rate. Thus, we conclude that there are high-performing agents who add significant value to the home selling process, but they constitute a minority of agents.

While some real estate agents appear to be exceptional, 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, which implies that there is not a significant trade-off between selling price and selling time. Nor do agents who sell at significant premiums appear to be especially good negotiators. If agents who obtain high prices were particularly good negotiators, we would expect them to pay less than anticipated when serving as a buying agent. However, that is not what we observe. Agents who sell homes for more than expected also appear to pay more when they work as a buying agent.

Finally, we focus on two possible determinants of agent performance, experience and firm size. We find that more experienced agents sell more quickly but at lower prices. For buying agents, we do not find any relationship between experience and price. Buying agents at large firms appear to slightly over-pay for homes when negotiating on behalf of their clients, which is consistent with larger firms steering buying agents clients to their colleagues' listings, even if that leads to their clients paying slightly higher prices.

References

Aaronson, D., L. Barrow, and W. Sander (2007). Teachers and student achievement in the chicago public high schools. *Journal of labor Economics 25*(1), 95–135.

Agarwal, S., J. He, T. F. Sing, and C. Song (2019). Do real estate agents have information advantages in housing markets? *Journal of Financial Economics 134*(3), 715–735.

Anglin, P. M., R. Rutherford, and T. M. Springer (2003). The trade-off between the selling price of residential properties and time-on-the-market: The impact of price setting. *The Journal of Real Estate Finance and Economics 26*(1), 95–111.

Bao, J. and A. Edmans (2011). Do investment banks matter for m&a returns? *The Review of Financial Studies 24*(7), 2286–2315.

Barwick, P. J., P. A. Pathak, and M. Wong (2015). Conflicts of interest and the realtor commission puzzle. Technical report, National Bureau of Economic Research.

Benefield, J., M. Pyles, and A. Gleason (2011). Sale price, marketing time, and limited service listings: the influence of home value and market conditions. *Journal of Real Estate Research 33*(4), 531–564.

Benefield, J. D., C. S. Sirmans, and G. S. Sirmans (2019). Observable agent effort and limits to innovation in residential real estate. *Journal of Real Estate Research 41*(1), 1–36.

Bernheim, B. D. and J. Meer (2013). Do real estate brokers add value when listing services are unbundled? *Economic inquiry 51*(2), 1166–1182.

Bertrand, M. and A. Schoar (2003). Managing with style: The effect of managers on firm policies. *The Quarterly journal of economics 118*(4), 1169–1208.

Bian, X., B. D. Waller, G. K. Turnbull, and S. A. Wentland (2015). How many listings are too many? agent inventory externalities and the residential housing market. *Journal of Housing Economics 28*, 130 – 143.

Engelhardt, G. V. (2003). Nominal loss aversion, housing equity constraints, and household mobility: evidence from the united states. *Journal of urban Economics 53*(1), 171–195.

Glower, M., D. R. Haurin, and P. H. Hendershott (1998). Selling time and selling price: The influence of seller motivation. *Real estate economics 26*(4), 719–740.

Han, L. and S.-H. Hong (2016). Understanding in-house transactions in the real estate brokerage industry. *The RAND Journal of Economics 47*(4), 1057–1086.

Haurin, D. R., J. L. Haurin, T. Nadauld, and A. Sanders (2010). List prices, sale prices and marketing time: an application to us housing markets. *Real Estate Economics 38*(4), 659–685.

Hendel, I., A. Nevo, and F. Ortalo-Magné (2009, December). The relative performance of real estate marketing platforms: Mls versus fsbomadison.com. *American Economic Review 99*(5), 1878–98.

Hsieh, C.-T. and E. Moretti (2003). Can free entry be inefficient? fixed commissions and social waste in the real estate industry. *Journal of Political Economy 111*(5), 1076–1122.

Johnson, K. H., T. H. Springer, and C. M. Brockman (2005). Price effects of non-traditionally broker-marketed properties. *The Journal of Real Estate Finance and Economics 31*(3), 331–343.

Krainer, J. (2001). A theory of liquidity in residential real estate markets. *Journal of urban Economics 49*(1), 32–53.

Levitt, S. D. and C. Syverson (2008). Market distortions when agents are better informed: The value of information in real estate transactions. *The Review of Economics and Statistics 90*(4), 599–611.

Liu, C. H., A. D. Nowak, and P. S. Smith (2020). Asymmetric or incomplete information about asset values? *The Review of Financial Studies 33*(7), 2898–2936.

Lopez, L. A. (2021). Asymmetric information and personal affiliations in brokered housing transactions. *Real Estate Economics 49*(2), 459–492.

Munneke, H. J., J. T. Ooi, C. Sirmans, and G. K. Turnbull (2015). Real estate agents, house prices, and liquidity. *The journal of real estate finance and economics 50*(1), 1–33.

Rutherford, R. and A. Yavas (2012). Discount brokerage in residential real estate markets. *Real Estate Economics 40*(3), 508–535.

Rutherford, R. C., T. M. Springer, and A. Yavas (2005). Conflicts between principals and agents: evidence from residential brokerage. *Journal of Financial Economics 76*(3), 627 – 665.

Shen, L. and S. Ross (2021). Information value of property description: A machine learning approach. *Journal of Urban Economics 121*, 103299.

Shen, L. and T. M. Springer (2022). The odd one out? the impact of property uniqueness on selling time and selling price. *Journal of Housing Research*, 1–21.

Springer, T. M. (1996). Single-family housing transactions: Seller motivations, price, and marketing time. *The Journal of Real Estate Finance and Economics 13*(3), 237–254.

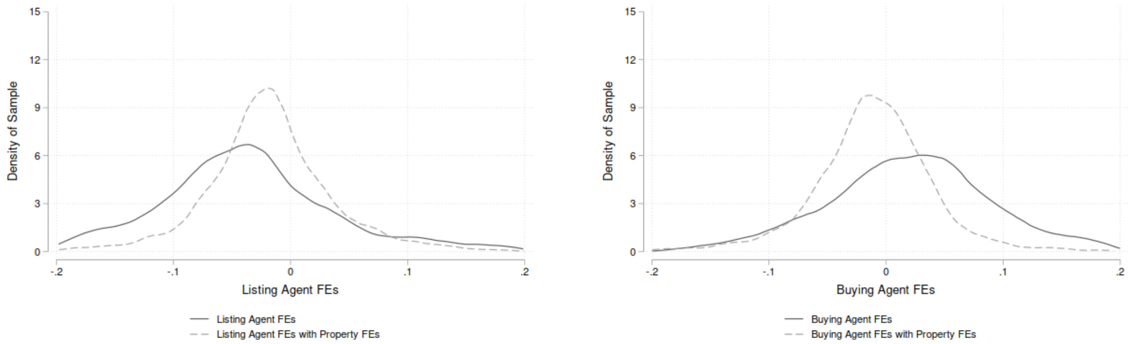
Turnbull, G. K. and J. Dombrow (2007). Individual agents, firms, and the real estate brokerage process. *The Journal of Real Estate Finance and Economics 35*(1), 57–76.

