Conflicts of Interest and Steering in Residential Brokerage*

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This paper documents uniformity in real estate commission rates offered to buyers' agents using 653,475 residential listings in eastern Massachusetts from 1998-2011. Properties listed with lower commission rates experience less favorable transaction outcomes: they are 5% less likely to sell and take 12% longer to sell. These adverse outcomes reflect decreased willingness of buyers' agents to intermediate low commission properties (steering), rather than heterogeneous seller preferences or reduced effort of listing agents. Offices with large market shares purchase a disproportionately small fraction of low commission properties. The negative outcomes for low commissions provide empirical support for regulatory concerns over steering.

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1 Introduction

Buyers are routinely advised by salespeople or intermediaries who are compensated by sellers. In many settings, there are concerns that buyers are steered towards products that are not in their interest.[1] We study this phenomenon for residential real estate, where intermediaries play an important role. In 2014, there were 4.94 million existing home sales valued in aggregate at $1.26 trillion dollars, and real estate agents assisted in 88% of sales (NAR, 2014a,b).[2] Brokerage commissions constitute a major component of housing transactions costs.

Regulators have repeatedly expressed concerns that high and uniform commission rates in the residential brokerage industry point to collusive behavior. The central question is how this structure can be sustained despite low entry barriers and a seemingly competitive marketplace with many firms and agents. One often cited factor is steering. In the conventional compensation arrangement where sellers pay for the commissions of their listing agents and potential buyers' agents, the latter have an incentive to prioritize properties that offer higher commissions. According to a 1983 report by the Federal Trade Commission (FTC), "(s)teering ... may make price competition a potentially unsuccessful competitive strategy, and it is our belief that this is the most important factor explaining the general uniformity of commission rates" (FTC, 1983, p. 12). To date, the current commission structure remains an important subject of policy debate and regulatory concern (GAO, 2005; FTC, 2007).

We investigate the consequences of steering behavior on sales outcomes using a dataset that includes commission rates offered to buyers' agents for 653,475 listed properties in eastern Massachusetts from 1998 to 2011. In addition, we observe detailed information on property attributes, agents, and brokerage offices that are involved in each transaction. Ninety percent of properties in our sample have a buying commission of 2.0 or 2.5 percent,[3] corroborating the common perception that commission rates are uniform. In addition, even in periods with substantial turnover among real estate brokerage firms and agents, the average commission rate exhibits only modest fluctuation.

After documenting limited commission variation in our sample, we track the performance of offices with different commission rates. We find that offices charging lower commission rates are much less likely to become the top 25% firms in terms of commission revenue or the number of listings, relative to comparable offices that charge higher commissions. Standard competitive forces, whereby a firm competes with rivals using lower prices, do not seem effective under the current commission arrangement.

This finding motivates our core analysis that examines the sales outcomes of properties listed with different buying commission rates. Consistent with real estate agents steering buyers to properties with high commissions, we find that if a property has a buying commission rate less than 2.5 percent, it is

[1] See Cummins and Doherty (2006) for a discussion on insurance products, Inderst and Ottaviani (2012) for financial advice, Jiang et al. (2012) for bond ratings, Christoffersen et al. (2013) for mutual funds, Chan et al. (2015) for mortgages, and Shapiro (2015) for the health sector.

[2] Throughout this paper, an 'agent' is an individual who assists buyers or sellers in housing transactions, an 'office' or a 'firm' is a broker that an agent works for, and an 'agency' refers to an agent and her broker.

[3] These correspond to a total commission of 4% or 5%, respectively, if commissions are equally split between listing agents and buying agents.

5% less likely to be sold and takes 12% longer to sell, compared to properties that offer buying agents 2.5 percent or more. There is little effect on the sale price. While it is possible that lower commission rates are associated with less desirable property attributes, our estimates are robust to specifications that include a rich set of property level measures that control for time-varying attributes and property fixed effects that control for time-invariant attributes.

We address two additional threats to our empirical analysis. First, the poor performance of low commission properties may reflect reduced listing agent effort, rather than an unwillingness of buyers' agents to be involved in low commission properties. To investigate this possibility, we report specifications focusing on properties that are more homogenous and relatively easier to sell. Then we control for time-invariant agent attributes using listing agent fixed effects. Third, we construct 'pairs' of properties that are listed by the same agent in the same year with listing commission revenues within a $500 bin, but offer *different* commission rates to the buying agent. Since these properties have the same payoff for the listing agent, they should induce the same level of effort from the listing agent, but may attract different number of buyers given the difference in buying commission rates. In this demanding analysis that exploits variation within an agent, property type, year, and commission bin, we continue to find that listings offering lower commission rates are associated with lower sales probabilities. All three investigations suggest that unobserved listing agent effort is not driving our main results.

The second threat we examine is that the adverse sales outcomes do not simply reflect behavior of buying agents, but the preferences of sellers. Some sellers might be more patient and willing to trade off a low sale probability with a high sale price. If these sellers are more likely to work with firms charging low commissions, then our results would be confounded by seller heterogeneity. We tackle this issue in several steps. First, we control for seller urgency using list price as a proxy. Next, we construct a patience-index, which is the ratio of the observed listing price to the predicted price from a hedonic regression. More patient sellers have higher index values. Sellers are divided into ten or a hundred groups according to this index. We use these group dummies as controls for seller patience. Finally, we merge our data with property deeds that record seller and buyer names and estimate models using seller fixed effects. Our analysis continues to report negative sales outcomes associated with lower commission rates, even accounting for fixed and time-varying seller preference.

After ruling out these alternative explanations, we show that properties that are more susceptible to steering suffer worse outcomes. For example, the sale probability and days on market worsen monotonically when we compare three groups of listings that offer more than 2.5 percent, exactly 2.5 percent, and below 2.5 percent, respectively. This is consistent with the fact that properties offering higher commission rates provide stronger financial incentives. Similarly, we find worse outcomes for low commission listings in neighborhoods with a larger fraction of high commission listings, listings by entrants, and listings by offices that used lower commission rate policies in the past.

To understand why low commission listings have worse performances, we examine the transaction patterns of dominant offices that intermediate a large fraction of purchases. We find that firms with higher market shares buy a smaller fraction of low commission properties. While our core analysis at the property level demonstrates that all firms prefer properties with high commissions, these results illustrate lower propensity of dominant firms to intermediate low commission properties. If we assume that dominant firms' diminished willingness to purchase low commission properties leads to a reduced number of potential buyers, this finding can explain about forty percent of the adverse sales outcomes reported above.

Our results illustrate that when a seller and her listing agency have to rely on a high commission rate to induce cooperation from the buying agency, a low commission strategy becomes less viable. They also rationalize our finding that offices charging lower commission rates are less likely to be successful, everything else equal. In addition, the negative sales outcomes associated with low commissions provide a lens to interpret sellers' reluctance to adopt such a strategy, which in turn reinforces the existing commission structure.

This paper makes several contributions. First, we construct a large dataset that documents individual buying commissions for about half a million properties and spans an entire housing business cycle. Second, to our best knowledge, we provide the first causal analysis of the consequence of buying agent commissions on economic outcomes. We use data from the traditional brokerage platform (the Multiple Listing Service) that accounts for the majority of real estate transactions and present evidence that supports regulators' concerns over steering behavior. Third, our paper highlights distortions when incentive schemes serve a dual role of eliciting agent effort and matching buyers and sellers. The negative consequences of low commissions reported here arise from the fact that sellers have only one instrument for two distinct purposes: to incentivize effort and to attract buyers' agents.

Our paper contributes to several literatures. The first literature studies implications of the fixed percentage commissions in the real estate brokerage industry (such as, Hsieh and Moretti (2003), Levitt and Syverson (2008a), and Han and Hong (2011). See Han and Strange (2015) for a review).[4] Our paper is most similar to Levitt and Syverson (2008b) that studies listings by flat-fee or limited service agencies and Hendel et al. (2009) that focuses on For-Sale-by-Owner (FSBO) transactions. Our results on steering behavior also resonate with other work documenting that consumers often receive advice from experts that is not in their interest. For example, Mullainathan et al. (2012), Christoffersen et al. (2013), and Guercio and Reuter (2015) study financial advisers and broker recommendations for mutual funds, Jiang et al. (2012) analyzes bond ratings, Schneider (2012), Anagol et al. (2013), and Shapiro (2015) examine the auto repair, insurance, and health industries, respectively.

Another related literature examines whether incentive schemes have adverse consequences on agent performance. Oyer (1998) investigates the implications of non-linear incentive schemes on fiscal targets. Larkin (2014) uses data from an enterprise software vendor to demonstrate the gaming of the deal closure time by salespeople in response to the vendor's accelerating commission schedule.

The rest of this paper is organized as follows. Section 2 discusses the institutional background. Section 3 describes the data and presents descriptive patterns of the housing market and commissions during

[4]Other recent work on real estate agents includes Rutherford et al. (2005), Nadel (2007), Jia and Pathak (2010), and Bernheim and Meer (2012).

our sample period. Section 4 analyzes property level sales outcomes for low commission properties. Section 5 explores why low commission properties suffer worse outcomes. In Section 6, we discuss the costs of a low commission rate strategy for home sellers. Section 7 concludes. Appendix A explains market definition and how we construct regressors used in our analysis. Additional results are presented in Appendix B and C, with Figure B1 in Appendix B and Tables C1 to C10 in Appendix C.

2 Institutional background

Real estate agents are licensed intermediaries who provide services to buyers and sellers in real estate transactions. The licensing requirements for Massachusetts are modest (see Barwick and Pathak (2015) for more details). For home sellers, agents help to advertise the house, suggest listing prices, conduct open houses, and negotiate with buyers. For home buyers, agents search for houses that match their clients' preferences, arrange visits to the listings, and negotiate with sellers. Agents can influence buyers' decisions in several ways, including which properties to show, which property attributes to highlight, and how much effort to exert during the offer and negotiation stages. Therefore, steering, which is known as "sell to the commission" in the industry (Harney, 2015), can manifest along multiple dimensions.

A contract between the seller and the listing agency usually includes the list price and the total commission the seller is obligated to pay to the listing agency in the event of a sale. Commissions are often quoted as a certain percentage of the sale price. In the greater Boston area, the norm for this rate is 5%. The National Association of Real Estate Exchanges (the predecessor to the National Association of Realtors (NAR)) institutionalized a commission rate norm when it adopted its first Code of Ethics in 1913. It stated that "(a)n agent should always exact the regular real estate commission prescribed by the board or exchange of which he is a member." In Boston, agents referred to the *Schedule of Broker's Commissions* published regularly by The Boston Real Estate Exchange. In the 1920s, the typical commission rate for the city of Boston was 2.5 percent (Benson and North, 1922).[5] This rate increased to 5 percent in 1940 and has prevailed ever since as the most common rate for listings in the area (BREE, 1940).

This paper focuses on the common practice of *bundling commissions* where a seller pays one commission to her listing agency, who then shares the total commission with the agency who finds a buyer. In particular, the commission rate paid to the buying agency is specified in the listing agreement *prior* to the knowledge of buying agents. When buying agents are informed of properties, they observe the property attributes as well as the buying commission rate for each property (buyers do not observe the commission rate). This practice began in the early twentieth century to minimize the problem of buyers and sellers circumventing the payment of brokerage fees (Davies, 1958; Wachter, 1987).

In many cases, the commission fee is evenly split between the listing and buying agencies. The 1913 Code of Ethics, for example, specifies that the eighth duty of members is to "... always be ready and willing to divide the regular commission *equally* with any member of the Association who can produce

[5]The fee was 2.5% up to $40,000 (or $460,000 in 2011 dollars) and 1% on the balance, with a minimum of $100.

a buyer for any client."[6] More recent data suggest this pattern of equal splits persists until today. To investigate the commission split between listing and buying agencies, we collect a random sample of 70 HUD-I housing settlement statements from 39 brokerage offices in 37 of our sample markets. A HUD-I settlement statement itemizes all financial obligations of the borrower and seller in a real estate transaction, including commissions paid to and rebates from the buying and selling agencies. About 90% of transactions in this random sample have even splits of commissions. For the remaining transactions, half pays more to the listing agency, and half pays more to the buying agency.

The commission to an agency is further split between agents and their brokers. According to a 2007 survey conducted by the NAR, most agents are compensated under a revenue sharing arrangement, with the median agent keeping 60% of her commissions and submitting 40% to her firm (Bishop et al., 2007). Similar to salespeople working in other professions (Joseph and Kalwani, 1998), many brokerage firms also include built-in 'accelerators' that entails proportionately higher earnings with higher gross commission revenue (NAR, 2009). For example, a major franchise, Keller Williams, has a profit sharing arrangement with "an elaborate seven-step function" that shares more with more productive agents (Inman News, 2014). Such non-linear incentive schemes that are based on revenue further enhance agents' preferences towards listings with higher commission rates.

To illustrate how commissions are typically split between agents and brokers, suppose a property is worth $500,000 and the commission rate is 5%. The total commission is $25,000. The listing and buying agency is compensated $12,500 each, which is further split so that the agent gets 60% ($7500) and the broker receives 40% ($5000).

3 Data and descriptive patterns

3.1 Sample coverage

The data for this study come from the Multiple Listing Service (MLS) network for eastern Massachusetts, a centralized platform containing information on property listings and sales. This area has a number of virtues for our analysis: the market experienced a boom-bust cycle during our sample period, with house prices peaking in mid-2000s and falling thereafter. The market also includes high-priced suburban towns with single-family homes and more densely populated inner urban areas where condominiums make up the bulk of transactions.

We collect information on all listed non-rental residential properties. Our sample contains 653,475 listings between 1998 and 2011, covering 85 towns and cities surrounding Boston. We combine 12 small cities with their closest neighbor. Given the size of Boston, we split it into 15 markets using Zillow's definition of neighborhoods and a variable in the MLS (*area*) that identifies neighborhoods within cities. This gives us a total of 87 markets. Appendix A provides more details on the sample construction and market definition.

[6]Emphasis added by authors.

For each listed property, we observe listing details (the listing date and price, the listing office and agent, the commission rate offered to the buyer's agent, and so on), a rich set of property characteristics, and transaction details when a sale occurs (the sale price, date, the purchasing office and agent). The number of days on the market is measured by the difference between the listing date and the date the property is removed from the MLS database. We complement the MLS data with a deeds data set from a commercial vendor that records seller and buyer names for all properties that change ownership during 1998 to 2008. This allows us to track home buyers and sellers overtime. We also merge in data from the Home Mortgage Disclosure Act (HMDA) which includes information on the income of buyers.

