Heterogeneous Real Estate Agents and the Housing Cycle [*]

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Abstract

The real estate market is highly intermediated, with 90 percent of buyers and sellers hiring an agent to help them transact a house. However, low barriers to entry and fixed commission rates result in a market where inexperienced intermediaries have a large market share, especially following house price booms. Using rich micro-level data on 8.5 million listings and an instrumental variables strategy, we first show that houses listed for sale by inexperienced real estate agents have a lower probability of selling, and this effect is strongest during the housing bust. We then study the aggregate implications of the distribution of agents' experience on housing market liquidity by building a dynamic entry and exit model of real estate agents with aggregate shocks. Several policies that raise the barriers to entry for agents are considered: 1) lower commission rates, 2) increased entry costs, and 3) more informed clients. Relative to the baseline, all three policies lead to an increase in average liquidity, with the largest effect during the bust.

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1 Introduction

The U.S. housing market is subject to strong boom-bust cycles. The collapse prior to the Great Recession provides a particularly severe illustration: from 2006 to 2008, house prices dropped by 18 percent. What is less known is that the drop in price was accompanied by an even larger fall in liquidity: the probability of a house selling within a year of listing fell by 28 percent from 66% in 2005 to 47% in 2008.[1] This paper focuses on the role of intermediaries, a prominent feature in this market, in this liquidity collapse. Real estate agents are central to the matching process between buyers and sellers – 88% of home buyers and 89% of home sellers use an agent (National Association of Realtors, 2017b) – but low barriers to entry and fixed commission rates result in a market where inexperienced intermediaries have a large market share, especially following house price booms.

Using micro-level empirical evidence and a dynamic model of entry and exit, we show that listings of inexperienced agents are less likely to sell than those of experienced agents, and that the ubiquity of these inexperienced agents has aggregate implications for the average sale probability of listed properties, which we call housing market liquidity. Moreover, these effects are amplified in the downturns that follow housing booms. Downturns are particularly affected for two reasons: first, the disadvantage of inexperienced agents in selling listings is nearly double during housing busts. Second, the distribution of experience is skewed towards low experience agents. This happens because the housing boom preceding the downturn attracts new agents into the profession, intensifying competition for clients and hindering the accumulation of experience. Many of these new agents remain during the onset of the downturn, capturing a sizeable market share of listings.

We begin by documenting two empirical facts using a rich micro-level dataset of 8.5 million transactions over the 2001–2014 period on 60 different Multiple Listing Service (MLS) platforms. First, an agent's work experience is highly predictive of how successfully and quickly they can sell homes. All else equal, listings with agents in the 10th percentile of experience sell with a 10 percentage point (pp) lower probability than those listed by agents in the 90th percentile. Second, this difference varies significantly over the housing cycle, ranging from 8.2 pps in the boom to 12 pps in the bust. When compared to the respective average sale probability of 69.1 and 50.1 percent in those periods, the effects correspond to a 11.9 percent and 24.0 percent advantage in liquidity.

[1] Source: authors' calculations using the S&P/Case-Shiller U.S. National Home Price Index and CoreLogic Multiple Listing Service database.

A key challenge in this empirical exercise is the lack of random assignment between listings and agents. As a result, two types of selection bias could confound our results: selection on property (or listing) characteristics and selection on listing client characteristics. For example, a more experienced agent might select to work with easier-to-sell properties or more motivated clients. To partially address these concerns, we control for a rich set of housing characteristics as well as zip-code-by-list-year-month fixed effects, and we present subsample analyses where those selection effects are less likely to be a concern.