Turnbull, G. K. and B. D. Waller (2018). (what) do top performing real estate agents deliver for their clients? *Journal of Housing Economics 41*, 142–152.

Wheaton, W. C. (1990). Vacancy, search, and prices in a housing market matching model. *Journal of political Economy 98*(6), 1270–1292.

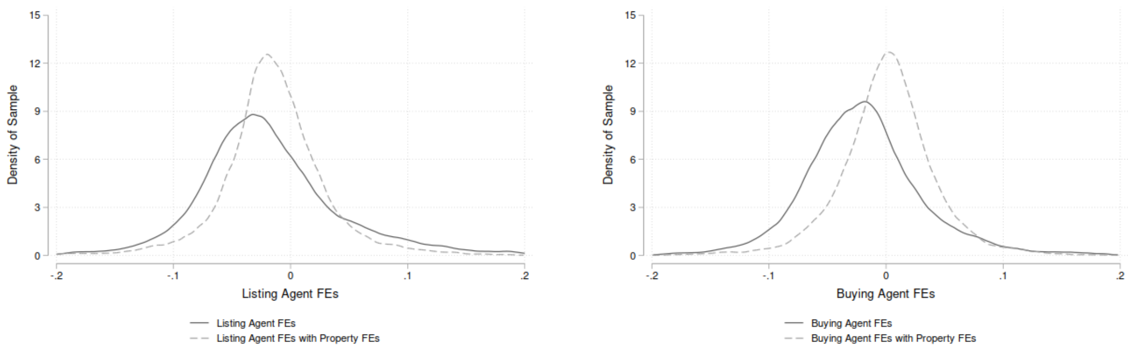
Figure 1: Kernel Density Estimates of Real Estate Agent Fixed Effects: Sale Prices

Panel A: Charlotte



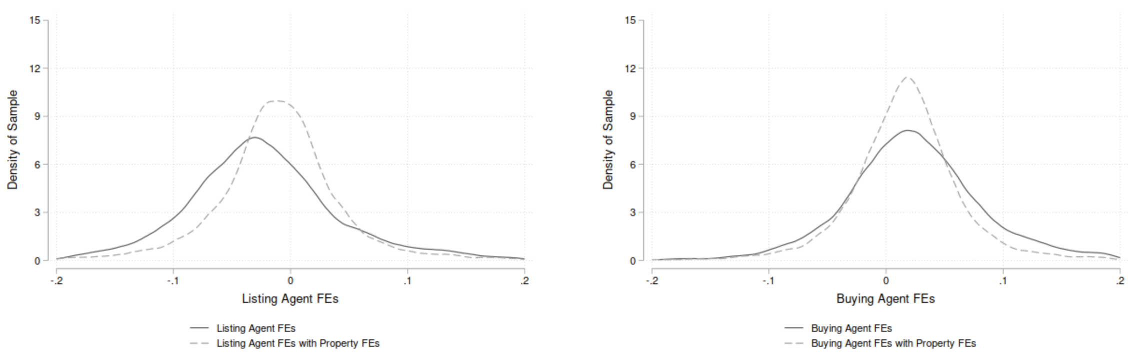
Listing Agent | Buying Agent

Panel B: Minneapolis



Listing Agent | Buying Agent

Panel C: Houston



Listing Agent | Buying Agent

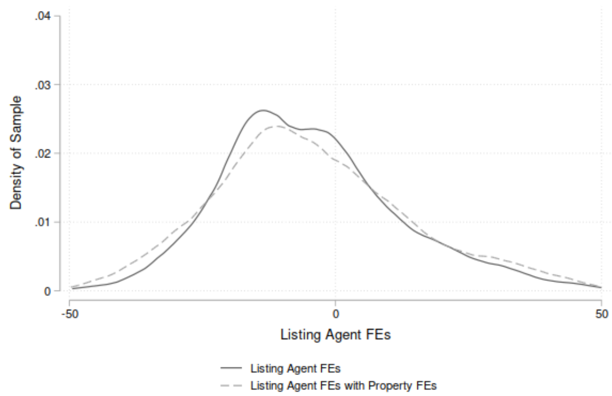
Notes: This figure displays kernel density estimates for the listing agent and buying agent fixed effects ($\alpha_r^{l,b}$ from the following hedonic regression model:

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

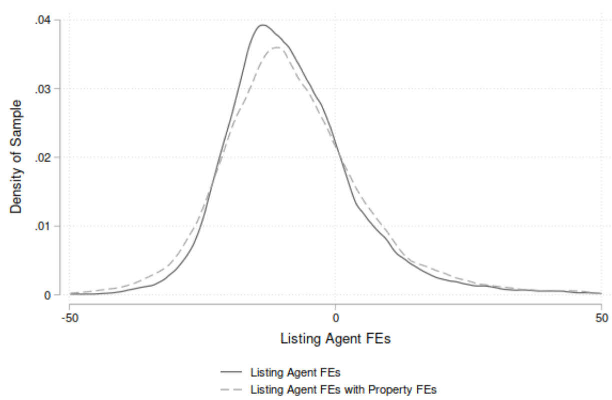
where i indexes the property, t is the year-quarter of the listing date, j is the ZIP code where the property is located, and r is the agent. The dashed density estimates include property fixed effects, η_i. The omitted category in the listing agent fixed effects models is flat-fee brokers, while the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