Our sample comprises three property types: condominiums (35%), single family homes (52%), and multifamily properties (13%). The average listing in our sample has 1840 square feet, 3 bedrooms, 2 bathrooms, and is 62 years old. The median list price is $420,000 and the median sale price is $398,000 (both in 2011 dollars). The properties in our sample are comparable in size, but are older and more expensive than the average home purchased in the United States between 2013 and 2014 (NAR, 2014c), which has 1,870 square feet, 3 bedrooms, 2 bathrooms, is 20 years old with a median sale price of $235,000.

3.2 Commission fees

There is surprisingly little information on commissions at the property level. The only exceptions that we are aware of include Woodward (2008) and Schnare and Kulick (2009) that are prepared for the Department of Housing and Urban Development and for the NAR, respectively. They investigate variation in buying commissions across real estate markets but do not examine the consequences of buying commissions on sales outcomes.[7] We are not aware of any study on U.S. markets that has information on listing commissions.

Critically, we observe the commission rate offered to buyers' agents for each of our 653,475 listings. The histogram in Figure 1 establishes that a lion's share of listings offer either a 2.5 percent or a 2 percent commission rate to the buyer's agent, with the rest scattering between 2 and 3 percent. Specifically, the most commonly observed rates are 2.5 percent (59% of listings), 2 percent (31% of listings), 3 percent (5% of listings), and 2.25 percent (3% of listings). Throughout our analysis, we define a *low commission rate* listing as one with a buying commission rate strictly below 2.5 percent and a *high commission rate* listing one with a rate at or above 2.5 percent. The only exception is Section 5.1, where we separate listings that pay exactly 2.5 percent from listings that pay more than 2.5 percent for some robustness analyses.

Commission rates display some geographical variation (Figure B1). Markets that are characterized by high household income and high house prices tend to have higher commissions. In addition, the average commission rate displays a modest U-shape over time, varying from 2.49 percent in 1998 to a low of 2.27 percent in 2005 before reverting back to 2.39 percent in 2011. This modest variation masks a relatively

[7] Goolsby and Childs (1988) and Zietz and Newsome (2001) report on buying commissions for a few hundred transactions.

large change in the fraction of listings at 2.5 percent: about 74% in 1998, 49% in 2005 (a period with a large influx of entering agents and offices as documented in Barwick and Pathak (2015)), and 62% in 2011.

Most offices have commission rate policies or norms. There appears to be systematic differences in commission rates charged by different offices. Among the six dominant chains – Coldwell Banker, Century 21, Remax, Hammond, Prudential, and GMAC – only Century 21 has a majority of listings at rates below 2.5 percent. Coldwell Banker, the largest chain that accounts for about 20% of all listings in our sample, rarely lists properties at rates below 2.5 percent. In contrast, 48% of independent offices and smaller chains have a majority of listings at rates below 2.5 percent. The firm level commission variation could reflect differences in costs, such as overhead, insurance charges, technology and marketing costs. It could also come from brand premium, prestige, and historical norms. Finally, there is evidence that firms set prices based on property types (condominiums usually list at high commission rates), demographics (such as average income of potential customers), and market conditions.

To investigate the sources of variation in commission rates, we present a set of regressions in Table 1 where the dependent variable is 1 if the commission rate for a listing is strictly below 2.5% ($RL25$). Column 1 only controls for market conditions using market-year and month fixed effects. Column 2 only includes property controls and property fixed effects. Column 3 only controls for office fixed effects. Column 4 includes 178,000 office-year-market-property type fixed effects. In addition to the R-squared, we also report how well we can predict $RL25$. We first predict $RL25$ using the controls in each column. We then define $R\hat{L}25$ as one if the predicted value is at least 0.5 and zero otherwise.[8] The share of listings where $R\hat{L}25$ equals $RL25$ is reported after the R-squared.

Across the columns, we are able to predict the low commission dummy with a high degree of accuracy, consistent with our discussion above that brokerage offices appear to be setting commission rates according to norms, market conditions, demographics, and property types. The high R-squared suggests that these are the primary determinants of commission rates. In particular, we can predict $RL25$ correctly for 91% of the listings using office-year-market-property type fixed effects (the R-squared is 0.72). Moreover, recent statistics show that many sellers do not shop for agents. Seventy percent of home sellers contact only one agent before selecting the one to assist with their home sale (NAR, 2014b). Only 3% of sellers report that the commission is the most important factor in choosing a listing agent (NAR, 2013). The seemingly idiosyncratic manner in which sellers approach commission rates is consistent with the view that most sellers are inexperienced (Akerlof and Shiller, 2015).

3.3 Brokerage firms and agents

There are a total of 8,888 offices and 35,129 agents in our data set. The ability to observe agent and office identifiers as well as their past transactions allows us to construct detailed measures of office and

[8] We also experimented with defining $R\hat{L}25$ as one when the predicted value is at least 0.3, 0.4, 0.6 and 0.7 instead of 0.5, or using probit instead of OLS. Results are similar.

agent quality, including experience, various sales performances (such as the fraction of listings that are sold each year, the average days on market), and property portfolio (the fraction of condominiums or single-family houses). For offices, we also observe the size and quality of their agents. We collect each office's street address from a variety of data sources and use this information to construct distance between offices.

A large number of offices and agents have only a few listings throughout our sample period. Offices (agents) whose average annual listings are above five (two) are responsible for 95% (92%) of the listings.[9]

3.4 Growth paths of low commission firms

One interesting pattern is that entrants (brokerage firms established in 1999 or later) that offer low commissions are much less likely to reach the top tier of the market in terms of revenue than entrants with high commissions. In Figure 2, we classify entrants into a low commission rate group (solid line) and a high commission rate group (dashed line) based on their observed commission rates in the first three years. An entrant belongs to the low (high) commission rate group if its fraction of *RL*25 listings in the first three years is in the top (bottom) quartile among all entrants in the same market. We define 'successful brokerage firms' as those whose listing revenues is ranked top quartile among all offices in the same market. Figure 2 illustrates the likelihood for low commission entrants and high commission entrants to become successful overtime. Both groups start small with a similar probability of being in the top quartile (less than 3%), but the gap widens over time. By the end of our sample period, entrants with high initial commission rates are 17% more likely be in the top quartile than entrants whose initial commission rate is low. The pattern remains the same if we define the 'top quartile' status using the number of listings instead of commission revenues.

One possible explanation is that entrants are not identical. Firms that are able to recruit talented agents or with more connections might charge a high commission rate and do well at the same time. When we adjust for observable differences between high and low commission firms in Table C1, we continue to find that firms with low commissions are less successful. These findings seem puzzling: competitive behavior, where offices charge *low* prices for comparable services, does not lead to successful outcomes. Instead of growing, these offices are more likely to remain small.

4 Results

Motivated by the patterns discussed above, our core analysis tests whether a low commission rate offered to the buyer's agent affects the sale performance of a listing. We first show that listings offering high versus low commission rates appear to be comparable, on average. We then present robust evidence that

[9]The average annual number of listings is the ratio of the total number of listings by an office or agent over the total number of years that office or agent spans our data (the last year minus the first year plus one).

the effect of commission rates on sales outcomes survives a rich set of controls for market conditions, property characteristics, seller, agent and office attributes, as well as an instrumental variable strategy.

4.1 Effect of commission rate on transaction outcomes

Our main listing level regression is of the following form:

$$y_{ipklmt} = \beta_1 RL25_{ipklmt} + PROP_{ipt}\beta_2 + AGT_{kmt}\beta_3 + OFFICE_{lmt}\beta_4 + \mu_{mt} + \tau_{month} + \pi_p + \varepsilon_{ipklmt} \quad (1)$$

where y_{ipklmt} is the sale outcome for the i'th listing of property p, by agent k and office l in market m and year t.

The key regressor is $RL25$, a dummy that is 1 if a listing offers a commission rate that is strictly below 2.5 percent. One major empirical challenge is that listings offering low commission rates may have less desirable attributes that lead to adverse outcomes (β_1 may be downward biased). There are many sources of confounders in our context because houses are differentiated along multiple dimensions and many parties are involved in a housing transaction. We include controls for property characteristics ($PROP$), attributes of listing agents (AGT) and listing offices ($OFFICE$), market by year fixed effects (μ_{mt}) for time-varying market conditions, month fixed effects (τ_{month}), and property fixed effects (π_p). To conserve space, we reserve a detailed description of all controls in Appendix A8. We examine three performance measures of a listing: the sale probability, as well as the days on market and the sale price if a listing is sold.

The parameter of interest is β_1. In an ideal setting where buying agents fully internalize interests of their clients, how much agents are compensated should not affect the sale outcome (β_1 should be 0, since buyers do not observe commissions). On the other hand, if buying agents steer their buyers towards high commission properties, a negative β_1 would reflect this conflict of interest. Our identification assumption is that $RL25$ is uncorrelated with the residual of sales outcomes, ε_{ipklmt}, conditioning on our regressors. Section 3.2 presents evidence that firms set commission rates based on property types, demographics, and market conditions. In the analysis below, we report estimates of β_1 as we gradually add controls.

Table 2 demonstrates that observable differences between listings offering high versus low commission rates are modest. Each row reports an OLS regression at the listing level where the dependent variable is a property characteristic and the regressor is the $RL25$ dummy. These tests only have one regressor but the results are similar if we add market by year fixed effects and month fixed effects to control for market conditions. We choose a list of property characteristics that are commonly included in hedonic regressions in the housing literature. Columns 1 and 2 report the mean and standard deviation of each dependent variable. Columns 3 and 4 report the coefficient on $RL25$ and the p-value. On average, low commission rate listings are 10 square feet larger, have 0.1 acre smaller lotsizes, are 8% less likely to be condominiums, 1% less likely to be single-family homes, one year older, have 0.2 more bedrooms, 0.07 fewer bathrooms, and 0.07 more other types of rooms. The last row indicates that list prices are 11%

lower for low commission listings, but this difference reduces to 1% after we condition on our full set of property controls and market by year fixed effects.

Table 3 presents estimates of β_1, the causal effect of offering a low commission rate on the probability of sale (Panel A). The dependent variable is a dummy that is one if the listing is sold within our sample period (the mean is 65%).[10] Standard errors are clustered at the market by year level (columns 1 to 2) and at the property level (columns 3 to 7). Column 1 includes the full sample of 653,475 listings.

Across all specifications, low commission rate listings are significantly less likely to sell than high commission rate listings. We begin with a parsimonious specification in column 1 that controls for market conditions since commission rates tend to be correlated across markets and time, as discussed in Section 3. Conditional on market by year and listing month fixed effects, low commission rate listings are 9 percentage points (p.p.) less likely to sell compared to high commission listings.

Next, we show that the lower sales probability survives controls of property attributes. We find a weaker effect in column 2 but the change is modest (- 7 p.p. compared to - 9 p.p. in column 1), after adding 148 property controls.[11] The smaller coefficient suggests that some of the effect in column 1 is driven by observed property attributes that make low commission listings harder to sell. However, the change in the β_1 estimate is not large, which is expected given the modest differences in observed property attributes reported in Table 2.

Furthermore, the estimate remains similar when we add more than 133,000 property fixed effects in column 3 to control for time-invariant property characteristics. This restricts the sample to properties with multiple listings during our sample period.[12] Here, the model is identified by comparing outcomes for the same properties that are listed at low versus high commission rates (36% of properties have within property variation in *RL*25). Notably, the R-squared increases from 10% to 46% but the effect (- 9 p.p.) remains similar.

Property fixed effects do not address time-varying property attributes, such as unobserved upgrades. We therefore construct keywords related to maintenance and renovations from property descriptions and include them as part of the 148 property controls from column 2 onwards.[13] Admittedly, regardless of how many controls are included in the regression, one can never completely eliminate the concern of unobserved attributes. However, as documented in Panel C, the *same* set of controls explains 97% to 99% of variation in sales prices. Hence, we conclude that unobserved housing attributes are unlikely to be a major concern here.

[10] The MLS data reports whether a listing was sold, cancelled, expired, or withdrawn. We code a listing as sold if its status is sold and zero otherwise. Later, we show that our results are not driven by right-censoring issues for the *sold* dummy (listings close to the end of the sample period may sell after the sample ends).

[11] These 148 property controls, together with market by year and month fixed effects, explain 85% of the variation in *ln(List price)* and 95% if we add property fixed effects.

[12] Restricting the sample to repeat listings might introduce a sample selection bias as properties that are listed multiple times might have lower quality. However, this issue appears inconsequential. When we repeat the specification in column 2 for the sample of repeat listings, the effect is -8.5 p.p.

[13] We create dummies for common keywords such as "Renovated", "Remodeled", "Maintained", "Needs updating". These dummies are part of the 148 property controls. See Appendix A8 for the full list of keywords.

Lower sales probabilities for low commission listings might be driven by seller preferences. In particular, we are concerned that patient sellers who are more likely to trade off high sales prices against low sales probabilities are also more likely to list at low commission rates (to maximize their proceeds net of commission). In column 4, we proxy for seller patience using the idea that patient sellers will list their properties at higher prices, relative to prices predicted from observed attributes. This also builds on the notion that patient sellers tend to have higher reservation prices than sellers eager to sell. We first calculate the ratio of the observed list price to a predicted hedonic price, then construct decile dummies for this ratio.[14] These decile dummies constitute our seller patience controls. The effect of low commission rate becomes less negative (- 6 p.p.) with these controls, but remain the same with other controls for seller patience and seller preferences that we investigate in Section 4.2.2 and Table 5.

We further probe the robustness of these results by adding measures of listing office and agent quality (columns 5 and 6). These additional controls alleviate concerns that lower quality offices or agents are more likely to list at low commission rates. For agents, we control for their experiences over time and also whether they are star agents (ranked in the top decile using agents' average annual listings). For offices, we control for the composition of agents in the office, the performances of listings by the office in each year (such as the fraction of listings that were sold, the average days on market for sold listings) and whether an office is the dominant office in a market in terms of average transaction volume. Higher quality offices and agents have higher sales probabilities through two channels. First, they are better at selecting properties that are easier to sell. Second, they are more knowledgable about local market conditions, have better social skills, and are better at selling.