Our main solution to selection uses an instrumental variables (IV) strategy. This approach exploits two features of the market: 1) homeowners tend to list their home with the same agent that helped them buy the home; and 2) homeowners whose buyer agents have exited tend to draw a new listing agent with experience that is representative of the overall pool of agents. This first feature – stickiness – means that initial buyer agent experience is highly predictive of subsequent listing agent experience. The second feature – regression-to-the-mean – means that the average experience of listing agents for sellers whose buyer agent has exited the market tends to be the same, irrespective of the (exited) buyer agent's experience. Both of these features on their own may face the selection issues, so we control for the direct effect of each and exploit the combination of the two channels.[2] Our instrument is highly predictive of listing agent experience and the resulting estimates from this IV strategy are comparable with our OLS estimates.

We also show the consequences of experience beyond the sale probability of the initial listing. During the housing bust, the ability to quickly sell a home was crucial for homeowners who had difficulty making their mortgage payments. Those who fell delinquent on their mortgages and failed to sell were forced into foreclosure. Listed homes that failed to sell in 2008 had a 5.5 percent chance of going into foreclosure in the next two years as compared to close to zero percent for sold properties. Highlighting the importance of experience in real estate agents, we find that houses that listed in the bust years with inexperienced agents are 0.9 pps more likely to subsequently foreclose (30 percent of the average probability of subsequent foreclosure during that period) compared to those listed with experienced agents. Thus, not only did the inexperienced agents affect individual sale outcomes, but they also contributed to negative externalities on the neighboring properties through the foreclosure channel.[3]

The experience effect on the probability of sale could be a combination of several mechanisms. One salient mechanism is strategic pricing. Since, ceterus paribus, properties with lower list prices are more likely to sell, if experienced agents list properties with lower list prices, they will then have higher listing liquidity. Using

[2] This empirical approach is similar to Abaluck et al. (2020).

[3] A body of papers have documented the externalities imposed by foreclosures on local housing markets, including Lin, Rosenblatt, and Yao (2009), Campbell, Giglio, and Pathak (2011), Mian, Sufi, and Trebbi (2015), and Gupta (2016).

repeat sales data, we show that on average, more experienced agents do list properties for lower list prices, leading to slightly lower sale prices. However, the difference in markup on a similar property is very small relative to the overall effect of experience on the probability of sale. Using a back-of-the-envelope calculation, we estimate that the price channel makes up roughly 20 percent of the overall impact of experience on listing liquidity. Hence, in our theoretical model, we focus on the overall effect and do not to distinguish between the mechanisms affecting the experience advantage.

In the second half of the paper, we use a dynamic structural model to assess policy interventions that improve aggregate housing liquidity through the real estate agent channel. A structural model allows us to endogenize the experience distribution arising from the entry and exit decisions of real estate agents, as well as the equilibrium accumulation of experience. The model embeds housing search in a dynamic labor market framework of real estate agents with aggregate market fluctuations. Consistent with our empirical findings, entry and exit decisions are affected by house prices, volume of listings, and the market tightness. In addition, agents' decisions respond to costs of entry, commission structure and their individual experience advantage in the market. We consider policies that change agents' incentives to enter and exit, resulting in a shift of the equilibrium distribution of experience towards more experienced agents, thus improving overall market liquidity.

The model features frictional search in the housing market, where agent earnings depend on their experience. Experience has three advantages. First, agents with higher experience work with more clients. We assume that some buyers and sellers look for an agent at random, while the rest seek a recommendation. This implies that each agent is approached by a number of clients (sellers and buyers) that is an increasing function of experience. Second, experienced agents have access to a more efficient matching technology for their seller clients and thus have a higher probability of finding them a buyer and of earning a commission. Finally, the model assumes that agents with higher experience get to keep a higher portion of their commission when splitting it with the office where they work in. While we do not explicitly model offices, the commission splits are important for agents' pay, so we assume that only a fraction of the earnings is retained by each agent.

We then embed the matching market of housing into an entry and exit model of real estate agents with aggregate market fluctuations. Our setup includes three aggregate states: bust, boom, and medium. Each state corresponds to the number of sellers willing to sell their house as well as the valuation for houses by the buyers. Agents' decisions to participate as intermediaries depend on aggregate market conditions, competition they face for clients, their success in earning commissions, and the value of accumulating experience and remaining in the industry in the future years. These features generate empirically realistic fluctuations in the overall entry and exit patterns of agents.