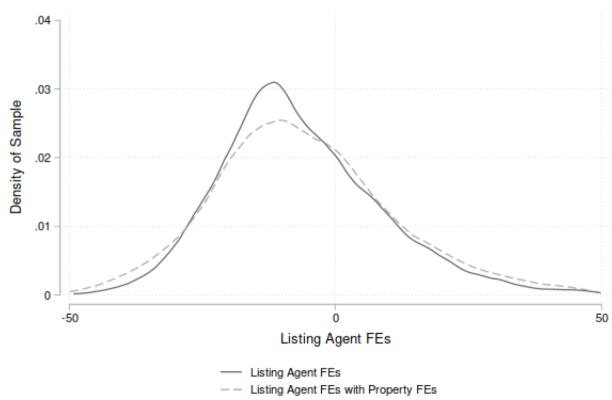
Panel A: Charlotte



Panel B: Minneapolis



Panel C: Houston



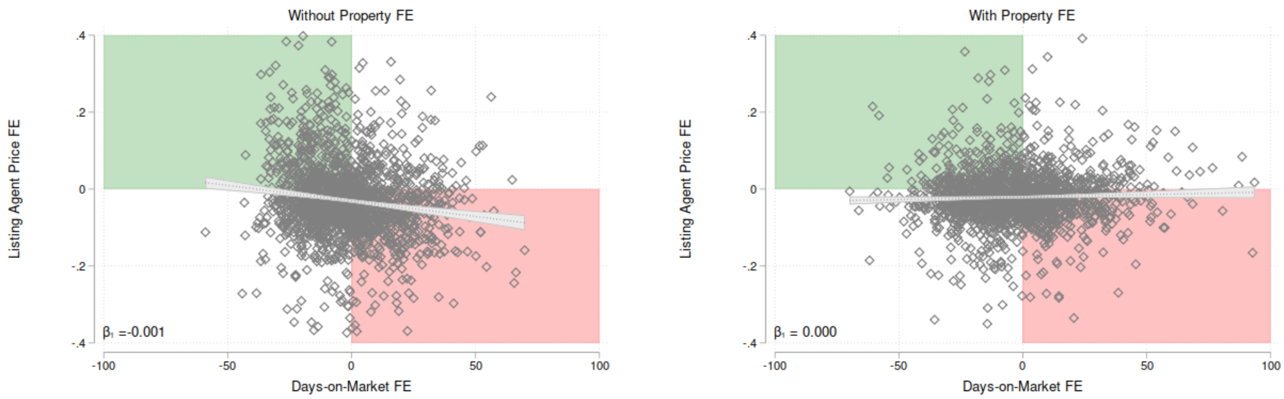
Notes: This figure displays kernel density estimates for the listing agent and buying agent fixed effects ($\alpha_r^{l,b}$ from the following DOM regression model:

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

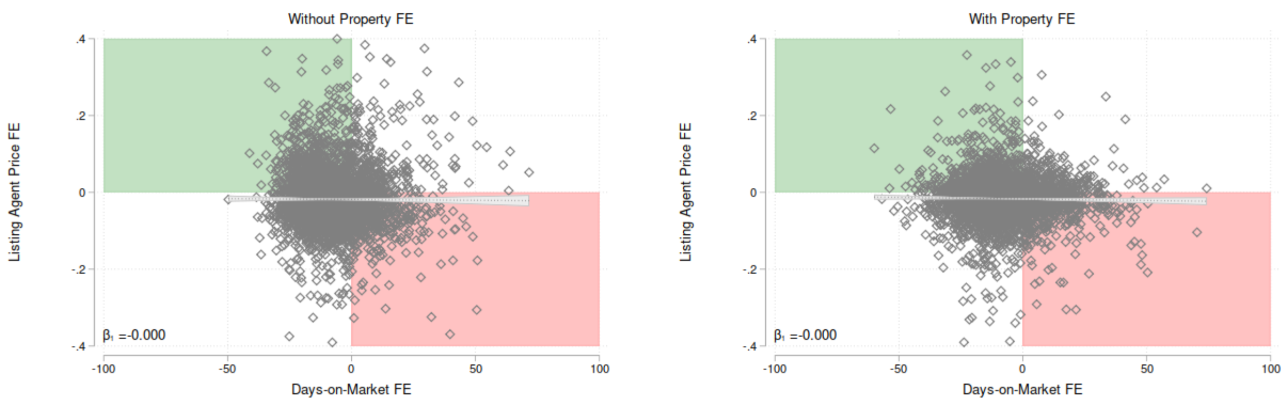
where i indexes the property, t is the year-quarter of the listing date, j is the ZIP code where the property is located, and r is the real estate agent. The dashed density estimates include property fixed effects, η_i. The omitted category is flat-fee brokers. The underlying data come from the CoreLogic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