Our most saturated OLS specification implies that low commission listings are 5 p.p. less likely to sell than observably identical high commission listings (column 6). Interestingly, the estimates are similar with or without office and agent controls. This could be because the first (selection) channel has been controlled for using property attributes and property fixed effects. While office and agent quality naturally affect the probability of sale, most of the variation seems to have been absorbed in our previous specifications. Additionally, our results survive more flexible controls for agent and office quality, including agent fixed effects (Table 4, column 2) and office fixed effects (Table C3, column 4).

While the stable estimates across different OLS specifications above are encouraging, we repeat the analysis exploiting an instrumental variable strategy (column 7). We begin with the observation that some chains appear to have different preferences for high versus low commission rates, based on our examination of the data and discussions with realtors. Among the three largest chains in our data, Coldwell Banker, Century 21, and ReMax,[15] Coldwell Banker has the lowest fraction of low commission listings (9%) and Century 21 has the highest fraction (53%). ReMax is in the middle (36%). There is suggestive evidence that customers of Coldwell Banker are less price-sensitive than those of Century 21. For exam-

[14]The hedonic regression uses our most saturated set of controls in column 6 (but drops $RL25$) on the full sample of listings. We include property fixed effects and a separate effect for properties with only one listing. Results are similar whether we use listing prices or sale prices for the hedonic regression.

[15]Each of these three chains have more than 60,000 listings in our data. The next large chain (Hammond) has fewer than 20,000 listings.

ple, the median income amongst buyers who are represented by Coldwell Banker is $105,000, compared to $80,000 for buyers represented by Century 21.[16]

Our instruments include the distances between the listing office and the nearest Coldwell Banker and Century 21 offices in each year, respectively. If prices are strategic complements, higher prices by rivals lead to higher prices by the listing office. Time series variation in our distance measures is driven by changes in the listing office and entry and exit of Coldwell Banker and Century 21 offices. We regress $RL25$ on the distance from listing office l to the nearest Coldwell Banker office in year t and the distance to the nearest Century 21 office in the same year, while maintaining the same set of controls as in column 6. Our first stage analysis confirms the hypothesis that distance between listing offices and the nearest Coldwell Banker (Century 21) in year t increases (decreases) the likelihood of low commission rates. The coefficients have the expected signs, with t-statistics of 34 (-11) for the distances to the nearest Coldwell Banker (Century 21) offices. The F statistic for the joint test of excluded instruments is 570.

The thought experiment behind the IV strategy is to examine the sale performance for the same property that is listed in year t by an office close to Coldwell Banker and also listed in year t' by an office close to Century 21. One concern is that distances to Coldwell Banker offices can have a direct effect on sales outcomes, perhaps because they tend to locate near desirable properties that are easier to sell. Since firm location choices were determined before the listing date, our time-varying market level controls help to mitigate this concern. In addition, we control for property attributes, office quality, and agent experience. Our assumption is that conditional on our set of extensive controls, distances to Coldwell Banker and Century 21 offices only affect sales outcomes through their impact on the pricing strategy of the listing office.

Reassuringly, the IV estimate continues to imply that low commission listings are less likely to sell. The estimate in column 7 is - 8 p.p., slightly more negative but not statistically different from that in column 6. The stability of the estimates across columns 6 and 7 is encouraging as these estimation strategies (OLS versus IV) leverage different sources of variation in the key regressor and are presumably identified from different sets of properties. We find similar results when we repeat the IV estimation but drop listings by Coldwell Banker and Century 21 offices.

Panel B of Table 3 reports the results for the number of days on market for sold properties.[17] The dependent variable is *ln(Days on market)*, where the number of days on market is censored above at 365 days. A total of 6,400 listings took a year or longer to sell. The average (median) time on market is 71 (44) days. The specifications across the columns are analogous to those for Panel A. Columns 1 and 2 include all sold listings. Column 3 onwards includes properties with repeat sales and controls for property fixed effects.

We find that low commission rate listings take 12% longer to sell, or 8 days for the average sold

[16] We merged our sample with data from HMDA through 2008 and obtained buyer income for 25% of purchases. We observe buyer income for 15,470 purchases intermediated by Coldwell and 10,762 purchases intermediated by Century 21.

[17] The number of days it takes to sell and sale price are only observed for sold properties. We use selection correction methods to address the selection bias (Heckman, 1979). Tables C7a and Tables C7b in Appendix C7 show that our conclusions remain the same when the selection bias is controlled for.

listing (column 6). The results are relatively stable between 11% and 14% across specifications. The IV estimate is larger (33%) but the standard errors are also large (12%). The test of whether the IV estimate in column 7 is different from the OLS estimate in column 6 has a p-value of 0.08.

Panel C provides results for our final transaction outcome, the sale price. The average (median) sale price is $479,000 ($398,000) in 2011 dollars. The dependent variable is *ln(Sale price)*. When we only control for market conditions (column 1), low commission listings sell at higher sales prices. Adding property controls and property fixed effects in columns 2 and 3 dampens the effect. If low commission rates are associated with lower property quality, adding property controls should mitigate the downward bias and increase the coefficient from column 1 to columns 2 and 3. The patterns reported here alleviate concerns over unobserved low property quality and echo our earlier discussion that patient sellers prefer high sales prices and low commission rates. Accordingly, controlling for seller patience (column 4 onwards) offsets this upward bias and reduces the effect of low commission on the sale price to be statistically insignificant.

Our results indicate that offering high versus low commission rates has no statistically significant impact on the sale price, conditional on property attributes and seller patience. This is consistent with Hendel et al. (2009) and Levitt and Syverson (2008b) that also find no effect on the sale price.[18] While it is possible that sellers can pass through part of the one p.p. difference in commission rate, we do not detect an effect on the sale price.

Next, we present analyses that address two remaining identification threats. We focus on the sale probability. Our results are similar for the other two outcomes (days on market and sale prices).

4.2 Potential threats

4.2.1 Unobserved effort by listing agents

The findings above that listings offering low buying commission rates experience worse outcomes are consistent with buying agents steering buyers towards high commission listings. However, the worse outcomes can also reflect diminished effort from listing agents who receive less commission revenues from lower commission rates.[19] To address this issue, we first examine properties where listing agent effort is less likely to be crucial and then proxy for listing agents' effort directly. If the lack of listing agent effort drives the negative sales outcome, then we should expect a less negative estimate for these specifications.

We continue to find that properties that are relatively homogeneous and easy to sell suffer worse outcomes when they are listed at low commission rates, and the magnitude is remarkably similar to what we report above for the full sample. Sixty percent of properties in our data set was built before the

[18] While high commission listings attract more search activity, prices may not be bid up, consistent with survey evidence that the median home seller only receives one offer (Coldwell Banker, 2015).

[19] We do not observe commissions to listing agents. However, the commission rates offered to listing and buying agencies are usually the same (see Section 2)

1960s and the median age is 63 years. Restricting our sample to new properties that are built within five years, listings with low commission rates are 5 p.p. less likely to sell (column 1 of Table 4). In addition, the coefficient is the same for condominiums, which are more homogeneous than other property types (column 3 of Table C2).

Our results also survive listing agent fixed effects that flexibly control for the time-invariant quality of listing agents (column 2 of Table 4). This is a demanding exercise with 284,000 observations and more than 142,000 controls.[20] The effect of low commission rates on the sale probability is -3 p.p. and precisely estimated. The estimate is slightly weaker than our base case, which is likely driven by the attenuation bias exacerbated by the large number of fixed effects.

Our final strategy is to proxy for listing agents' effort using potential listing commission revenues. Assuming the buying and listing commission rates are the same, the listing commission revenue is the product of the observed commission rate and the list price. An agent is likely to exert the same effort in selling two properties that offer the same listing commission, for example, a \$500,000 property at 2% vs. a \$400,000 property at 2.5%. On the other hand, these two properties offering different buying commission rates might attract different numbers of buying agents and hence have different sales outcomes.[21]

To implement this idea, we create bins of listings that deliver similar commission revenues for a listing agent in a given year and property type. For example, one bin could be all condominiums that are listed by Mary Smith in 2000 that generate gross listing commission revenues that differ by at most \$500. Given that an agent typically keeps 60% of the gross commission revenues, the actual difference in the net commission revenues across different properties in the same bin is even smaller than the bin size. We restrict each bin to the same property type to limit the extent of property heterogeneity. Column 3 of Table 4 illustrates our result when we restrict the commission difference to a maximum of \$500. We have a total of 92,026 bins, accounting for 231,385 listings.[22] These bin fixed effects represent agent by property-type by year by bin-size fixed effects. Our coefficient is identified from 15% of the bins with within-bin variation of *RL25*. We include the same set of controls as those in column 2, with the exceptions of agent fixed effects and agent-year controls (which are absorbed by the bin fixed effects) and property fixed effects (since few properties are listed and sold more than once by the same listing agent within a year).

We find a similar negative impact of low commission rates on the sale probability when comparing listings offering different buying commission rates within the same bin (- 5 p.p.). Columns 4 and 5 repeat the same analysis, with wider bins: the maximum difference in the gross listing commission revenues is \$1000 and \$1500, respectively. The coefficient of *RL25* is stable across different bin sizes.

[20] We restrict our analysis to agents with average annual listings above 3. This drops 60,600 listings with the benefit of saving roughly 15,000 agent fixed effects. The 142,000 controls include agent fixed effects in addition to the full set of controls in column 6 of Table 3.

[21] For example, if a buyer is looking for a three-bedroom single-family that is worth \$500,000, her buying agent has an incentive to steer her to comparable properties at around the same price range but offer high commission rates 2.5%.

[22] Listings that cannot be grouped with others are excluded from this analysis. All bins have two or more listings.

We do not control for property fixed effects in columns 3 to 5 but unobserved property heterogeneity within a commission bin is unlikely to be an issue (observed property attributes are included in these analyses). First, note that even though we do not include property fixed effects, the goodness of fit is comparable to those with property fixed effects: the R-squared is 0.57 in column 3, versus 0.51 in the main specification (column 6 in Table 3). The bin fixed effects, as well as the remaining set of controls, appear adequate to explain the variation of sale probability at the property level. Second, if our effect is driven by unobserved attributes that make some property harder to sell, then our results should also be sensitive to the set of property controls. Replacing the full set of property controls with a limited set of eight attributes as those reported in Table 2 delivers virtually identical estimates (-0.05 for all three comission bins).

Our calculation of the listing commission revenue relies on the assumption that the commission split between the listing and buying agencies is 50/50. However, the findings are robust to measurement errors in the commission revenue. If the listing and buying commission rates are positively correlated, our measure of the commission revenue will be positively correlated with the true commission revenue received by the listing agent and should still proxy for listing agent effort. If they are negatively correlated, then properties with low buying commission rates have high listing commission rates and should elicit *more* effort from the listing agent. The higher effort levels cannot explain the worse outcomes that we find. We conclude that our results are not driven by unobserved listing agent effort.[23]

4.2.2 Seller preferences

Table 5 addresses the threat that differential sales outcomes could reflect heterogeneity in seller preferences. For example, the lower sale probabilities for low commission rates could be driven by downward biases from contrasting patient sellers (who choose to offer low commission rates and are less likely to sell) against impatient sellers.

First, we present evidence that our parameter estimates are stable across different proxies for seller types. Patient sellers are less urgent and are more likely to list at a high price and less likely to sell. For example, some sellers with no urgency to sell might "test" the market by listing at very high prices and withdrawing their listing if their reservation prices are not met. Our nine decile dummies in the main specification serve as fixed effects for different seller types. One concern is that the nine decile dummies are not adequate and there may be residual correlation between seller attributes and the low commission dummy. To assess this potential bias, we directly control for *ln(List price)* in place of the decile dummies in column 1. The list price proxies for the reservation price of a seller (Genesove and Mayer, 2001) and has been shown to affect bargaining and search behavior (Han and Strange, 2014). Next, we replace the decile dummies with percentile dummies, which constitute a finer set of patience controls. Reassuringly, we find similar results when we control for list price directly (-6 p.p.) and when we control for the

[23] Kickbacks are not reported in our data. If agents intermediating high commission properties are more likely to give side payments, the difference in commission revenues between high and low commission listings will be lower than reported here, which works against us and makes the negative consequences we find even more striking.

percentile dummies (-5 p.p.).

Third, we control for both time-varying seller attributes as well as seller fixed effects (columns 3 and 4). We obtain seller names by merging our MLS data with county records of housing transactions that include price, transaction date, address, and seller and buyer names. We restrict the analysis to 31,432 listings by sellers with multiple listings. There are 14,223 seller name fixed effects, and 29% of listings have within seller variation in *RL*25. Standard errors are clustered at the seller level.

The specification with seller fixed effects and seller patience controls delivers a similar effect on the sale probability (-7 p.p.) compared to the -5 p.p. effect we find above. This model is identified by comparing listings by the same seller offering different commission rates, conditional on time-varying seller patience and other regressors in column 6 of Table 3 (except property fixed effects). Consistent with the discussion above that unobserved property attributes are unlikely to drive our results, repeating columns 3 and 4 with a limited set of property controls delivers similar results (the coefficient is -7 p.p. and -8 p.p., respectively). Finally, since some common names might represent different sellers, we drop seller names that occur more than five times in column 4 and obtain a similar estimate.

Overall, our analyses provide compelling evidence that listings offering low commission rates experience adverse sales outcomes compared to high commission listings. We find that low commission rate listings are 5 p.p. less likely to sell, a sizable effect considering the sample average of 56% for repeat listings (and 65% for the full sample). In addition, conditional on a sale, low commission listings take 12% (8 days) longer to sell, but sell at comparable prices to those with high commission rates.

Compared to the existing literature, our analysis has several advantages. First, our sample is large with ample variation. Since the typical property only transacts every four years in our setting, a long panel has the benefit of having more properties and sellers with repeated listings and sales. We have 133,900 properties with 344,800 repeat listings and 62,800 properties with 137,100 repeat sales. Second, our controls have a high explanatory power: our preferred specification (column 6 in Table 3) has an R-squared of 51% for the probability of sale, 57% for days on market, and 99% for the sale price. Moreover, we control for all parties involved in listing a property: the listing office, listing agent, and seller. Third, about 35% of our listings offer low commission rates. Having a large sample of low commission listings also allows us to perform richer analyses of heterogeneous effects.