The distribution of agent experience depends on the entire history of aggregate state realizations and is a payoff-relevant variable on which real estate agents base exit and entry decisions. Keeping track of the full distribution of experience effectively makes the state space infinite. To address this, we adopt an oblivious equilibrium concept, introduced in Weintraub, Benkard, and Van Roy (2010). In this equilibrium, agents do not perfectly observe the entire distribution of experience but instead approximate it by conditioning the experience distribution on the aggregate state in the current and previous period.

Using this dynamic model calibrated to our empirical moments, we consider the impact of three counterfactual policies: reducing commission rates, increasing entry costs, and informing clients of the importance of experience. Relative to the baseline, three policies — doubling entry costs, halving commission rates, and decreasing the share of uninformed clients who look for an agent at random — all lead to a three percent increase in average liquidity, with the largest effect of nearly four percent during the bust and a smaller two percent increase during the boom. However, each policy acts through different channels.

While the three policies have comparable effects on aggregate liquidity, they have different effects on seller valuations and on the level of employment of real estate agents. Reduction in commission rates has the largest positive effect on seller valuations, while decreasing the share of clients who look for an agent at random has the smallest negative impact on the level of employment. Interestingly, doubling entry costs is less effective along both margins but may be the policy that is most straightforward to implement, for example, by raising licensing fees. This would also allow states to collect additional revenues and may be the most politically expedient.

This paper contributes to a literature applying search-and-matching framework to models of housing to understand aggregate housing market fluctuations (Head, Lloyd-Ellis, and Sun, 2014; Ngai and Tenreyro, 2014; Anenberg, 2016; Guren, 2018). Our key contribution relative to this literature is to incorporate the heterogeneity in match technology due to real estate agents' differential experience. This builds upon a large literature, summarized in Han and Strange (2015), which studies the role of real estate agents in search models.[4]

Our paper most closely relates to Barwick and Pathak (2015), who study data from the Greater Boston area for years 1998–2007 and examine inefficiencies associated with cheap entry of real estate agents. An important distinction of our paper is that our data cover 60 different markets across the US and extends through 2014, allowing us to explore the recent housing bust in a setting that is not specific to one area. We also bring a unique identification strategy to solve issues of selection, and identify the effect of experience on

[4] Buchak et al. (2020) also study the importance of intermediaries in housing liquidity, but focus on the role of the new emerging "iBuyers" who provide a source of liquidity for sellers.

subsequent foreclosure. Hsieh and Moretti (2003) and Han and Hong (2011) also study the effect of cheap entry on market efficiency, specifically focusing on the business-stealing externality and abstracting from experience all together.

More broadly, this paper contributes to a literature on the value of real estate agents. Hendel, Nevo, and Ortalo-Magné (2009) compare listing outcomes from an FSBO (for sale by owner) platform to those who were facilitated by an agent. They find that agents provide little value added. Levitt and Syverson (2008) find that agents can obtain a better price when they are selling their own homes rather than those of their clients. These papers abstract from agent heterogeneity, which has a significant impact on home sales.

This paper also connects to a macrofinance literature studying the significance of expectations, financial conditions, and other frictions in generating and amplifying the housing cycle (see Davis and Van Nieuwerburgh (2015) and Guerrieri and Uhlig (2016) for literature review on financial frictions and the housing cycle). While the aggregate movements in the housing cycle play an important role in our empirical and theoretical analysis, we take the overall aggregate movements in liquidity across the boom and bust as given, and instead focus on the relative contribution of intermediaries to market liquidity within each period.

The rest of the paper is structured as follows. Section 2 describes industry background. Section 3 describes data and our choice of measure of experience. In Section 4, we present the empirical analysis. Section 5 outlines the model and the calibration exercise. Section 6 presents results from the counterfactual analysis. We conclude in Section 7.