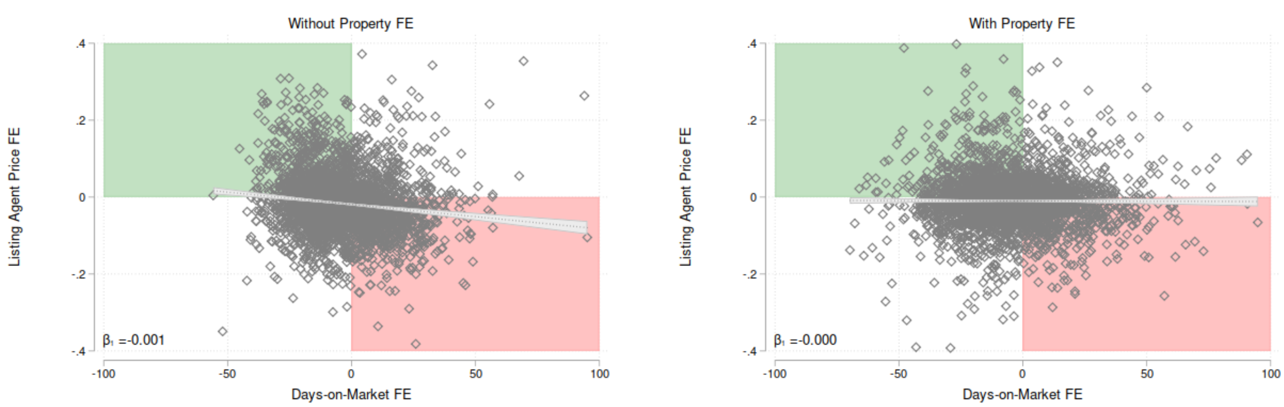
Panel A: Charlotte, NC



Panel B: Minneapolis, MN



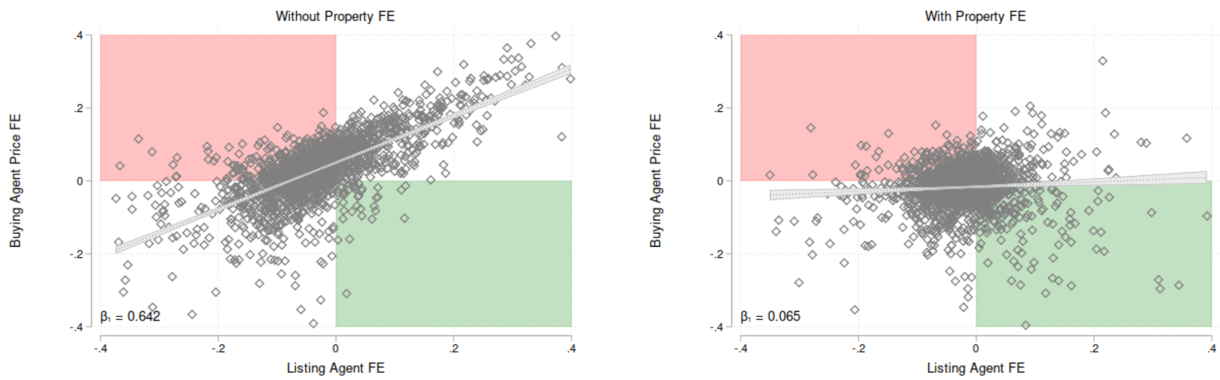
Panel C: Houston, TX



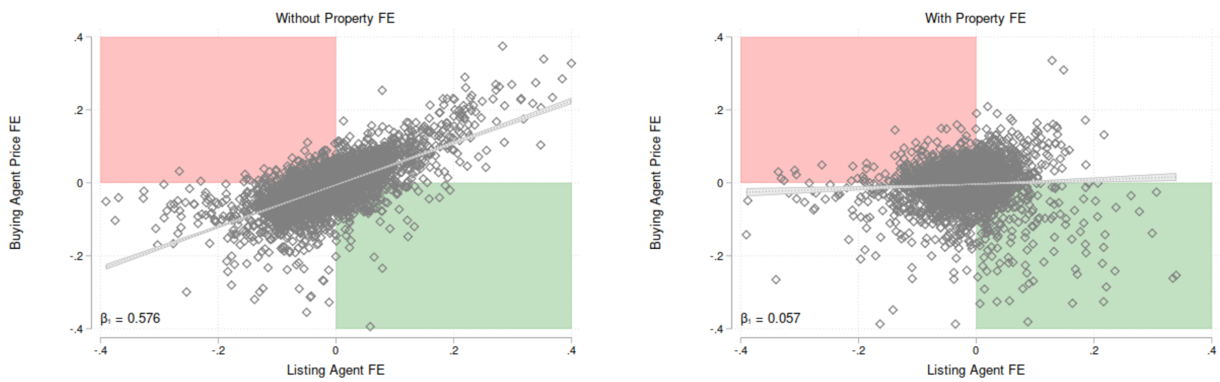
Notes: This figure displays scatter plots of listing agent price fixed effects vs. listing agent DOM fixed effects. Plots on the right side of each panel are derived from specifications that include property fixed effects. In each plot a linear regression is fit through the points. The underlying data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

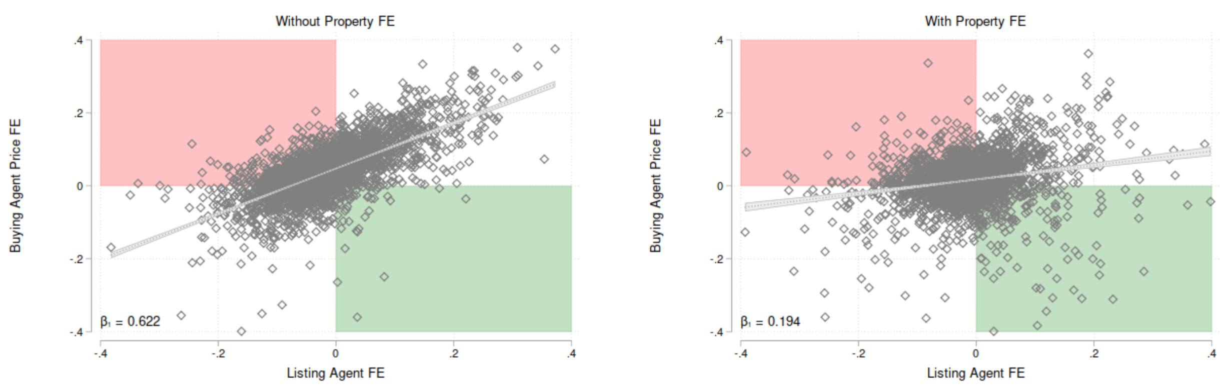
Panel A: Charlotte, NC



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 $)	259	203	268	172	246	216
DOM (# of Days on Market)	113	86.1	86.3	59.1	103	75.6
Living Area (100s Square Feet)	22.7	9.9	20.4	8.8	23.9	9.5
# Bathrooms	2.81	0.97	2.35	0.94	2.33	0.72
# Bedrooms	3.55	0.82	3.26	0.91	3.53	0.73
Building Age (Years)	20.2	21.9	35.4	30.7	20.2	19.5
Lot Size (Acres)	0.47	0.71	0.58	1.15	0.49	0.95
Fireplace (d)	.	.	0.578	.	0.906	.
New Construction (d)	0.184	.	0.050	.	0.183	.
Renovated (d)	0.017	.	0.030	.	0.028	.
View (d)	0.027	.	0.029	.	0.034	.
Gated (d)	0.014	.	0.001	.	0.042	.
Waterfront (d)	0.022	.	0.087	.	0.017	.
Owner Agent Transaction (d)	0.000	.	0.001	.	0.001	.
Dual Agent Transaction (d)	0.107	.	0.075	.	0.067	.
Flat Fee Broker (d)	0.012	.	0.010	.	0.004	.
Listing Agent Experience (Years)	5.29	4.76	5.96	5.30	5.83	5.07
Buying Agent Experience (Years)	5.68	4.80	6.64	5.45	6.15	5.12
Firm Size (1000s Listing Agents)	3.04	3.58	4.07	3.76	6.86	13.43
Firm Size (1000s Buying Agents)	2.56	2.70	4.05	3.73	4.60	4.75
# Transactions	376,042		796,646		1,096,800	

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	258	204
DOM (# of Days on Market)	98.0	72.2	113	86.2
Living Area (100s Square Feet)	24.0	9.48	22.7	9.92
# of Bathrooms	2.90	0.887	2.81	0.972
# of Bedrooms	3.65	0.81	3.55	0.82
Building Age (Years)	21.5	19.9	20.2	22.0
Lot Size (Acres)	0.45	0.62	0.47	0.71
New Construction (d)	0.000	.	0.187	.
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	.	0.107	.
# Transactions	4,568		371,474	