These patterns are remarkably consistent across a battery of robustness checks that are presented in Appendix C. We show that the estimates are stable across different samples (Table C2), different types of controls (Table C3), and are robust to a two-way clustering of standard errors (Table C4). We also address concerns of right censoring for the sold dummy (Table C5) and estimate the effect on probability of sale using probit instead of OLS (Table C6). We provide selection corrections for the effects on days on market (Table C7a) and the sales prices (Table C7b). Finally, we repeat the seller fixed effect regressions for an alternative sample with higher quality matches for seller names (Table C8).

5 Why do low commission listings experience adverse outcomes?

So far, our results demonstrate that worse outcomes for listings offering low commission rates are not driven by common property, seller, listing office, and listing agent confounders. Rather, they point to buying agents best responding to financial incentives in commission rates. Next, we provide further support to this argument by examining why listings offering low commission rates experience adverse outcomes. We first document heterogeneous effects on the probability of sale.[24] Then, we provide direct evidence that dominant offices have a lower propensity to purchase low commission rate listings.

5.1 Outcomes for properties more susceptible to steering

We first present a more disaggregated analysis with three groups of listings offering commission rates that are below 2.5 percent, exactly 2.5 percent, and above 2.5 percent, respectively, in column 1 of Table 6. Consistent with steering incentives being stronger for higher commission rates, we find a monotonic pattern of sale outcomes when commission rates vary from high to low. Compared with listings that offer more than 2.5 percent (the bulk of them being 3 percent), listings at exactly 2.5 percent are 3 p.p. less likely to sell while listings at less than 2.5 percent (the bulk of them being 2 percent) are 8 p.p. less likely to sell. These differences are statistically significant from each other and from the omitted group. Results for days on market are similar: compared with the default group, listings offering 2.5 percent take 9% longer to sell while listings below 2.5 percent take 20% longer to sell. Both these estimates are statistically different from each other.

We next demonstrate that low commission listings offered by independent entrants (new firms that do not belong to top six chains) suffer worse outcomes. Entrants have little market power, possess few contacts, and are more dependent on cooperation from other agents and brokerage offices to sell properties. Hence, they are more vulnerable to steering. In column 2, we extend our main specification with two additional regressors: a dummy if the listing office is an entrant not affiliated with the six dominant chains and its interaction with the low commission dummy.[25] The coefficient on the interaction term suggests that low commission listings by independent entrants are an extra 2 p.p. less likely to sell, in addition to the -5 p.p. direct effect of *RL25* for all low commission listings. This effect is unlikely to be driven by the worse quality of entrants because the direct effect of entrants is small and insignificant (-0.003, s.e. 0.01) and we maintain the same set of office controls as in Table 3. Additionally, we find even more negative consequences for low commission listings by these entrants during their first three years (-3 p.p. for the interaction term), when they have even less market presence than in later years.

We next examine low commission listings in neighborhoods with a large fraction of high commission listings. All else equal, it is conceivable that buying agents are less likely to visit low commission listings that are surrounded by similar properties with high commission rates.[26] The key variable of interest is

[24] We find similar patterns for effects on days on market.

[25] We define entrants as offices that first appear in our dataset in 1999 or later (the results are similar if we use 2000 or 2001).

[26] For example, an agent asks:"Why would I sell my buyer a home for half the commission when I can take them elsewhere?"

the interaction between the low commission rate dummy for listing i and the fraction of high commission listings in the same census block group and same listing year. We demean this fraction so that the coefficient for the low commission dummy reflects the effect for the average census block group-year. We include block group-year fixed effects but exclude property fixed effects.[27]

Our results confirm that low commission listings are harder to sell if they are surrounded by more high commission listings in the same year. The -0.03 coefficient of the interaction term in column 3 of Table 6 implies that a one standard deviation increase in the fraction of high commission listings nearby translates to a 1 p.p. decrease in the probability of sale (relative to the direct effect of - 5 p.p.). The estimate is stable whether we use a sparse or a full set of property controls, consistent with our discussion above that unobserved property attributes are unlikely to be a significant source of confounders. Column 4 shows that this effect is larger for condominiums, which are more homogeneous within a census block group. Thus, it is easier to steer buyers toward condominiums that pay higher commissions.

Our final heterogeneous analysis is motivated by accounts of traditional agents' retaliatory behavior against those who deviate from the norm and charge low commissions (column 5 of Table 6).[28] We implement this idea by investigating the dynamic consequences on offices that adopt a low commission pricing strategy in the past.[29] In column 5, we add a proxy for an office's past pricing strategy, which is a three-year cumulative fraction of low commission listings up to year $t-1$ for each office. It measures an office's propensity to list below 2.5 percent in the past three years. The -0.04 coefficient implies that a one standard deviation increase in the cumulative fraction in the past leads to a 2 p.p. decline in the sale likelihood today. The direct effect of $RL25$ remains similar, which is - 4 p.p. compared to - 5 p.p. in Table 3. This analysis includes small offices with few listings, whose past commission policy might be noisily measured. When we restrict the sample to listings by offices whose average annual listings is at least five, the result is almost identical.

Overall, these patterns consistently point towards worse outcomes for low commission listings that are more vulnerable to steering. Moreover, the findings in the last two columns echo our results above that low commission offices and entrants are less likely to grow (Figure 2 and Table C1).

(Svaldi, 2013).

[27] We augment equation (1) by keeping the direct effect of the low commission dummy for listing i in block group g in year t, $\beta_1 RL25_{igt}$, and adding an heterogeneous effect, $\rho_1 RL25_{igt} * frcRH25_{gt}$. Variable $frcRH25_{gt}$ is the fraction of listings in block group g and year t that have high commission rates, properly demeaned. The direct effect of $frcRH25_{gt}$ is absorbed by the block group-year fixed effect. We drop all block group-years that have fewer than 5 listings to avoid imprecision in $frcRH25_{gt}$ due to small samples.

[28] In a recent survey of agents, 50% of the 503 respondents agreed that some brokers do not compete on commissions because they fear retaliation (Inman News, 2014). Several lawsuits also allege different methods of retaliation against discount brokers charging low commissions, including "group boycotts" and "blacklisting" discount brokers, offering to pay discount brokers "punitive splits" instead of the standard 50/50 split (see Hawker (2006) for a discussion of court cases).

[29] This test is similar in spirit to Christie and Schultz (1994) which provides evidence that market makers of active NASDAQ stocks appear to be colluding by avoiding odd-eighth price quotes. However, we lack the high frequency transactions they have since properties only transact every four years in our data.

5.2 Dominant offices less likely to purchase low commission listings

Having documented negative consequences of low commission rate policies, we now describe the purchasing patterns of different brokerage offices.[30] As shown above, all offices and agents dislike low commission rate listings. In the analysis below, we ask whether dominant offices with greater market power are even less likely to purchase listings offering low commission rates. We estimate the following equation:

$$ln(FrcBL25_{lmt}) = \delta ln(Share_{lm,t-1}) + X_{lm,t-1}\beta + \mu_{mt} + \varepsilon_{lmt}, \quad (2)$$

where the dependent variable is log of the fraction of office l's purchases that have low commission rates in market m and year t. The key regressor $ln(Share_{lm,t-1})$ is log of office l's market share in market m and year $t-1$, which we use as a proxy for market dominance. An office's market share is its commission revenue from all of its sold listings in a market and year divided by the aggregate listing commission revenue in the same market and year. To mitigate potential confounding factors, we exclude buying commission revenues in the calculation of market share, since an office's buying commissions in the previous year are likely correlated with the dependent variable. Office attributes $X_{lm,t-1}$ are lagged one year and include office performance, agent composition, and age of the firm. All regressions control for market by year fixed effects μ_{mt}. To reduce measurement errors, we focus on active offices with an average annual number of listings above 5. As discussed in Section 3.3, these offices account for 95% of listings. Standard errors are clustered at the office level.

Dominant offices are less likely to purchase low commission rate listings (Table 7). The first specification with market by year fixed effects (column 1) suggests that doubling an office's market share reduces the fraction of low commission listings it purchases by 14%. This is almost a third of the sample average of 44%, a sizeable number considering the fact that the average market share for offices affiliated with top six dominant chains is 2.8 times larger than that for non top-chain offices.

In column 2, we show that the effect remains the same after adding controls for office quality. For example, it is possible that buyers of high commission listings prefer to work with high quality offices or high quality agents. We add office controls (lagged a year) to proxy for the past performance and agent composition of an office, including the fraction of listings that are sold, average days on market for sold listings, the fraction of agents who are the top ten percent highest performing agents, an entrant dummy and an interaction with the age of the firm, and a dummy for offices located in our cities.

Next, we address concerns that δ may be biased downwards if dominant offices tend to represent wealthy buyers who prefer properties listed at high commission rates. First, note that the observable differences in property attributes between listings offering high versus low commission rates are modest, as documented in Table 2. Nonetheless, we construct several variables to capture differences in offices' portfolios, including the average square footage, average number of bedrooms and bathrooms, average listing price, etc. (column 3). These averages are calculated using office l's listings in market m and year

[30] We use the word 'purchase' to refer to properties that offices intermediate on behalf of their buyers.

$t-1$.[31] The coefficient remains the same at -0.14.

Moreover, some chains may prefer high commission listings independent of their size. In column 4, we add 171 chain fixed effects to capture brand preferences (chains are constructed as described in Appendix A). Given that more than 90% of listings by Coldwell Banker and Hammond have high commission rates, it is not surprising that their coefficients are sizeable (-0.34 and -0.57, respectively), indicating a relatively strong preference for high commission listings. After controlling for fixed brand preferences, the estimate for δ is slightly weaker at -0.10 but still significant.

In the last column, we address concerns that the negative effect might be driven by office level policies that are correlated with market shares and purchase patterns. After adding office fixed effects, the magnitude is smaller (-0.04) but still significant.

Market shares vary widely in our sample. The average market share for offices that are not affiliated with the top six chains is 6%, while that for offices affiliated with the top six chains is 17%. At our most conservative estimate of an elasticity of 4% (column 5), a threefold increase in an office's market share would translate to a noticeable reduction in its fraction of purchases that go to low commission rate properties.

How does a dominant office's diminished propensity to purchase low commission properties relate to our main findings above? Our back-of-the-envelope calculation (details in Appendix D) suggests that the reduced purchase propensity from the six dominant chains could lead to a 2 p.p. reduction in the sale probability. This accounts for 40% of the negative consequence of low commission policies. While these calculations suffer from various caveats, they suggest a potentially important channel through which dominant offices could sustain the current commission structure.

Table 8 presents evidence that our findings are robust across different samples, different market share metrics, and different dependent variables. Columns 1 and 2 correspond to the last two columns in Table 7. The first three rows repeat the analysis using all offices (row 1), active offices with average annual listings equal to or above seven (row 2), as well as offices outside Boston (row 3). Our results are robust across these samples.

Next, we consider different market share metrics to proxy for market dominance. One concern with using commission revenues as the key regressor is that commissions could be affected by the dependent variable. In row 4, we show that the results are similar if we proxy for market shares using the number of listings instead of commission revenues. Another concern is that annual listing commission revenues can be volatile for some offices that only have a few listings a year. Our third measure of market dominance uses a three-year average listing commission revenue, again lagged one year. Across these different specifications, we continue to find that dominant offices are less likely to buy low commission properties, all else equal.

Finally, we explore other related behavior that may contribute to the negative effect. Sometimes listings are purchased by buying agents in the same office as the listing agents or are intermediated by

[31] We exclude office l's purchases in calculating these attributes to mitigate endogeneity concerns, although including them leads to almost identical estimates.

the same agent (dual-agency). We refer to both cases as in-house transactions (Han and Hong, 2016). If in-house transactions are more common in large offices with a big inventory of properties and more selections, and if large offices tend to charge higher commission rates, then the coefficient δ will be biased downwards by this network effect. We repeat our analysis excluding in-house transactions and find similar effects. Additionally, the estimates are identical if we further drop transactions between two brokerage offices within the same chain. Overall, our finding that dominant offices are less likely to purchase low commission listings is robust across a variety of robustness specifications.

6 Costs of low commissions

So far, our discussion has focused on the magnitude of the negative impacts of low commissions. Is it in a seller's interest to use a low commission rate?

A third of the listings in our sample do not sell. When this occurs, some sellers relist their property and attempt to sell again. To examine the length of the entire selling process, we group different listing attempts for the same property together and define cumulative days on market as the difference between the *first* listing date and the sold date (details in Appendix A7). This grouping affects 11% of the 137,100 sales in our estimation sample, or 14,700 properties that are sold in the second or third listing attempt.[32] Since risk averse sellers care about the magnitude at the tails in addition to the mean, we report the effect of the commission rate on the entire distribution of cumulative days on market. We focus on the commission rate when a property is listed for sale the first time because only 3,900 properties change commission rates during the course of a sale.

As expected, properties that are initially listed at a low commission rate are more likely to stay on the market for an extended period of time until they sell. Figure 3 plots the percent of sold listings whose cumulative days on market are 0 to 30 days, ..., 120 to 150 days, and 180 days or more. The impact of commission rates is most pronounced at the lower and upper tails of the distribution. At the lower tail, 38% of high commission listings sell within 30 days compared to 32% of low commission listings. At the upper tail, 14% of high commission listings take 180 days or longer to sell compared to 17% of low commission listings. This difference is driven by the fact that not selling a property the first time is costly, since missing the peak-season and selling during the off-peak season (winter time and during the school year) could lead to a much longer time on the market.

What is the cost of a typical home staying on the market for six months? At the 5.3% annual user cost of owning a property (Himmelberg et al., 2005), the six-month carrying cost for a $479,000 property would amount to $12,700, or 20% of the median annual household income of Massachusetts residents in 2010. This is likely a conservative estimate, as it ignores potential cash constraints sellers face or psychological costs a lengthy selling process imposes on sellers.

[32] For our core analysis in Table 3, a property that is taken off the MLS platform but listed again after 90 days is treated as a separate listing, following the rules of MLS. In this analysis, we group the same property's different listings within a year as one listing. For example, this will include properties listed in the summer and re-listed in the following spring.

Figure 3 does not control for property attributes. Using the same set of controls as in column 6 of Table 3, low commission properties are 4.8 p.p. less likely to have a quick sale (cumulative days on market less than 30 days), and are 5 p.p. more likely to stay on the market for six months or longer. On average, properties that list at low commission rates take 20 days longer to sell from their initial listing (Table C9).