2 Real estate agents in the United States

Despite the existence of numerous FSBO platforms, the housing market in the US remains highly intermediated, with 87 percent of buyers and 89 percent of sellers hiring an agent to facilitate buying or selling a home (National Association of Realtors, 2017b). There are many reasons why consumers find agents valuable. First, an agent has access to the local MLS database, which provides detailed information on all the listings currently available in the area and allows sellers to advertise to potential buyers.[5] Second, an agent plays an invaluable role as an adviser. For example, a listing agent suggests improvements, or “staging,” to make the property more attractive to buyers, provides input on an appropriate listing price, and advises on whether to accept the incoming offers. Last, an agent gives a client representation in a negotiation process in the final stages of the transaction, making an agreement with the counterparty more likely. Through these three channels, hiring an agent gives access to a more efficient matching technology between home buyers and sellers. Thus, a listing

[5] The creation of web platforms such as Zillow and RedFin has reduced agents’ monopoly over the information on available listings, but agents maintain the exclusive ability to list on the MLS to advertise for-sale properties to other agents.

agent not only attracts more buyers to the listing but also makes buyers more likely to bid on the property and facilitates the transaction once a buyer is found.

Despite the important role of real estate agents, the costs to enter the profession are as low as 30 hours of classes and nominal exam and licensing fees.[6] While these classes familiarize agents with essential terminology and state laws, they provide little insight into local real estate markets or into the most effective ways to create transactions. Hence, agents have a substantial room for improvement after entry. In addition to learning about the local housing market and the tacit knowledge of selling, agents accrue an accumulated network of former clients, other agents, and a long list of useful professionals, such as construction workers, plumbers, electricians, mortgage brokers, appraisers, photographers, and interior designers. Tapping into these networks makes a sale more likely by increasing the number of potential counterparties for their clients and by ensuring that the property is "fixed up" and is more desirable for a buyer. Hence, the inexperience of brand-new agents will likely make them worse at getting properties sold when compared to incumbent experienced agents. This is a key empirical issue that we assess in Section 4.

While there are potentially large differences in the experience of agents, the compensation paid by buyers and sellers to real estate agents does not appear to vary across agents. As highlighted in other work studying agents, commissions in the market appear to be relatively fixed across agents, regardless of agent quality (Hsieh and Moretti, 2003; Barwick and Pathak, 2015; Barwick, Pathak, and Wong, 2017; Barwick and Wong, 2019). The ease of entry and fixed pricing results in many agents entering the industry for short periods of time.

Despite being paid the same commissions as experienced agents, inexperienced agents appear able to attract clients. In 2017, the National Association of Realtors (NAR) found that 74 percent of sellers and 70 percent of buyers signed a contract with the first agent they interviewed (National Association of Realtors, 2017b). While the first agent contacted is not always chosen at random, the survey indicates that clients do not approach the choice decision with much care. One reason may be that clients do not realize the importance of choosing the right agent or find it difficult to gauge experience. Alternatively, with so many people in the profession, many clients personally know someone who is a licensed agent and hire them to avoid social consequences. As a result, as we show below in Section 3, these inexperienced agents have a non-negligible share of the market.

It is not just clients who are affected by the prevalence of new and inexperienced agents. The industry has raised alarms about this phenomenon. In 2015, real estate agents identified the number one challenge to their industry to be "Masses of Marginal Agents Destroy Reputation" in a report commissioned by the NAR: "[t]he

[6]The requirements vary somewhat across states, with class time ranging from 30–90 hours, the exam fees from $25-$150, and the cost of a license from $50-$300.

real estate industry is saddled with a large number of part-time, untrained, unethical, and/or incompetent agents. This knowledge gap threatens the credibility of the industry." In another report commissioned by *Inman*, an industry periodical, 77 percent of agents responded "low-quality agents" to the question "what are the challenges that the real estate industry is currently facing?"[7]