Panel B: Minneapolis

	Flat-Fee		Non Flat-Fee	
	Mean	Sd	Mean	Sd
Sale Price (Thousands $)	290	141	268	172
DOM (# of Days on Market)	88.6	59.3	86.3	59.1
Living Area (100s Square Feet)	21.2	8.21	20.4	8.78
# Bathrooms	2.42	0.893	2.35	0.935
# Bedrooms	3.35	0.893	3.26	0.913
Building Age (Years)	38.4	29.7	35.3	30.7
Lot Size (Acres)	0.51	0.99	0.59	1.15
Fireplace (d)	0.658	.	0.578	.
New Construction (d)	0.000	.	0.050	.
Renovated (d)	0.050	.	0.030	.
View (d)	0.043	.	0.029	.
Gated (d)	0.002	.	0.001	.
Waterfront (d)	0.112	.	0.087	.
Owner Agent Transaction (d)	0.001	.	0.001	.
Dual Agent Transaction (d)	0.021	.	0.076	.
# Transactions	8,241		788,405	

Panel C: Houston

	Flat-Fee		Non Flat-Fee	
	Mean	Sd	Mean	Sd
Sale Price (Thousands $)	275	216	245	216
DOM (# of Days on Market)	96.5	66.5	103	75.6
Living Area (100s Square Feet)	24.4	9.01	23.9	9.45
# Bathrooms	2.34	0.695	2.33	0.724
# Bedrooms	3.57	0.73	3.53	0.732
Building Age (Years)	26.0	20.8	20.2	19.5
Lot Size (Acres)	0.41	0.70	0.49	0.96
Fireplace (d)	0.885	.	0.907	.
New Construction (d)	0.000	.	0.183	.
Renovated (d)	0.063	.	0.028	.
View (d)	0.036	.	0.034	.
Gated (d)	0.047	.	0.042	.
Waterfront (d)	0.020	.	0.017	.
Owner Agent Transaction (d)	0.000	.	0.001	.
Dual Agent Transaction (d)	0.016	.	0.068	.
# Transactions	4,880		1,091,920	

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)	0.915***	0.914***	0.531***	0.545***	0.544***	0.186***	0.840***	0.840***	0.354***
	(0.026)	(0.026)	(0.054)	(0.023)	(0.023)	(0.017)	(0.022)	(0.022)	(0.037)
# Bedrooms	-0.055***	-0.056***	0.020***	0.020***	0.020***	0.034***	-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***	0.055***	0.061***	0.061***	0.085***	0.121***	0.121***	0.104***
	(0.006)	(0.006)	(0.013)	(0.006)	(0.006)	(0.009)	(0.007)	(0.007)	(0.012)
New Construction (d)	0.056***	0.062***	0.075***	0.146***	0.144***	0.079***	0.040***	0.044***	0.025**
	(0.010)	(0.010)	(0.011)	(0.006)	(0.007)	(0.006)	(0.008)	(0.009)	(0.009)
Renovated (d)	0.080***	0.078***	0.151***	0.023***	0.023***	0.086***	0.070***	0.070***	0.114***
	(0.010)	(0.010)	(0.017)	(0.004)	(0.004)	(0.006)	(0.005)	(0.005)	(0.008)
Building Age	-0.007***	-0.007***	-0.016***	-0.006***	-0.006***	-0.012***	-0.010***	-0.010***	-0.019***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(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***	0.023***	0.043***	0.043***	0.020***
	.	.	.	(0.006)	(0.006)	(0.003)	(0.006)	(0.006)	(0.005)
Ln(Lot Size)	0.100***	0.100***		0.084***	0.084***		0.094***	0.094***	
	(0.006)	(0.006)		(0.003)	(0.003)		(0.005)	(0.005)	
View (d)	0.105***	0.105***		0.095***	0.095***		0.113***	0.113***	
	(0.013)	(0.013)		(0.013)	(0.013)		(0.011)	(0.011)	
Gated (d)	0.163***	0.163***		0.076**	0.076**		0.042**	0.042**	
	(0.022)	(0.022)		(0.024)	(0.024)		(0.013)	(0.013)	
Waterfront (d)	0.286***	0.286***		0.108***	0.108***		0.200***	0.199***	
	(0.043)	(0.043)		(0.012)	(0.012)		(0.029)	(0.029)	
Owner Agent (d)		0.033	0.111		0.012	0.076**		0.060***	0.053***
		(0.044)	(0.056)		(0.013)	(0.024)		(0.010)	(0.013)
Dual Agent (d)		-0.005	0.010		0.020***	0.006		-0.018***	-0.007*
		(0.005)	(0.005)		(0.003)	(0.003)		(0.004)	(0.003)
Flat-Fee Broker		0.043***	0.030***		0.010*	0.014**		0.022**	0.014**
		(0.007)	(0.006)		(0.005)	(0.004)		(0.007)	(0.005)
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	376,042	376,042	206,603	796,476	796,476	484,361	1,096,800	1,096,800	563,761
Adjusted R^2	0.843	0.843	0.940	0.794	0.794	0.909	0.862	0.862	0.949
Mean Ln(Price)	12.25	12.25	12.28	12.37	12.37	12.33	12.19	12.19	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)	19.024***	18.984***	19.761**	16.744***	16.688***	1.398	31.239***	31.291***	11.210
	(2.357)	(2.411)	(6.573)	(1.069)	(1.062)	(1.490)	(1.433)	(1.418)	(6.230)
# Bedrooms	-2.540***	-2.489***	0.580	-2.238***	-2.216***	0.109	-2.679***	-2.603***	0.860
	(0.693)	(0.691)	(1.186)	(0.293)	(0.292)	(0.411)	(0.347)	(0.341)	(1.027)
# Bathrooms	5.356***	5.362***	0.504	2.408***	2.402***	0.186	4.781***	4.845***	3.770**
	(0.645)	(0.628)	(1.889)	(0.266)	(0.266)	(0.705)	(0.458)	(0.443)	(1.331)
New Construction (d)	55.517***	57.876***	48.925***	12.961***	12.711***	15.209***	42.722***	47.740***	45.006***
	(2.503)	(2.661)	(3.147)	(2.199)	(2.192)	(2.439)	(2.043)	(2.203)	(3.152)
Renovated (d)	-0.798	-0.681	1.907	-3.169***	-3.196***	-2.512*	-0.201	-0.203	0.790
	(1.121)	(1.116)	(2.357)	(0.765)	(0.766)	(0.994)	(0.578)	(0.577)	(1.190)
Building Age	0.269***	0.264***	-0.087	-0.617***	-0.614***	-0.881***	0.227***	0.228***	-0.338
	(0.064)	(0.064)	(0.222)	(0.039)	(0.039)	(0.085)	(0.041)	(0.041)	(0.216)
Building Age2	-0.000	-0.000	0.002	0.005***	0.005***	0.006***	-0.000	-0.000	0.004*
	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Fireplace	.	.	.	0.368	0.356	-0.837	-1.349	-1.702*	1.349
	.	.	.	(0.298)	(0.297)	(1.021)	(0.751)	(0.696)	(1.538)
Ln(Lot Size)	6.761***	6.585***		3.593***	3.583***		7.077***	7.077***	
	(0.722)	(0.714)		(0.235)	(0.235)		(1.446)	(1.446)	
View (d)	3.731**	3.679**		7.064***	7.021***		3.855***	3.724***	
	(1.311)	(1.309)		(0.886)	(0.883)		(0.895)	(0.891)	
Gated (d)	25.043***	24.861***		3.374	3.316		6.033***	5.844***	
	(3.501)	(3.490)		(3.466)	(3.474)		(0.911)	(0.878)	
Waterfront (d)	13.099***	13.027***		5.382***	5.336***		5.710**	5.670**	
	(1.799)	(1.808)		(0.619)	(0.618)		(1.929)	(1.905)	
Owner Agent (d)		8.737	11.859		-5.600*	-8.287*		-5.200**	-3.633
		(11.415)	(37.488)		(2.176)	(3.986)		(1.706)	(3.755)
Dual Agent (d)		0.691	-0.503		2.457***	0.116		2.136**	0.891
		(0.960)	(1.215)		(0.485)	(0.564)		(0.701)	(0.918)
Flat-Fee Broker		0.389	3.747		6.373***	7.969***		4.959***	6.752***
		(1.218)	(2.265)		(1.060)	(1.237)		(1.109)	(1.907)
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	376,042	376,042	206,603	796,476	796,476	484,361	1,096,800	1,096,800	563,761
Adjusted R^2	0.145	0.146	0.195	0.128	0.128	0.163	0.130	0.131	0.166
Mean Ln(Price)	113.11	113.11	106.92	86.33	86.33	83.51	102.53	102.53	97.37