Putting everything together, the negative consequences of paying a low commission rate include a 5 p.p. difference in the sale probability and, conditional on selling, a reduced likelihood of a quick sale, an increased probability of a lengthy selling process, and 20 more cumulative days on market. The trade-off is a saving of $4790 in commission fees (which is 1% of the average sale price of $479,000). If sellers are cash constrained and prefer a faster sale (because they rely on the sales proceeds from their existing home for the down-payment of their next house, or if they are risk averse, our calculations could help to rationalize their reluctance to list at low commission rates.

Finally, our finding is in line with the inter-temporal substitution patterns of home sellers in the literature. Genesove and Mayer (1997) report that sellers whose loan-to-value ratios are below 100% forgo a 4% gain in sale price in exchange for selling 70 days earlier, which is equivalent to trading off 1% in sale price against 18 days. Similarly, Hendel et al. (2009) find that FSBO sellers save $1625 (about 0.8% of the sale price) and their properties take 16 days longer to sell.

7 Conclusion

This paper demonstrates that listings offering buying agents low commission rates suffer worse sales outcomes, consistent with concerns that real estate agents face incentives to steer their buyers toward properties paying high commission rates. While on average all offices and agents prefer listings with higher commissions, firms with higher market shares buy a disproportionately smaller fraction of low commission listings. These negative consequences on sales outcome discourage sellers from listing their properties at low commissions. All of these considerations are likely to counteract competitive pricing pressures that are brought by technological innovation and entry of new firms and keep commission rates high. Our findings provide empirical support for regulators' long-standing concern of steering behavior contributing to the lack of variation in commission rates (GAO, 2005; FTC, 1983, 2007).

Compared to other industrialized countries, commission fees in the United States are high. For example, commission rates average less than 2% in the United Kingdom and the Netherlands, compared to the typical rates of 5% and 6% in the United States (Delcoure and Miller, 2002). Given the sheer size of aggregate housing transaction values, even modest reductions in commission fees could lead to a non-trivial reduction in transactions costs. Moreover, lower commission fees will likely limit excessive entry into the residential brokerage industry, translating into additional efficiency gains (Hsieh and Moretti, 2003; Barwick and Pathak, 2015). Finally, reduced agency conflicts could also give rise to better matches of buyers to properties.

Our findings are relevant for on-going debates regarding state laws that ban rebates or impose minimum service requirements, and suggest that such regulations could foster anti-competitive forces in the real estate brokerage industry. New developments in the spirit of encouraging competition include firms that provide rebates to buyers, as well as recent efforts to lift rebate bans and relax the minimum service requirements in several states (DOJ, 2015). Important directions for future work include incorporating commission rates paid to both listing and buying agents and assessing the welfare implications of alternative commission structures.

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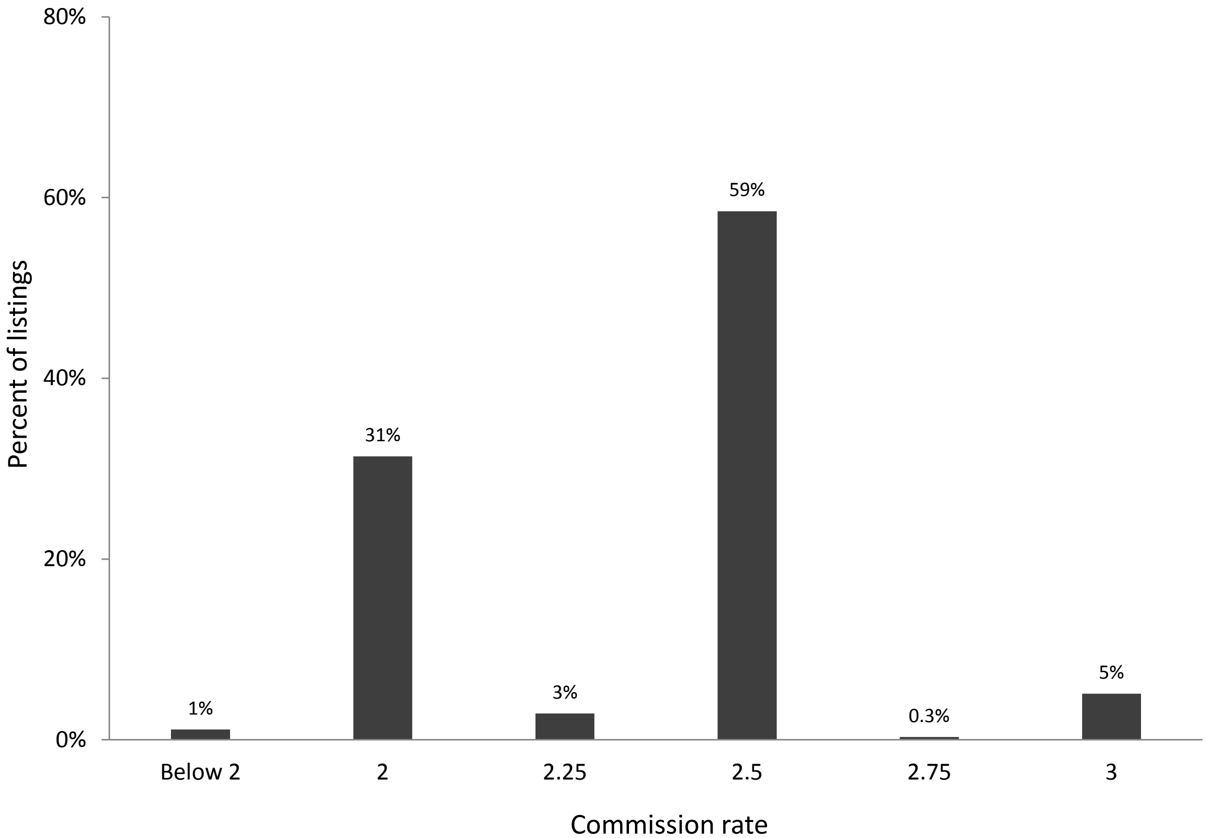
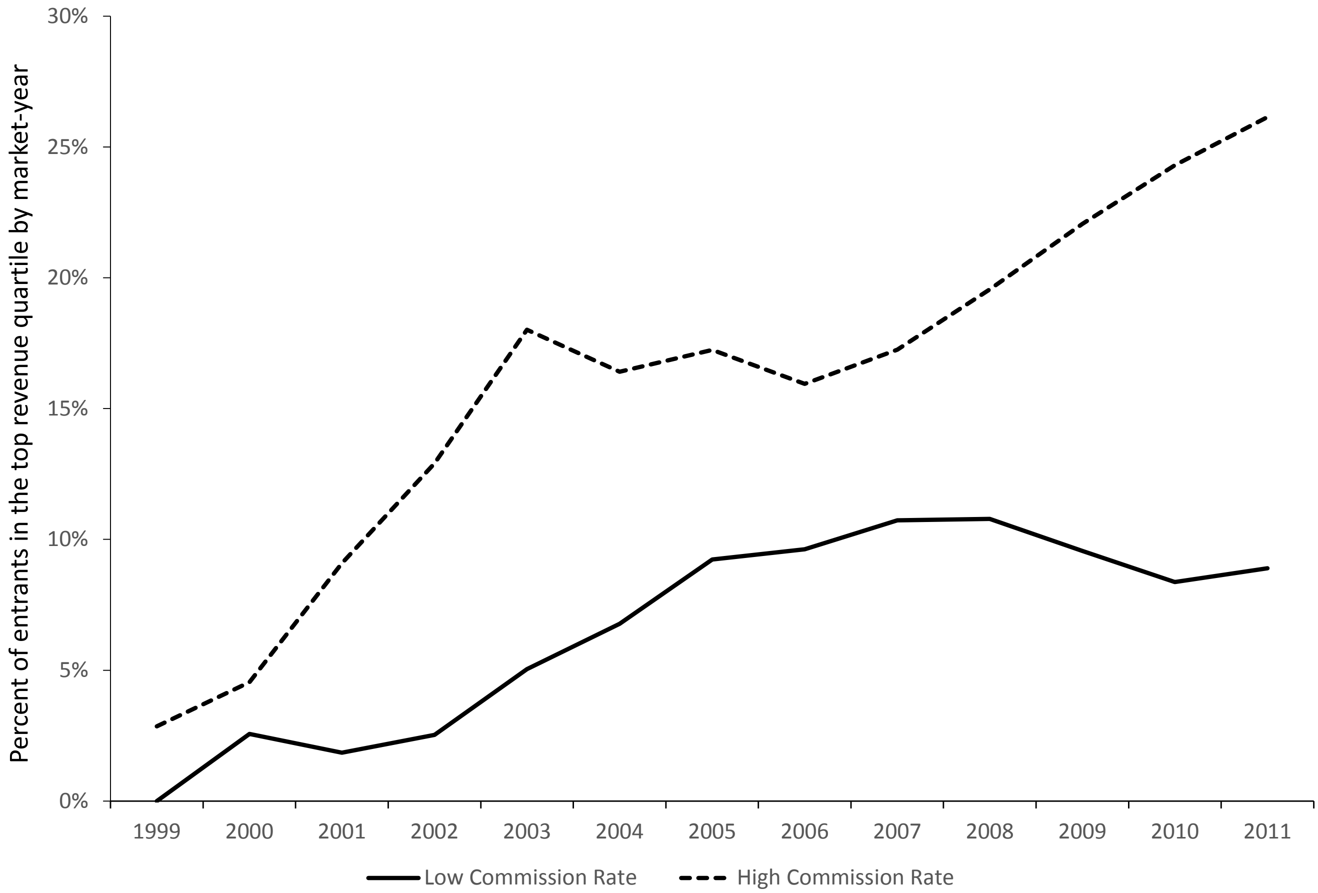
Figures

Figure 1: Distribution of commission rates



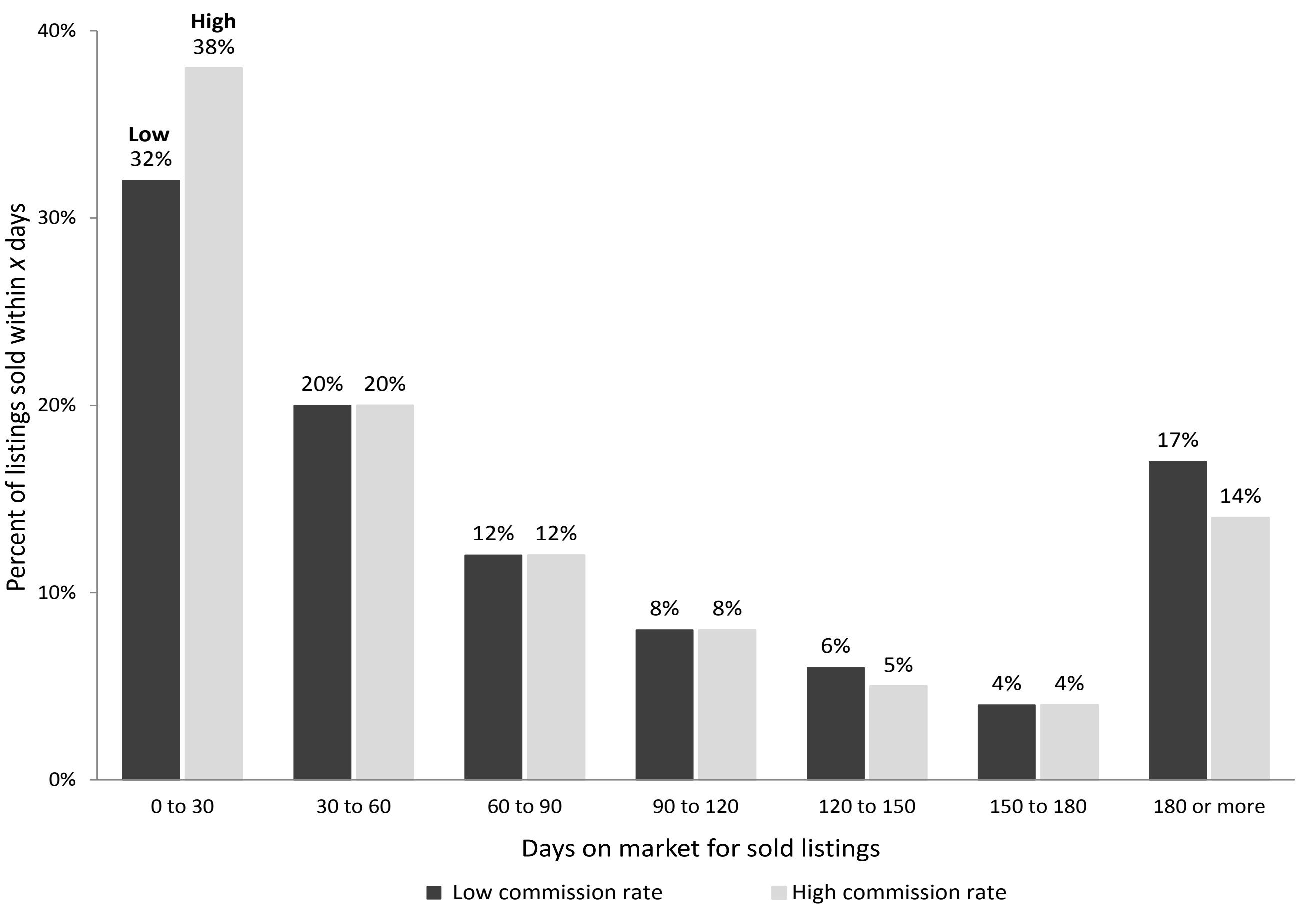
Notes: Distribution of commission rates offered to buyers' agents. The figure reports data for 99.3 percent of listings. The rest are scattered between 2 and 5 percent.

Figure 2: Growth paths for high and low commission entrants



Notes: Entrants are firms that first appear in our sample in 1999 or later. We classify entrants into the *high commission rate* group and *low commission rate* group using their commission rates in the first three years. Entrant *i* is in the *high commission rate* group (or *low commission rate* group) if its fraction of high commission listings in the first three years is in the top 25% (bottom 25%) among all entrants in the same market. An entrant's top-revenue-quartile status is defined using its listing commission revenue in a market and year against all offices in the same market-year.