There are three channels through which agents might be affected by the widespread presence of inexperienced competitors. First, the inexperienced competitors may be less effective at matching their clients, thus lowering the expectation of the value of intermediaries by potential home buyers and sellers. This can discourage clients from buying and selling homes. Second, as described in Hsieh and Moretti (2003), the ease of entry results in an excessive amount of real estate agents in the industry, which results in any one agent working with fewer clients, thus lowering their total profits. Finally, with the intensified competition, agents focus a large amount of their time attracting clients rather than directly working with buyers and sellers. As a result, they cannot accumulate the relevant experience to become better at matching their clients. This is a second form of "crowding" out: in addition to social waste from agents spending resources to take business from one another, as described in Hsieh and Moretti (2003), agents also take from each other the ability to improve their matching technology by accumulating experience.

3 Data and measurement

In this section, we describe our data sources and the various sample restrictions that we use. We then discuss how we measure real estate agent experience and summarize our measure.

3.1 Data sources

For our main empirical analysis, we use a comprehensive listing-level dataset on residential properties for sale collected by CoreLogic. The data come from MLS platforms operated by regional real estate boards. Each MLS varies in size but, on average, covers a geographical area that is approximately equal to a commuting zone. Each observation in the data represents a listing on an MLS platform, with a large number of variables describing the property and the status of the listing. These include the date the property is listed, the associated listing agent (as well as secondary agent in some cases), the original list price, the last observed list price, and detailed property characteristics such as the living area, number of bedrooms and bathrooms, number of parking spaces, and age of the structure. If the listing sells, we observe the date of sale, the sale price, and the associated buyer

[7]A relevant respondent quote in the *Inman* report: "A great many agents are part-time. Other than the few transactions they finagle out of their family/ friends yearly they have very little to do with the industry and don't care to educate themselves or increase their skills. This is a disservice to their clients and gives real estate professionals a bad name." For more information about the Danger Report commissioned by the NAR, see their website: https://www.dangerreport.com/usa/. The *Inman* report is available here: https://www.inman.com/2015/08/13/special-report-why-and-how-real-estate-needs-to-clean-house/.

agent. If the property fails to sell, we also observe when the property is pulled from the market. Crucial for our analysis is that each real estate agent in an MLS is given a unique identifier such that we can track them throughout the sample.

The full CoreLogic MLS dataset has information on over 150 MLS platforms. However, the history for each MLS in this dataset begins at different times due to variation in CoreLogic's contracts with each MLS, with some data beginning as late as 2009. Since we are interested in studying the boom period starting in 2001, we restrict our analysis to the subsample of MLS whose data begin in 2001. Additionally, due to data quality issues, we drop several MLS whose data begins in 2001 or earlier but have large jumps in the number of listings during the sample period from 2001–2014 (more than 100 percent growth in the number of listings in a given year). This final restriction drops an additional 10 MLS and leaves 60 MLS platforms in our sample. Within these MLS, we exclude listings with asking prices below $1,000. Finally, we focus on real estate agents who do no more than 200 transactions a year to avoid potential measurement error in agent identifiers. This leaves us with 8.5 million observations. Appendix Figure H1 shows the coverage map of the final sample. A key feature of our dataset is that while we do not have full coverage of the United States, we have near-exhaustive coverage *within* a geographic location, ensuring that we observe all potential transactions by real estate agents in an area. Over the sample period from 2001 to 2013, we observe 569,282 different agents, with an average of 183,665 active agents in each year.

In addition to the MLS data, our robustness analysis makes use of two additional datasets. First, we use proprietary deed-level data purchased from CoreLogic, which contain information on housing transactions and their associated transaction prices recorded at county deeds offices. Using this data allows us to supplement our analysis in two ways: first, we identify properties that subsequently fall into foreclosure. Second, we identify the price that a listing was previously transacted at, which gives us a way to control for unobserved heterogeneity of properties.