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
Owner Agent (d)	0.039	5.437	0.006	-5.199*	0.059***	-4.680*
	(0.045)	(11.718)	(0.009)	(2.135)	(0.011)	(1.777)
Dual Agent (d)	-0.008	0.323	0.018***	2.127***	-0.021***	1.879**
	(0.005)	(0.946)	(0.003)	(0.465)	(0.004)	(0.698)
Flat-Fee Broker (d)	0.038***	0.787	0.016**	6.804***	0.018*	5.299***
	(0.007)	(1.216)	(0.005)	(1.045)	(0.007)	(1.139)
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	376,038	376,038	796,463	796,463	1,096,786	1,096,786
Adjusted R^2	0.852	0.155	0.806	0.137	0.871	0.144
Mean Dependant Var.	12.3	110.7	12.4	85.2	12.2	101.2

Panel B: Flat-Fee Purchasers

Dependent Variable: Ln(Price)						
	Charlotte		**Minneapolis**		**Houston**	
	(1)	(2)	(3)	(4)	(5)	(6)
Flat-Fee Purchaser (d)	0.008	-0.010	-0.020***	-0.031**	-0.006	-0.015
	(0.007)	(0.008)	(0.005)	(0.009)	(0.006)	(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	371,474	202,068	788,236	475,837	1,091,920	559,028
Adjusted R^2	0.843	0.940	0.795	0.909	0.862	0.949
Mean Ln(Price)	12.25	12.28	12.37	12.33	12.19	12.24

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 ≤ 1 year)	**Charlotte**		**Minneapolis**		**Houston**	
	(1)	(2)	(3)	(4)	(5)	(6)
Flat-Fee Broker	-0.096***	-0.111***	-0.078***	-0.098***	-0.061***	-0.090***
	(0.008)	(0.011)	(0.008)	(0.010)	(0.008)	(0.010)
Owner Agent	-0.049	-0.108	-0.033*	-0.011	-0.041**	-0.046*
	(0.043)	(0.086)	(0.016)	(0.021)	(0.015)	(0.022)
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	Y	Y	Y	Y	Y
Parcel Char.	Y	N	Y	N	Y	N
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	614,114	473,324	1,288,323	1,055,143	1,780,973	1,304,192
Adjusted R^2	0.128	0.151	0.360	0.319	0.089	0.115
Mean Dependent Var	0.60	0.55	0.44	0.40	0.61	0.54

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						Adj R^2
			5th	25th	50th	75th	90th	95th	
Charlotte									
Listing Agent	No	2,751	-0.25	-0.09	-0.04	0.00	0.06	0.12	0.87
	Yes	2,746	-0.12	-0.05	-0.02	0.01	0.05	0.08	0.93
Buying Agent	No	3,011	-0.11	-0.03	0.02	0.07	0.11	0.16	0.85
	Yes	3,011	-0.10	-0.04	-0.01	0.02	0.04	0.07	0.92
Minneapolis									
Listing Agent	No	6,197	-0.11	-0.06	-0.03	0.01	0.06	0.10	0.82
	Yes	6,192	-0.09	-0.04	-0.02	0.01	0.04	0.06	0.90
Buying Agent	No	6,789	-0.10	-0.05	-0.02	0.01	0.04	0.07	0.81
	Yes	6,789	-0.07	-0.02	0.00	0.02	0.05	0.07	0.89
Houston									
Listing Agent	No	7,161	-0.14	-0.07	-0.03	0.01	0.07	0.11	0.88
	Yes	7,153	-0.11	-0.04	-0.01	0.02	0.05	0.08	0.93
Buying Agent	No	8,604	-0.07	-0.01	0.02	0.06	0.10	0.14	0.87
	Yes	8,603	-0.06	-0.01	0.02	0.04	0.07	0.09	0.93

Panel B: DOM Regressions

	Property FE	N	Percentile of Distribution						Adj R^2
			5th	25th	50th	75th	90th	95th	
Charlotte									
Listing Agent	No	2,751	-29.57	-16.23	-6.39	5.15	19.53	29.33	0.18
	Yes	2,746	-34.15	-16.79	-6.05	8.72	28.26	43.03	0.21
Minneapolis									
Listing Agent	No	6,197	-24.85	-16.20	-9.79	-1.98	7.00	13.64	0.17
	Yes	6,192	-27.51	-16.75	-9.44	-0.78	8.77	17.23	0.19
Houston									
Listing Agent	No	7,161	-29.05	-17.03	-8.62	2.44	14.37	22.39	0.17
	Yes	7,153	-33.06	-17.67	-7.27	4.53	18.46	28.96	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: Effect of Agent Experience and Firm Size