Figure 3: Cumulative days on market for sold listings (initially high versus initially low commission rate)



Notes: The dark (light) grey bars correspond to properties that initially list at low (high) commission rates. Each bar represents the percent of listings sold within a 30-day bin, except the last pair of bars to the right that indicates the percent of listings sold in 180 days or more.

Tables

Table 1: Variation in low commission listings

	(1)	(2)	(3)	(4)
R-squared	0.32	0.63	0.44	0.72
Fraction of correct predictions	0.78	0.87	0.81	0.91
N	653475	344832	653475	653475
Market-year, month FE	Y	N	N	N
Property controls, property FE	N	Y	N	N
Office FE	N	N	Y	N
Office-year-market-property type FE	N	N	N	Y

Notes: This table reports results from listing-level OLS regressions where the dependent variable is 1 if the commission rate is strictly below 2.5%. Column 1 controls for 1228 market-year fixed effects and month fixed effects. Column 2 controls for 148 property controls and 133,902 property fixed effects. Column 3 controls for 7055 listing office fixed effects. Column 4 includes 178,291 office-year-market-property type fixed effects. The sample includes all listings, except for column 2 which has property fixed effects and is restricted to the sample of repeat listings only. To calculate the fraction of correct predictions, we first predict the dependent variable after estimating the OLS regression in each column. We then define $\hat{RL}25$ to be one if the predicted value is at least 0.5 and zero otherwise. Finally, we calculate the fraction of listings where $\hat{RL}25$ is equal to the observed low commission dummy.

Table 2: Observable differences between high and low commission listings

Dependent variable:	Mean	SD	Coefficient	p-value
	(1)	(2)	(3)	(4)
Square footage ('000s)	1.84	1.14	0.01***	[0.004]
Lot size (acres)	0.33	0.98	-0.10***	[0.000]
1(property is condominium)	0.35	0.48	-0.08***	[0.000]
1(property is single family)	0.52	0.50	-0.01***	[0.000]
Age of the property (years)	61.73	41.59	1.10***	[0.000]
Number of bedrooms	3.07	1.52	0.21***	[0.000]
Number of bathrooms	1.86	0.95	-0.07***	[0.000]
Number of other types of rooms	3.67	1.81	0.07***	[0.000]
Ln(List price)	5.20	3.88	-0.11***	[0.000]
Number of listings				**653,475**

* p<0.1, ** p<0.05, *** p<0.01

Notes: This table reports results from OLS regressions testing whether high versus low commission rate listings have similar attributes. Each row reports results from a regression where the dependent variable is a property attribute and the regressor is a dummy for the commission rate below 2.5%. Columns 1 to 2 report the mean and standard deviation, respectively. Column 3 reports the coefficient on the low commission rate dummy. Column 4 reports the p-value. The full sample includes 653,475 listings.

Table 3: Effect of a low commission rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Probability of sale						
Low commission listings	-0.09***	-0.07***	-0.09***	-0.06***	-0.05***	-0.05***	-0.08**
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.03)
N	653475	653475	344832	344832	344832	344832	344832
R-squared	0.08	0.10	0.46	0.51	0.51	0.51	0.51
	Panel B: Ln(Days on market)						
Low commission listings	0.13***	0.11***	0.14***	0.12***	0.12***	0.12***	0.33***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.12)
N	419116	419116	136624	136624	136624	136624	136624
R-squared	0.11	0.14	0.56	0.56	0.57	0.57	0.56
	Panel C: Ln(Sale price)						
Low commission listings	0.06***	0.01***	0.03***	-0.0006	0.0003	0.0003	-0.01
	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.01)
N	421329	421329	137085	137085	137085	137085	137085
R-squared	0.45	0.86	0.97	0.99	0.99	0.99	0.99
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	IV
Market-year FE, month FE	Y	Y	Y	Y	Y	Y	Y
Property controls	N	Y	Y	Y	Y	Y	Y
Property FE	N	N	Y	Y	Y	Y	Y
Seller patience	N	N	N	Y	Y	Y	Y
Office controls	N	N	N	N	Y	Y	Y
Agent controls	N	N	N	N	N	Y	Y

* p<0.1, ** p<0.05, *** p<0.01

Notes: Columns 1 to 6 of Panel A report OLS regressions at the listing level for the effect of low commission rate (a dummy that is 1 for commission rate below 2.5%) on the probability of sale (a dummy that is 1 if the listing is sold). The full estimation sample for columns 1 and 2 includes 653,475 listings. Column 1 has 1228 market by year and month fixed effects. Column 2 adds 148 property controls (see Appendix A8 for a full list of controls.). Column 3 adds 133,902 property fixed effects and restricts the sample to properties with repeat listings only. For seller patience (column 4), we first estimate a hedonic regression of *ln(List price)* on the full set of controls in column 6 (except the low commission rate dummy). We index sellers by the ratio of their observed list price to the predicted list price and create dummies for each decile of this ratio. These dummies constitute our seller patience controls. Columns 5 and 6 add controls for office and agent quality. Column 7 includes the same set of controls as in column 6, but uses an instrumental variable strategy. The instruments are the distances between the listing office and the nearest Century 21 and Coldwell Banker office in that year. Standard errors are clustered by market by year (columns 1-2) and by property (columns 3 to 7). Panel B repeats the analysis for log of days on market and restricts the estimation sample to sold properties (columns 1-2) and properties with repeat sales (columns 3 to 7, where we include 62,841 property fixed effects). We lose 2,207 sales with 0 days on market and 6 with negative days on market after taking logs. Panel C estimates the effect on sales prices.

Table 4: Robustness check, controlling for listing agent effort

Dependent variable:	Probability of sale				
	(1)	(2)	(3)	(4)	(5)
Specification	New Properties	Agent FE	$500 bins	$1000 bins	$1500 bins
Low commission listings	-0.05***	-0.03***	-0.05***	-0.04***	-0.04***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.005)
N	30036	284249	231385	302225	341608
R-squared	0.67	0.60	0.57	0.54	0.51
Market-year FE, month FE					
Property, office, seller controls	Y	Y	Y	Y	Y
Property FE	Y	Y	N	N	N
Agent controls	Y	Y	N	N	N
Agent FE	N	Y	N	N	N
Bin FE	N	N	Y	Y	Y

* p<0.1, ** p<0.05, *** p<0.01

Notes: OLS regressions at the listing level for the effect of low commission rates on the probability of sale, with different specifications to control for listing agent effort. Column 1 repeats the most saturated OLS specification in Panel A of Table 3 (column 6), but restricts the sample to new properties (built within 5 years). Column 2 repeats the same specification, but adds 8829 listing agent fixed effects and drops 60,583 listings by agents with average annual number of listings below 3. Column 3 groups listings that have the same listing agent, year, and property type, and offer commission fees within a $500 bin. Commission fee is calculated as the commission rate multiplied by the list price. This column excludes bins that have only 1 listing. Columns 4 and 5 are similar to column 3, but use $1000 and $1500 bins, respectively. We include 92026, 109414, 115550 bin fixed effects in columns 3 to 5, respectively (agent fixed effects and agent-year controls are absorbed by these bin fixed effects). Standard errors are clustered by property (columns 1-2) and bins (column 3 onwards).

Table 5: Robustness check, controlling for seller preferences

Dependent variable:	**Probability of sale**			
	(1)	(2)	(3)	(4)
Specification	List price	Finer patience controls	Seller name	No common names
Low commission listings	-0.06***	-0.05***	-0.07***	-0.07***
	(0.004)	(0.003)	(0.02)	(0.02)
N	344832	344832	31432	30144
R-squared	0.50	0.51	0.48	0.49
Market-year FE, month FE				
Property, agent, office controls	Y	Y	Y	Y
Property FE	Y	Y	N	N
Ln(List price)	Y	N	N	N
Seller patience	N	Y	Y	Y
Seller FE	N	N	Y	Y

* p<0.1, ** p<0.05, *** p<0.01

Notes: OLS regressions at the listing level for the effect of low commission rate on the probability of sale, with different specifications to control for seller preferences. Columns 1 and 2 are similar to the most saturated OLS specification in Panel A of Table 3 (column 6). Column 1 controls for $ln(List price)$ instead of seller patience deciles. Column 2 controls for seller patience using percentile dummies. Column 3 includes 14,223 seller fixed effects (defined using seller names). This specification restricts the sample to sellers with multiple listings and seller names that could be identified using the county records. Column 4 is similar to column 3, but drops common names (names that occurr more than 5 times in our data).

Table 6: Effect of a low commission rate on properties more susceptible to steering

Dependent variable:	Probability of sale				
	(1)	(2)	(3)	(4)	(5)
Listings offering less than 2.5 percent (RL25)	-0.08***	-0.05***	-0.05***	-0.06***	-0.04***
	(0.01)	(0.004)	(0.002)	(0.004)	(0.004)
Listings offering 2.5 percent	-0.03***				
	(0.01)				
RL25 × Independent entrant		-0.02***			
		(0.01)			
Independent entrant		-0.003			
		(0.005)			
RL25 × (Fraction of high comm. listings in a block group-year)			-0.03***	-0.04***	
			(0.01)	(0.01)	
Lagged three-year cumulative fraction of low comm. listings					-0.04***
					(0.01)
N	344832	344832	612210	213372	313421
R-squared	0.51	0.51	0.20	0.27	0.54
Month FE, property, seller, agent, and office controls	Y	Y	Y	Y	Y
Market-year FE	Y	Y	N	N	Y
Property FE	Y	Y	N	N	Y
Block group-year FE	N	N	Y	Y	N

* p<0.1, ** p<0.05, *** p<0.01

Notes: Similar to Panel A of Table 3, but examines heterogeneous effects on the probability of sale. Column 1 adds a dummy for listings offering exactly 2.5%, in addition to keeping the dummy for listings offering below 2.5% (the omitted group includes listings offering more than 2.5%). Column 2 adds a regressor that is 1 for independent entrants (offices that entered in 1999 or later and are not affiliated with the six dominant chains) and its interaction with *RL25*. Column 3 includes an interaction between the low commission rate dummy *RL25* and the fraction of listings in the same year and the same census block group that have high commission rates (de-meaned by the average of this fraction, so that the main estimate of *RL25* reflects the effect of low commission rates on the sale probability for the average block group-year). This specification includes 29,687 census block group by year fixed effects and drops property fixed effects and market by year fixed effects. We drop block group-years with fewer than 5 listings. Column 4 restricts the sample to condominiums only. Column 5 repeats column 6 of Panel A in Table 3, but adds the three-year cumulative fraction of low commission rate listings for the listing office, up to time $t-1$. We lose 31,411 listings when we include this lagged variable.

Table 7: Propensity of dominant offices to purchase low commission listings

Dependent variable:	**Ln(Fraction of purchases with low commission rate)**				
	(1)	(2)	(3)	(4)	(5)
ln(Shares), lagged 1 year	-0.14***	-0.14***	-0.14***	-0.10***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	10352	10352	10352	10352	10352
R-squared	0.65	0.66	0.66	0.69	0.81
Market-year FE	Y	Y	Y	Y	Y
Office controls	N	Y	Y	Y	Y
Portfolio controls	N	N	Y	Y	Y
Chain FE	N	N	N	Y	Y
Office FE	N	N	N	N	Y

* p<0.1, ** p<0.05, *** p<0.01

Notes: This table reports OLS regressions at the office-year level for the relationship between an office's lagged market share and the fraction of its purchases that are low commission rate listings. The dependent variable is ln(Fraction of purchases in an office-year that have low commission rates). The main regressor is the log of the one-year lagged market share of an office, defined using its listing commission revenues in a year. Each office is assigned to one primary market in each year. The sample includes all offices with five or more average annual number of listings. Office controls (lagged a year) include the fraction of listings that are sold, average days on market for sold listings, fraction of agents who are the top ten percent highest performing agents, an entrant dummy (1 if the office appears in 1999 or later), age of the firm interacted with the entrant dummy, and 1 if the office location is in our list of cities. Portfolio controls (lagged a year) include the fraction of listings that are condominiums, the fraction that are single family, average square footage, number of bedrooms, number of bathrooms, listing price, age of the property, averaged among an office's listings in a year. There are 171 chain fixed effects. The last column controls for 1852 office fixed effects. Standard errors are clustered at the office level.

Table 8: Robustness check, propensity to purchase low commission listings

	(1)	(2)
1. Sample: All offices	-0.12***	-0.03***
	(0.01)	(0.01)
2. Sample: If average annual listings≥7	-0.09***	-0.04***
	(0.01)	(0.01)
3. Sample: Not in Boston	-0.11***	-0.03**
	(0.01)	(0.01)
4. Market share: ln(Shares of listings)	-0.09***	-0.05***
	(0.01)	(0.01)
5. Market share: ln(Shares of three-year cumulative listing revenue)	-0.10***	-0.03**
	(0.01)	(0.01)
6. Dependent variable: ln(Fraction of purchases, no in-House)	-0.09***	-0.03***
	(0.01)	(0.01)

* p<0.1, ** p<0.05, *** p<0.01

Notes: This table reports robustness checks for Table 7. Columns 1 and 2 report robustness checks corresponding to the last two columns in Table 7, with chain fixed effects (column 1) and office fixed effects (column 2). The first three rows repeat the dominant office regressions using different samples of offices: all offices (row 1), offices with average annual listings equal or greater than 7 (row 2), and offices that are not in Boston (row 3). The next two rows keep the same set of offices (average annual listings equal or greater than 5) as in Table 7, but use different market share metrics. In row 4, we calculate market shares using the number of listings instead of the commission revenue from listings. In row 5, we calculate market shares using the three-year cumulative listing commission revenue. The last row drops all purchases that are in-house transactions. In-house transactions refer to those whose listing and buying agents work in the same office (they could be the same individual).

Online Appendix

Conflicts of Interest and Steering in Residential Brokerage

Panle Jia Barwick   Parag A. Pathak   Maisy Wong

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A Appendix: Sample and variable construction

A1 Housing transactions

We begin with 722,925 non-rental listings for condominiums, single-family, and multi-family properties. We first drop 52,226 duplicate listings, 221 listings with list or sale prices that are below $10,000, and 5,546 listings with problematic listing office codes. We then keep listings whose status is cancelled, expired, sold, or withdrawn (this removes 4,721 listings) and drop 4,377 listings with missing market information. We lose 1512 listings with 0 commission rates, 540 listings with missing commission rates, and 307 listings with buying commission rates greater than 5 percent (which implies a total commission rate greater than 10 percent). This leaves us with a final sample of 653,475 listings and 421,329 sold listings. We have geocoded street addresses and property identifiers for 646,460 listings. We are able to identify 133,903 properties that have repeat listings (for a total of 344,832 listings) and 62,843 properties with repeat sales (for a total of 137,085 sales).