Our second dataset is Zillow's publicly available zip-code-level house price index. We use this time series to construct a measure of "inferred price" for listings of previously transacted properties. To do so, we take the listed properties' previously transacted price and use the realized house price appreciation in the listing's zip code to identify the approximate market price for the listing.

3.2 Measurement of experience

We next describe how we measure real estate agent experience. Ideally, our measure captures three features of real estate agent activity. First, our measure should be consistent over the sample period. Thus, a backward-looking measure, such as time spent as a real estate agent, will be inaccurate because our information about agents' history is censored in 2001 at the beginning of sample. Second, our measure should be consistent over locations. Hence, using an income-based measure will inaccurately assign higher experience to agents who work in high price areas. Third, the measure should capture as many sources of potential experience as possible.

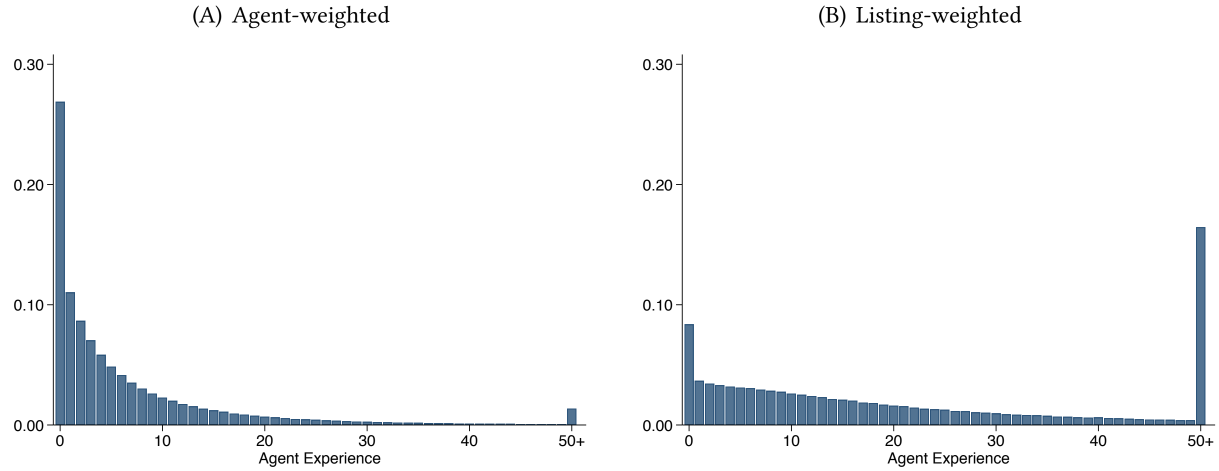
Our preferred measure is the number of clients an agent had in the previous calendar year, as it closely matches those requirements. This measure captures three types of transactions: the number of listings sold by the agent in the previous year, the number of listings unsold by the agent in the previous year, and the number of buyers represented by this agent in a transaction that closed in the previous year.[8] Our measure of experience is in terms of recent *output*, rather than calendar time since entry, and has a high discount rate so that any clients who were served two or more years prior do not count toward the current experience. This provides a consistent measure that can be calculated across all time periods, except 2001, in our sample. Moreover, our measure assumes that all clients contribute to the experience level equally, no matter the outcome of the listing, so that both unsold and sold properties count toward the listing agent experience. This helps ensure that markets with higher and lower levels of sales and prices will be counted equally and also exploits all transactions that we observe in the data.

In Appendix A, we discuss alternative measures and approaches to measuring experience, such as weighting listings differently depending on sale outcome, discounting older listing differently, or using years since entry for agents where we observe entrance. We find that these alternative measures do not materially affect our results but either limit our sample (due to the longer required time period) or complicate the mapping to a theoretical measure of experience in our model.