	Charlotte			Minneapolis			Houston		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Var:	Ln(Price)	Ln(Price)	DOM	Ln(Price)	Ln(Price)	DOM	Ln(Price)	Ln(Price)	DOM
Listing Agent Experience (Years)	-0.002***		-1.485***	-0.001***		-0.807***	-0.001**		-0.995***
	(0.001)		(0.263)	(0.000)		(0.158)	(0.000)		(0.172)
Listing Agent Firm Size	0.001		-0.102	0.000		-0.188*	0.000*		-0.312***
	(0.000)		(0.234)	(0.000)		(0.079)	(0.000)		(0.074)
Buying Agent Experience (Years)		-0.001*			0.000			0.001*	
		(0.000)			(0.000)			(0.000)	
Buying Agent Firm Size		0.000			0.001*			0.000	
		(0.000)			(0.000)			(0.000)	
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.	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	Y	N	Y	Y	N	Y	Y	N	Y
Buying Agent FE	N	Y	N	N	Y	N	N	Y	N
# Observations	206,603	194,100	206,603	484,361	474,440	484,361	563,761	519,134	563,761
Adjusted R^2	0.951	0.944	0.222	0.925	0.914	0.191	0.954	0.952	0.194
Mean Dependent Var	12.25	12.25	113.11	12.37	12.37	86.33	12.19	12.19	102.53

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 Agency Value-Added Using Real Estate Transactions

Appendix

This appendix supplements the empirical analysis in Cunningham, Gerardi, and Shen (2022). Below is a list of the sections contained in this appendix.

Table of Contents

A.1 Sample Filters **2**

A.2 Flat Fee Transaction Trends **3**

A.3 Effect of Experience and Firm Size on Agent Fixed Effect Distributions **5**

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 of 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 agents who specializes in distressed sales. Between 15 and 40 thousand sales met this criterion.

Finally, we eliminate extreme values from the sample. The listing agents input the MLS data and can be subject to data entry errors. We made 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 with 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

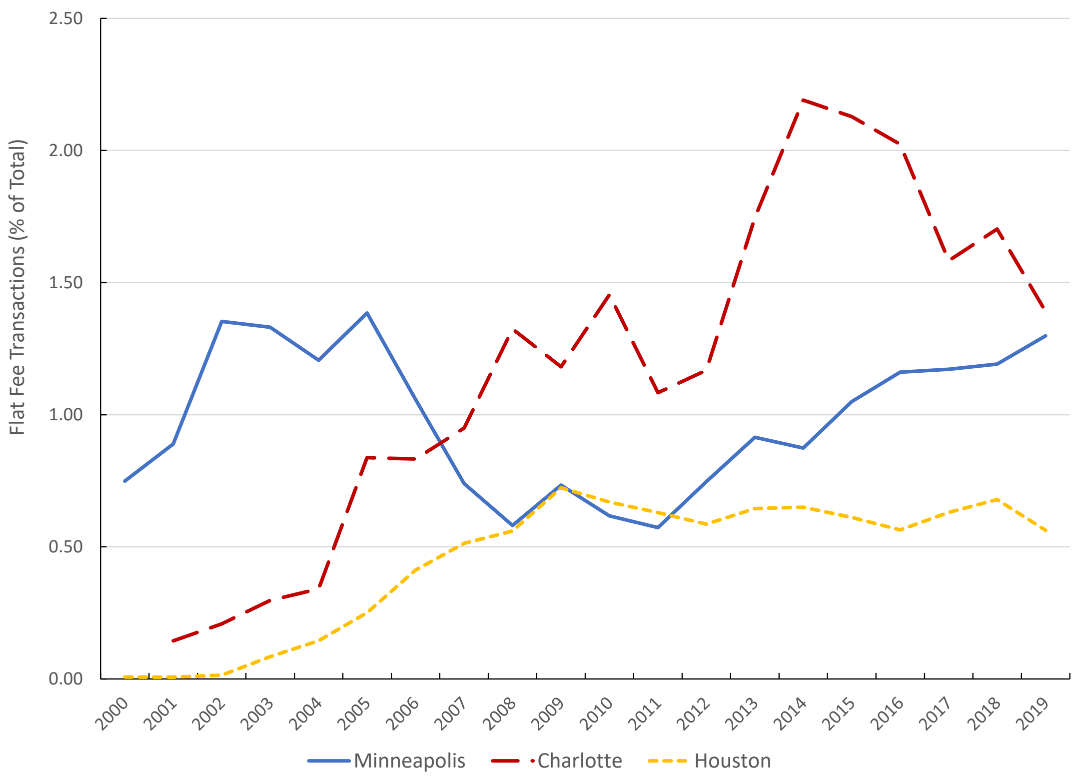
	Charlotte	**Minneapolis**	**Houston**
Original Sample	790,318	1,400,996	1,502,039
Keep Single Family Housing	697,185	1,290,618	1,354,282
Keep Sample Years	654,578	1,221,614	1,268,029
Drop Distressed Sales	601,050	1,088,237	1,143,856
Drop Extreme Values	585,142	1,042,758	1,128,251
Keep Observations Within Designated CBSAs	376,747	797,457	1,098,212
Drop Zipcodes with Less Than 100 Listings	376,184	796,739	1,097,035
Drop New Construction Sold with Flat-Fee Agent	376,042	796,646	1,096,800

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 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

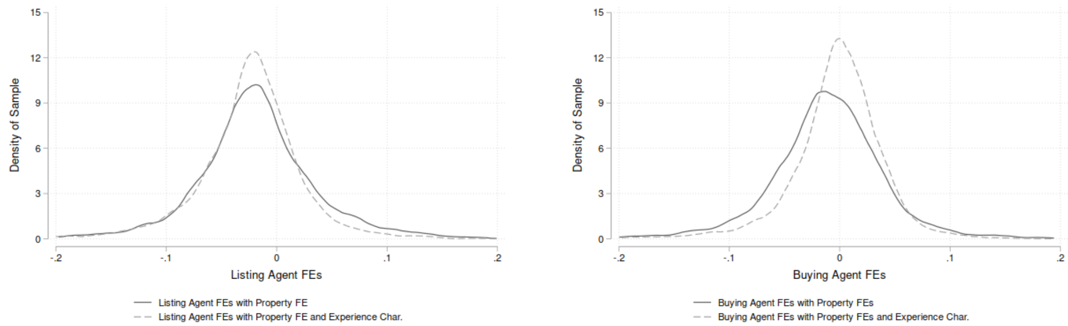


A.3 Effect of Experience and Firm Size on Agent Fixed Effect Distributions

Figures A.2 and A.3 below show how the price and DOM distributions of agent fixed effects is affected when we control for agent experience and firm size. The solid kdensity plots in the figures replicate the kdensity plots (with property fixed effects) displayed in Figures 1 and 2 in the main text where we did not control for either variable. The dashed kdensity plots in the figures add controls for both variables. The impact on the price fixed effects is marginal in all three cities while the effect on the DOM fixed effects distributions is essentially zero. Thus, we conclude that agent experience and firm size does not explain the significant amount of heterogeneity in agent skill that we have documented.