A2 Offices

Each office is identified by an office ID. Two big chains (Coldwell Banker and Dewolfe) merged in 2002. Some offices changed office IDs as a result of this merger but kept the same office location. We recognize them as the same office and assign them a unique office ID. In addition, offices that use the same office location (e.g., 1000 Mass Ave, Fl 2, Cambridge, 02138) during the same time period are recognized as the same office and assigned a unique office ID.

We identify 172 chains, representing 486,189 listings (74%) and 316,571 purchases (75%). We first identify offices that have multiple locations and offices that have at least 100 listings and purchases. Within this group, we group offices that have similar names as chains. For example, all offices that have "Century 21" in the name are categorized under the Century 21 chain.

Many agents and offices have only a few transactions in our sample. We determine which offices and agents are active according to the *average annual number of transactions*, which is the total number of transactions divided by the number of years an office or agent spans our data (calculated as the last year the office or agent is in our data minus the first year, plus one). We use this average to identify active and top offices and agents. Our analyses focus on offices with five or more average annual number of listings and agents with two or more average annual number of listings. They account for 95% and 92% of listings, respectively.

In our office-year analyses (Table 7 and Table C1), each office is assigned a primary market in each year. We define a primary market by ranking the total number of listings and purchases by an office in a market in a year, followed by the total value of transactions. Ties are broken by the alphabetical order of market names.

A3 Defining markets

We have a total of 87 markets. Outside of Boston, markets are defined by cities and towns. We combine small markets with a nearby continguous market that account for the most cross-market listings by brokerage offices in these small markets. The combined markets include Cohasset-Hull, Avon-Holbrook, Lynn-Nahant, Sherborn-Natick, Topsfield-Middleton, Lincoln-Wayland, Concord-Carlisle, Danvers-Wenham, Stow-Acton, Dover-Wellesley, Millis-Medfield, and Handon-Rockland. We split the city of Boston into 15 sub-markets according to a GIS shapefile of Boston neighborhoods defined by Zillow. These sub-markets include Dorchester, Allston-Brighton, Back Bay-Beacon Hill, Charlestown, East Boston, Fenway-Kenmore, Jamaica Plain, Roslindale, Roxbury, West Roxbury, South Boston, South End, Central, Hyde Park, and Mattapan. A few thousand listings with missing cities or GIS location are assigned to a market using a variable called *area* in the MLS dataset. We end up with 87 markets from 84 cities outside Boston, less 12 small cities plus 15 neighborhoods in Boston.

A4 Sale outcomes

A listing is sold if its reported status is sold or under agreement. There are 2,649 sold listings with missing sales prices. We replace these missing values with their listing price. Listings and sales prices are winsorized at the top 1 percent. For sold properties, the days on market is measured by the difference between the listing date and the sold date.

A5 Distance instruments

We have two distance instruments: distance to the nearest Coldwell Banker office in each year and distance to the nearest Century 21 office in each year. We geocode office locations to obtain latitudes and longitudes. Eighteen Coldwell offices and ten Century 21 offices have missing latitudes and longitudes. We winsorize distances at the top percentile and replace missing distances with the median distance. The IV coefficients are similar if missing distances are not replaced with the median.

A6 Seller fixed effects

We obtain seller names for sold listings from county deed records up to 2008. We merge MLS and deeds data using property address, sale date (within 28 days), and sale price (within $10,000). We are able to fill in seller names for listings that are not merged by tracing the chain of ownership. We assume that when a property is sold, the buyer in that transaction becomes the seller of subsequent MLS listings of the same property, until the next change in ownership. Likewise, the seller of a property remains the same through different listings until the property is sold.

A7 Cumulative days on market

We define *cumulative days on market* by combining unsold listings for the same property into the same *marketing history*. For example, if we see a listing for a property on January 1st 2001 that was withdrawn on June 30th 2001, but re-listed on December 1st 2001 and sold on February 1st 2002, we combine these two listings and calculate the *cumulative days on market* as the difference between the initial listing date and the final date when the property is off the market (the cumulative days on market is $365+31=396$ days in this example). To belong to the same marketing history, listing dates have to be less than one year apart. Using the same example, if the property was also listed on January 1st 1998 and was withdrawn on June 30th 1998, we do not combine this 1998 listing with the 2001 listing.

A8 Full list of controls for transaction-level analyses

Property controls

-Square footage in thousands of square feet (0 to 40+)

-10 dummies for number of bedrooms, including a dummy for missing values

-14 dummies for number of bathrooms in half bath increments

-9 dummies for number of other types of rooms

-9 dummies for groups of years (6-10 years, 11-25 years, and so on up to 151+ years, plus a dummy for missing age values. The omitted group is 0 to 5 years

-1 if property type is multifamily, 0 otherwise. The omitted group is condominiums

-1 if property type is singlefamily, 0 otherwise. The omitted group is condominiums

-Lot size in acres

-Master bathrooms: 1 if yes, 0 if no

-Finished basement is included in sqft estimation

-1(Beach front), 1(Water front)

-Availability of adult community

-Basement: 1 if yes, 0 if no

-4 dummies: 0, 1, 2 or 3 fireplaces, 99 (missing)

-Entry only: Listing agent's only service is to enter property info into MLS

-Lender owned

-Seller disclosure

-Short sale with lender approval required

-Sub-agency relationship offered

-9 dummies for types of listing agreement, including Exclusive Right to Sell with Named Exclusion, Exclusive Agency, Exclusive Right To Sell With Variable Rate of Commission, Exclusive Right To Sell With Dual Rate of Commission, Facilitation/Exclusive Right To Sell, Facilitation/Exclusive, Facilitation/Exclusive Right To Sell With Variable Rate of Commission, Missing information

-14 dummies for different types of showing methods

-Dummies for the following phrases: Needs Updating, Estate Sale, Foreclosure, Handyman, As-Is, Needs Tlc, Rehabber'S, Bank-Owned, Priced For A Quick Sale, Motivated, Potential, Youthful, Close, !, New, Spacious, Elegance, Beautiful, Appealing, Renovated, Remodeled, Vintage, State-Of-The-Art, Maintained, Wonderful, Brandnew, Fantastic, Charming, Stunning, Amazing, Granite, Immaculate, Breathtaking, Neighborhood, Spectacular, Landscaped, Art Glass, Builtin, Tasteful, Must See, Fabulous, Leaded, Delightful, Move-In, Gourmet, Copper, Corian, Custom, Unique, Maple, Newer, Hurry, Pride, Clean, Quiet, Dream, Block, Huge, Deck, Mint, Stately, Priced To Sell

Listing office controls

-One year lagged fraction of listings sold in a year by an office

-Ln(number of active agents in the Office+1), lagged by one year

-Lagged fraction of agents who are in the top 10 percentile of average annual listings and purchases

-Top 4 office in a market, by average annual number of listings

-1(office has at least 2 entry-only listings or share of exclusive right to sell listings is less than 50%, by office-market). Under exclusive right-to-sell contracts, the listing broker acts as the representative of the seller, and the seller agrees to pay a commission to the listing broker, regardless of whether the property is sold through the efforts of the listing broker.

Listing agent controls

-Whether among top decile of all agents, by average number of listings

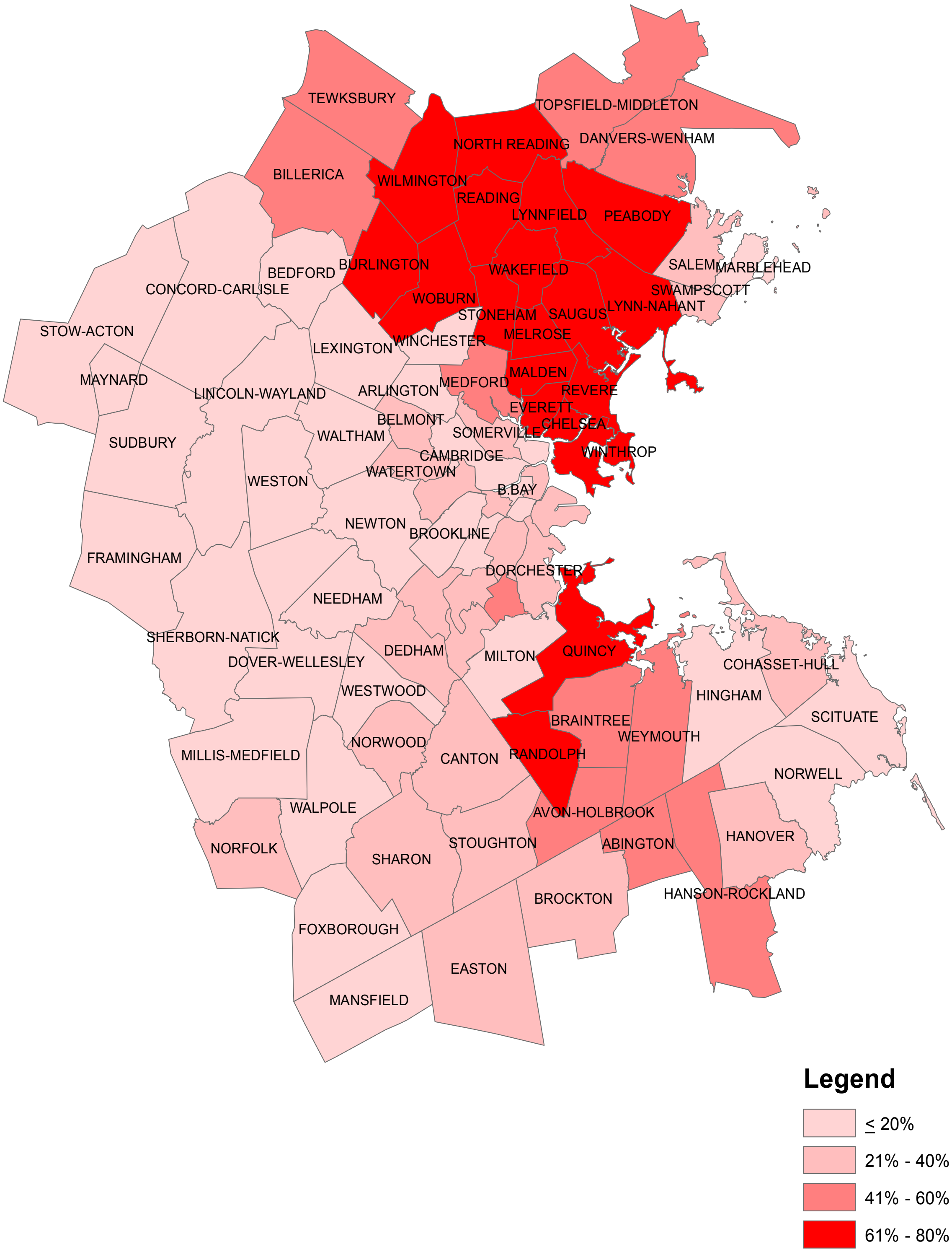
-Agent's average annual number of listings is at least the median amongst listing agents (the median is 2)

-Ln(Cumulative number of listings/purchases by a listing agent, up to the last year)

-Agent's experience in years

B Appendix: Figures

Figure B1: Percent of listings with low commission rates by market



Notes: Percent of listings in a market with commission rates below 2.5 percent.

C Appendix: Tables

C1 Growth paths for low and high commission firms

We refine the comparison in Figure 2 by controlling for firm attributes in the following regression:

$$1(TopRev_{lmt}) = \gamma frcRtL25_{lm,t-1} + X_{lm,t-1}\beta + \mu_{mt} + \varepsilon_{lmt}, \tag{3}$$

where $1(TopRev_{lmt})$ is 1 if office l's listing commission revenue is in the top quartile in market m and year t, X represents office controls and μ represents market-year fixed effects. The key regressor is $frcRtL25_{lmt}$, the fraction of office l's listings that is below 2.5 percent in the most recent three years $t-2$ to t. Results using a one-year window instead of a three-year window are similar but noisier because some entrants have few listings in a year. The one-year lag of $frcRtL25_{lmt}$ alleviates concerns that it might be jointly determined with the dependent variable. A two-year lag of $frcRtL25_{lmt}$ leads to similar results. Firms' top-quartile status tends to be persistent over time, thus we control for a one-year lagged top status in X (except in the specification with office fixed effects to avoid biases due to the correlation between the residual and the lagged dependent variable). Results without the lagged status are more pronounced.

Table C1 reports estimates of γ for entrants (Panel A) and all offices (Panel B). Column 1 includes market-year fixed effects. Column 2 adds office quality, including the fraction of listings that are sold, average days on market for sold listings, fraction of agents who are the top ten percent highest performing agents, log of the number of active agents, age of the firm in years. Column 3 controls for the composition of an office's listings by adding the fraction of listings that are condominiums, the fraction that are single family, the square footage, number of bedrooms, number of bathrooms, age of the property, and list price, averaged among an office's listings at time t. This mitigates concerns that the weak performance of low commission entrants is driven by their tendency to list properties that deliver lower commission revenues. Column 4 adds office fixed effects.

Across the columns, low commission entrants are significantly less likely to be top-revenue firms, even after adjusting for observable differences among them. Our specification with the most saturated set of controls and office fixed effects suggests that an entrant that specializes in low commissions ($frcRtL25 = 1$) in the past is 12 percentage points (p.p.) less likely to report top-quartile revenues than an entrant that specializes in high commissions ($frcRtL25 = 0$). This effect is considerable given that the mean of the dependent variable is only 17%. When we repeat the analysis using all offices in Panel B, we continue to find much weaker performance for low commission offices. Although not shown, our results are robust to using different measures of dominance (the number of listings, the number of listings and purchases, etc.) and different sample cuts.