In Figure 1(A), we plot the distribution of experience of active agents, pooling across all years in our sample. Notably, almost 30 percent of all agents are completely inexperienced, with no previous clients. In Figure 1(B), we again plot the distribution of experience, this time weighted by the agents' active listings in that year. While inexperienced agents now represent fewer listings, compared to their unweighted presence in the market, they still hold considerable market share. Twenty-five percent of listings are handled by agents who had 4 or fewer clients in the past year, and 50 percent are listed with agents with an experience of 12 clients or fewer. In other words, the majority of sellers used a listing agent who worked with one client a month (or less) in the past year. Hence, if experience matters for liquidity, the prevalence of inexperienced agents could have large aggregate effects in the housing market.

[8]We are unable to measure clients with buyers agents who do not buy.

Figure 1: Distribution of agent experience



Note: This figure plots the distribution of agent experience. Panel A plots the distribution of experience at the agent-year-level. Panel B plots the distribution of experienced at the agent-year-level, weighted by the number of listings that an agent participated in that year. In both panels, agents with experience greater than 50 are pooled with agents who have experience of 50. Agent experience is defined as the number of clients an agent worked with in the previous calendar year. See Section 3 for more details on the data sample and definition of experience.

4 Empirical results

In this section, we use our measure of experience to show a strong link between real estate agent experience and listing liquidity that varies over the housing cycle. We then highlight how the effect of experience on liquidity affected foreclosures during the housing bust of 2008–2010. Finally, we discuss the challenge of counterfactually changing agent experience. We show how agent experience itself varies over the cycle and responds endogenously to market conditions, demonstrating the need for a structural model that accounts for agents' endogenous acquisition of experience.

4.1 Estimation approach

To examine the effect of agent experience on listing outcomes, we estimate versions of the following regression:

$$y_{i,t} = \alpha_{i,t} + \sum_{p \in \text{periods}} \beta_p \log(1 + \text{experience}_{i,t}) + \delta W_{i,t} + \epsilon_{i,t}, \tag{1}$$

where $y_{i,t}$ is the outcome for listing i in time t, $\text{experience}_{i,t}$ is the experience of the listing agent for listing i in time t, $W_{i,t}$ is a vector of property-specific controls such as square footage and number of bedrooms, and $\alpha_{i,t}$ denotes time and location fixed effects based on the listing's location. For most outcomes, time t indicates the year-month of the listing, except for sale outcomes, where time t denotes the year-month of the sale. To account for the highly skewed distribution of experience, we use log of one plus experience as our main explanatory variable.[9] In all regressions, unless noted otherwise, errors are clustered at the MLS level to account for within-MLS correlation between our experience measure and unobservable shocks (Bertrand, Duflo, and Mullainathan, 2004; Abadie et al., 2017).

In our estimation, we allow the effect of experience to vary by time period. We do this in two ways. First, for graphical illustration, we allow the effect of experience to vary year-by-year and then plot the effect for each year. Second, in anticipation of the calibration of our model in Section 5, we define three time periods—boom, medium, and bust—that reflect the aggregate state of the housing market in each year. The assignment of each year to period is based on 12-month real house price growth, as measured from 1960 to 2017 by the Case-Shiller index, deflated by the Consumer Price Index less costs of shelter. Years with growth rates above the 75th percentile are identified as booms, those below the 25th percentile are busts, and those in between are assigned to a medium period. Appendix Figure H2 illustrates this assignment procedure.[10] In our main tabular results, we report estimates pooled into each of the three time periods.

The challenge for this exercise is lack of random assignment between listings and agents. Selection may confound our OLS results, through the unobservable listing properties', or listing clients' characteristics. For example, a more experienced agent might work with easier-to-sell properties or with more motivated-to-sell clients. As a result, a regression of probability of sale on agent experience would be biased upward, capturing other features of the homes or clients instead. One approach to alleviate selection is examining a set of alternative explanations and analyze subsamples of data where those selection effects are less likely to be a concern. We include the description of this analysis in Section 4.5 with more details in Appendix Section B.