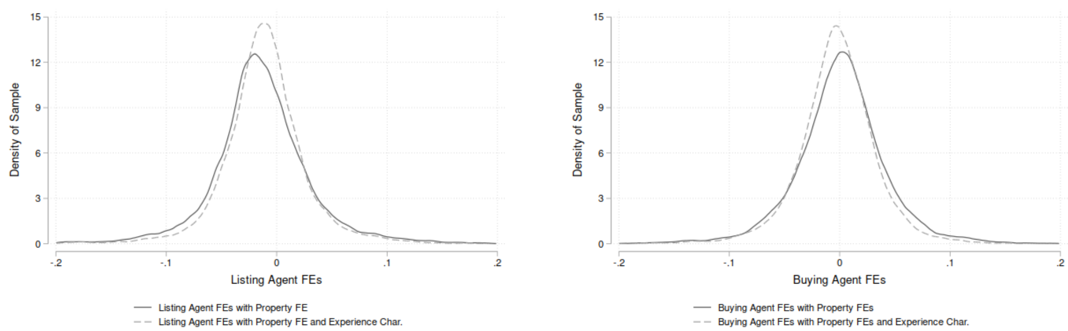
Figure A.2: Kernel Density Estimates of Agent Fixed Effects Controlling for Experience and Firm Size: Sale Prices

Panel A: Charlotte



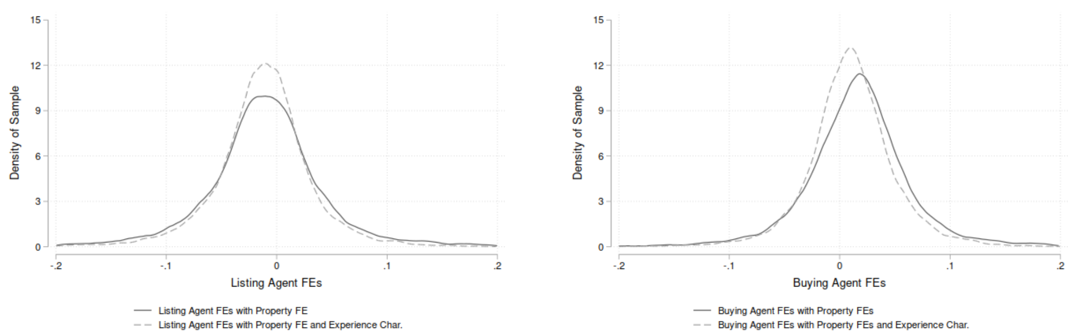
Listing Agent Buying Agent

Panel B: Minneapolis



Listing Agent Buying Agent

Panel C: Houston



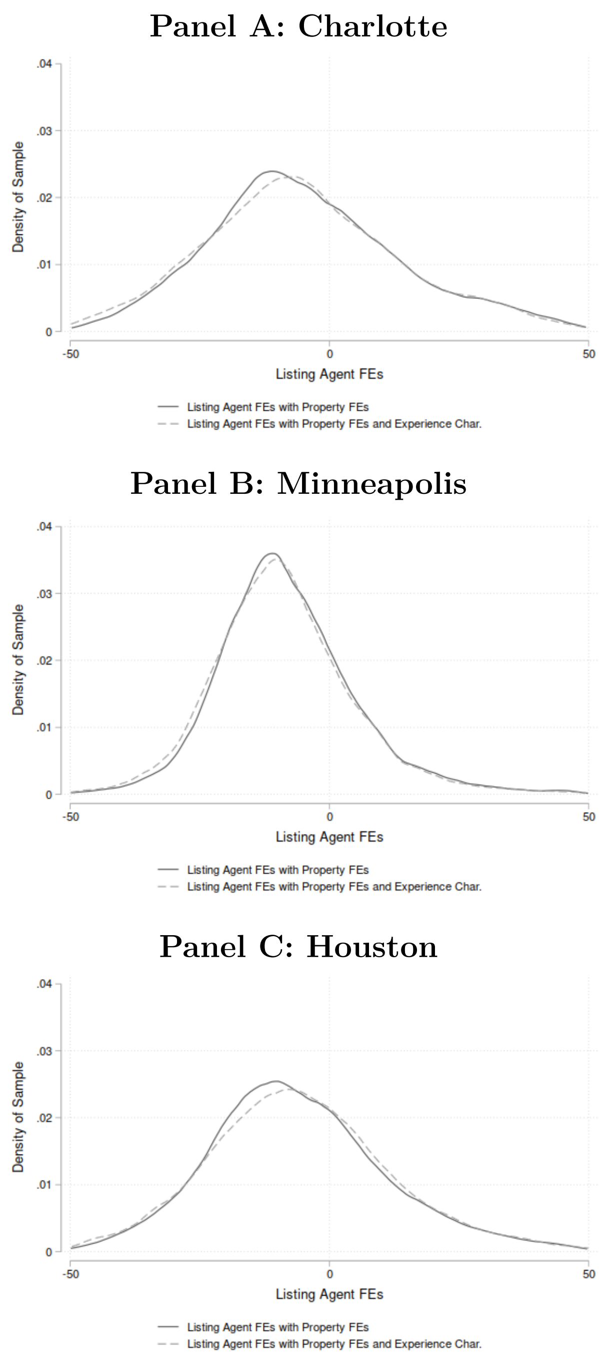
Listing Agent Buying Agent

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:

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

where i indexes the property, t is the year-quarter of the listing date, j is the ZIP code where the property is located, and r is the real estate agent. The dashed density estimates include agent experience and firm size in the vector of control variables while the solid line estimates do not. Both estimates include property fixed effects, η_i. The omitted category in the listing agent fixed effects models is flat-fee brokers, while the omitted category in the buying agent models is dual agent transactions. The underlying data come from the CoreLogic Multiple Listing Service Database and include listings posted between January 2000 and December 2019 (inclusive).

Figure A.3: Kernel Density Estimates of Agent Fixed Effects Controlling for Experience and Firm Size: Days-on-Market



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:

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

where i indexes the property, t is the year-quarter of the listing date, j is the ZIP code where the property is located, and r is the real estate agent. The dashed density estimates include agent experience and firm size in the vector of control variables while the solid line estimates do not. Both 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).