Table C1: Effect of past commission policy on office success

Dependent variable:	Whether top quartile in market-year			
	(1)	(2)	(3)	(4)
Panel A: Entrants				
Low comm. offices	-0.08***	-0.06***	-0.05***	-0.12***
	(0.01)	(0.01)	(0.01)	(0.04)
N	6,294	6,294	6,294	6,294
R-squared	0.53	0.57	0.58	0.69
Panel B: All offices				
Low comm. offices	-0.08***	-0.05***	-0.05***	-0.10***
	(0.01)	(0.01)	(0.01)	(0.03)
N	13,255	13,255	13,255	13,255
R-squared	0.62	0.66	0.66	0.72
Market-year FE	Y	Y	Y	Y
Office controls	N	Y	Y	Y
Portfolio controls	N	N	Y	Y
Office FE	N	N	N	Y

* p<0.1, ** p<0.05, *** p<0.01

Notes: This table reports the effect of past commission rate policy on the probability of becoming a top quartile revenue firm, where *revenue* is total listing commission revenue, and *top quartile* is defined by market-year among all offices in that market. Firm *i*'s fraction of listings with a low commission rate at year *t*, *frcRtL25*, is the ratio of the total number of listings under 2.5% to total listings in year *t-2* to year *t*. We only keep firms whose average annual listing is at least five (these are active firms that represent 95% of listings) and firms with two or more firm-year observations. Panel A restricts to entrants, i.e., firms that first appear in our sample in 1999 or later. There are 902 market-year fixed effects in all columns and 1202 office fixed effects in the last column. Panel B uses all firms. There are 1131 market-year fixed effects and 1898 office fixed effects. Office controls and portfolio controls are lagged by a year. Standard errors are clustered at the office level.

C2 Robustness to heterogeneous samples

Table C2 shows that our estimates are stable across different samples. We repeat our main specification in column 6 of Table 3 for all three outcomes.

The results are similar for listings in Boston and listings outside Boston (columns 1 to 2), for condominiums, single-family houses and multi-family properties (columns 3 to 5). The last two columns divide the sample into high and low income markets using the median income in the city from the 2010 census (the results are similar if we use the median income in 2000 or the mean income in 2010).

Table C2: Robustness checks across different samples for all sales outcomes

	Boston	**not Boston**	**Condos**	**Houses**	**Multifamily**	**High Income**	**Low Income**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Probability of sale							
Low commmission listings	-0.05***	-0.05***	-0.06***	-0.05***	-0.05***	-0.05***	-0.05***
	(0.01)	(0.004)	(0.01)	(0.005)	(0.01)	(0.01)	(0.004)
N	58474	286358	105306	191059	48467	113306	231526
R-squared	0.52	0.51	0.53	0.51	0.53	0.52	0.51
Panel B: Ln(Days on market)							
Low commmission listings	0.14***	0.11***	0.09***	0.13***	0.16***	0.13***	0.12***
	(0.05)	(0.02)	(0.03)	(0.02)	(0.05)	(0.03)	(0.02)
N	18443	118181	38979	82196	15449	48809	87815
R-squared	0.57	0.57	0.59	0.58	0.59	0.58	0.56
Panel C: Ln(Sale price)							
Low commmission listings	0.0005	0.0003	0.0009	-0.0009	0.001	-0.0005	0.0001
	(0.003)	(0.001)	(0.002)	(0.001)	(0.004)	(0.002)	(0.001)
N	18548	118537	39197	82356	15532	48910	88175
R-squared	0.99	0.99	1.00	0.99	0.98	1.00	0.99
Controls in Table 3 column 6	Y	Y	Y	Y	Y	Y	Y

* p<0.1, ** p<0.05, *** p<0.01

Notes: The effect of low commission rates on all three outcomes, by sub-samples. The sub-samples are: Boston only (column 1), outside Boston (column 2), condominiums (column 3), single-family (column 4), multi-family (column 5), high and low income markets (columns 6 and 7, respectively, where cities are split using median income in 2010 from the census). Each column repeats column 6 in Table 3.

C3 Robustness checks using different controls

Table C3 explores robustness to different types of controls. We first explore whether the results change when we use different geographic units to control for market conditions. Column 1 replicates column 6 in Table 3, column 2 uses zipcode-year fixed effects instead of market-year fixed effects, and column 3 uses tract-year fixed effects. In column 4, we add office fixed effects to our main specification.

Table C3: Robustness checks using different controls

Dependent Variable:	**Probability of sale**			
	(1)	(2)	(3)	(4)
Low commission listings	-0.05***	-0.05***	-0.05***	-0.03***
	(0.003)	(0.003)	(0.004)	(0.004)
N	344832	344832	344832	326054
R-squared	0.51	0.52	0.53	0.54
Market-year FE	Y	N	N	Y
Zipcode-year FE	N	Y	N	N
Tract-year FE	N	N	Y	N
Office FE	N	N	N	Y

* p<0.1, ** p<0.05, *** p<0.01
Notes: Columns 1 to 3 replicate the main OLS specification in column 6 of Table 3 but with different set of controls for market conditions. Column 1 uses 1217 market-year fixed effects (same as Table 3), column 2 uses 3178 zipcode-year fixed effects, and column 3 uses 9030 tract-year fixed effects. Column 4 adds 2239 listing office fixed effects to our main OLS specification. This analysis only includes offices with average annual listings at or above 5 and drops 18,778 listings.

C4 Two-way clustering of standard errors

Table C4 shows that our main results are robust to a two-way clustering of standard errors by property and year (Cameron et al., 2011).

Table C4: Robustness to two-way clustering of standard errors

Dependent variable:	**Pr(Sold)**	**Ln(Days on market)**	**Ln(Sale price)**
	(1)	(2)	(3)
Low commission listings	-0.05***	0.12***	0.0003
	(0.005)	(0.01)	(0.0008)
N	344832	136624	137085
Controls in Table 3 column 6	Y	Y	Y

* p<0.1, ** p<0.05, *** p<0.01
Notes: Repeats column 6 of Table 3, but cluster standard errors by property and year.

C5 Robustness to right censoring for probability of sale

Here we address concerns that the probability of sale regression is affected by right censoring in the *sold* dummy (some listings in 2011 are sold after our sample period ends). We repeat our probability of sale analysis using whether a listing is sold within 30, 60, 90, and 180 days of the listing date as alternative dependent variables. We also experiment with dropping properties that are listed after 2009. Our conclusions are similar in all cases.

Table C5: Probability of sale within 30, 60, 90, 180 days

Dependent variable:	**Sold within:**			
	30 Days	60 Days	90 Days	180 Days
	(1)	(2)	(3)	(4)
Low commission listings	-0.03***	-0.05***	-0.06***	-0.06***
	(0.003)	(0.003)	(0.003)	(0.003)
N	344832	344832	344832	344832
R-squared	0.51	0.52	0.53	0.52

* p<0.1, ** p<0.05, *** p<0.01
Notes: The controls are the same as in column 6 of Panel A of Table 3. The dependent variable for each column is whether the listing is sold within 30 days, 60 days, 90 days, and 180 days, respectively.

C6 Robustness to probit for probability of sale

Next, Table C6 shows that our probability of sale results are robust to using probit instead of OLS. Our probit analysis resembles the OLS analysis in Panel A of Table 3, except we do not include property fixed effects and use all listings instead of repeat listings only. Our STATA program of probit with property fixed effects does not converge despite numerous attempts. Our most saturated probit specification in column 5 controls for market-year and month fixed effects, as well as the full set of 148 property controls, seller patience, office and agent controls.

Table C6: Effect of low commission on probability of sale using probit

Dependent variable:	**Probability of sale**				
	(1)	(2)	(3)	(4)	(5)
Low commission listings	-0.09***	-0.07***	-0.07***	-0.05***	-0.05***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
N	653475	653475	653475	653475	653475
Market-year FE, month FE	Y	Y	Y	Y	Y
Property controls	N	Y	Y	Y	Y
Seller patience	N	N	Y	Y	Y
Office controls	N	N	N	Y	Y
Agent controls	N	N	N	N	Y

* p<0.1, ** p<0.05, *** p<0.01

C7 Selection correction for sold listings

Table C7a and Table C7b repeat the analyses for the effects on days on market and sale price for sold listings, using selection correction methods to address the concern these two outcomes are unobserved for properties that do not sell.

Panel A implements the Heckman (1979) selection correction method. We first estimate a probit model with the sold dummy as the dependent variable and the full sample of 653,475 listings. Our controls for the probit estimation include market-year and month fixed effects, the full set of 148 property controls, seller patience, office and agent controls. We do not include property fixed effects. We then construct the inverse Mills ratio using our probit estimation and include it as a control in our sale price and days on market regressions.

Panel B controls for the selection bias non-parametrically using fixed effects to relax the distributional assumption that the error terms in the outcome and selection equations are jointly Normally distributed. We first estimate the same probit model and predict the probability of sale. We then create dummies for each decile of the predicted probability of sale and include these decile fixed effects in our outcome regressions. In both cases, the results are similar to those in Table 3.

Table C7a: Selection correction for effects on days on market

Dependent Variable:	**Ln(Days on Market)**					
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Inverse Mills Ratio					
Low commission listings	0.10***	0.10***	0.12***	0.12***	0.12***	0.12***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
N	419116	419116	136624	136624	136624	136624
R-squared	0.11	0.14	0.56	0.56	0.57	0.57
	Panel B: Decile bins for selection probability					
Low commission listings	0.10***	0.10***	0.12***	0.12***	0.12***	0.12***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
N	419116	419116	136624	136624	136624	136624
R-squared	0.12	0.14	0.56	0.57	0.57	0.57
Market-year FE, month FE	Y	Y	Y	Y	Y	Y
Property controls	N	Y	Y	Y	Y	Y
Property FE	N	N	Y	Y	Y	Y
Seller patience	N	N	N	Y	Y	Y
Office controls	N	N	N	N	Y	Y
Agent controls	N	N	N	N	N	Y

* p<0.1, ** p<0.05, *** p<0.01

Table C7b: Selection correction for effects on sale price

Dependent Variable:	Ln(Sale Price)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Inverse Mills Ratio					
Low commission listings	0.02***	-0.01***	0.003*	-0.0005	0.0003	0.0003
	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
N	421329	421329	137085	137085	137085	137085
R-squared	0.53	0.88	0.98	0.99	0.99	0.99
	Panel B: Decile bins for selection probability					
Low commission listings	0.02***	-0.01***	0.004**	-0.0004	0.0003	0.0003
	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
N	421329	421329	137085	137085	137085	137085
R-squared	0.53	0.88	0.98	0.99	0.99	0.99
Market-year FE, month FE	Y	Y	Y	Y	Y	Y
Property controls	N	Y	Y	Y	Y	Y
Property FE	N	N	Y	Y	Y	Y
Seller patience	N	N	N	Y	Y	Y
Office controls	N	N	N	N	Y	Y
Agent controls	N	N	N	N	N	Y

* p<0.1, ** p<0.05, *** p<0.01

C8 Regressions with seller fixed effects

Next, Table C8 repeats the seller fixed effect regressions, but drops properties listed after 2008. Our county deeds data with seller names end in 2008. The analysis in the paper with seller fixed effects (Table 5) includes listings from 2008 to 2011 for which we could trace the seller names. To address the concern that we might mismatch sellers to listings after 2008, we repeat the seller fixed effect analysis using only listings between 1998 and 2008. The results are similar to those reported in Table 5.

Table C8: Seller fixed effect regressions, 1998-2008

Dependent variable:	**Probability of sale**	
	(1)	(2)
Specification:	Seller name	No common names
Low commission listings	-0.07***	-0.07***
	(0.02)	(0.02)
N	30597	29333
R-squared	0.48	0.49
Controls in Table 5 column 3	Y	Y

* p<0.1, ** p<0.05, *** p<0.01

C9 The effect of commission rates on cumulative days on market

Table C9 investigates the distributional effect of low commission rate on cumulative days on market. The dependent variable is the cumulative days on market between the first listing date and the sold date. The key regressor is whether the initial listing for the entire marketing history is strictly below 2.5 percent. Column 1 replicates column 6 in Panel B of Table 3 using the cumulative days on market. Columns 2 to 7 report quantile regressions for the 25th, 50th, 75th, 90th, 95th, and 99th percentiles, respectively. The controls for the quantile regression are similar to those in column 6 of Table 3, except we use market fixed effects plus year fixed effects instead of market by year fixed effects and we drop property fixed effects.

Table C9: The effect of commission rate on cumulative days on market

Dependent variable:	**Cumulative days on market**						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Initially low commission	20.22***	2.71***	6.68***	13.21***	23.92***	29.78***	38.42***
	(1.58)	(0.19)	(0.36)	(0.72)	(1.33)	(1.96)	(5.00)
N	137081	417887	417887	417887	417887	417887	417887
Statistic	Mean	25th	50th	75th	90th	95th	99th

* p<0.1, ** p<0.05, *** p<0.01

Notes: This table reports results on *cumulative days on market* discussed in Section 6. Column 1 replicates our main OLS specification. We drop 4 repeat sales with outliers (days on market below -90 or above 1500 days). Standard errors are clustered at the property level. The quantile regressions in columns 2 to 7 use all sold listings (not just repeat sales), but drops the 9 outliers and 3,433 sales with missing property identifiers (we need property identifiers to cumulate days on market for each property).

D Appendix: Reduced number of buyers

This section explains the back-of-the-envelope calculation discussed in Section 5.2. We use the estimate in column 5 of Table 7 (-0.04) to calculate the reduction in the number of potential buyers visiting a low commission property as a result of large offices steering buyers to high commission properties. The six dominant chains account for 54% of buyers. The average market share for offices affiliated with these chains is 17%, which is 2.8 times bigger than that for non top-chain offices (6%). At an elasticity of 0.04, this translates to a 6 p.p. reduction (54%*2.8*.04) in the number of potential buyers visiting low commission properties.

According to NAR (2014b), a listing is visited by on average ten potential buyers. We make the simplifying assumptions that the matching event between a potential buyer and a seller is i.i.d. across individuals, and that the successful match rate is identical across properties and individuals. Suppose the probability that a listing matches with a potential buyer is x, then the probability that a listing is sold is 1 minus the probability that all of the ten potential matches fail, which is $1-(1-x)^{10}$. On average, 64.7% of all listings are sold, implying x is 9.9%.

From a base of ten potential buyers, a 6 p.p. reduction in the number of buyers lowers the likelihood of being sold to 62.5% (which is $1-(1-9.9\%)^{9.4}$). This accounts for about 40% of the 5 p.p. reduction in the sale probability that is documented in the paper. The magnitude is similar when the number of potential buyers is assumed to vary between five and twenty.