Our preferred approach to address the selection problem is our instrumental variable strategy. This approach exploits the two features of the market: first, homeowners are much more likely to list their homes with the agent that they bought the house with; and second, when the real estate agent with whom they bought has exited the market, homeowners tend to redraw agents who look like the average population of agents. We now describe this approach in more detail.

Our research design uses a subsample of listings where we observe the previous purchase of the home. Among these listings, the sellers have substantial inertia in which agent they list with, choosing the same agent who represented them in the purchase of the home 33% of the time if that agent is still active. However, if their buying agent is no longer active, the seller is forced to pick a new agent from the market. Importantly, the new agent that sellers select tend to have similar experience on average, irrespective of the previous buyer's

[9] To account for data errors and outliers, we focus on agents who have less than 200 experience.

[10] Years 2007, 2008, 2009, 2010, and 2011 are assigned to the bust period; years 2006 and 2012 are in the medium period; and years 2002, 2003, 2004, 2005, and 2013 correspond to the boom period.

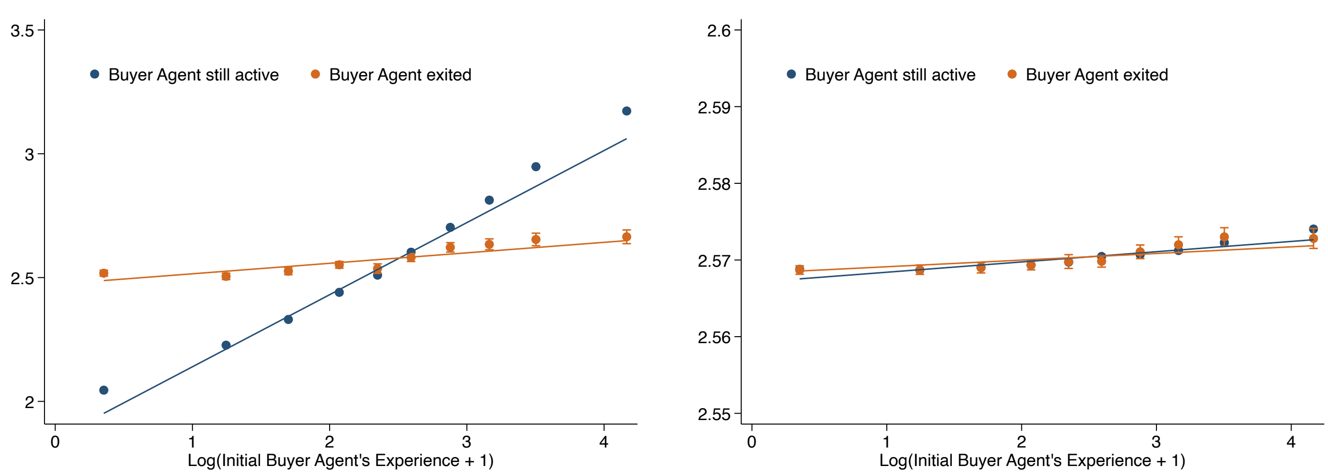
agent experience. As a result, if the initial buyer agent was relatively inexperienced compared to the average agent in the market, the seller of the home will experience a positive shock in listing agent experience if their buyer agent has exited between the homeowner's purchase and listing decision. In contrast, if their buying agent was relatively experienced, the seller of the home will experience a downward shock in experience if their buying agent has exited.

In Figure 2(A), we illustrate the impact of inertia and mean reversion in our quasi-experimental design. On the x-axis, we plot the experience of the agent with whom the homeowner initially bought the property, measured in the most recent period ($X_{i,t}$).[11] On the y-axis, we plot the experience of the listing agent used to list the property. The two lines represent the estimated relationship between previous agent's experience and the listing agent's experience, split based on whether the previous agent is still active in the market ($T_{i,t}$). If every homeowner used their buying agent as their listing agent, the "still active" plot would be a 45 degree line. While not quite a 45 degree line, the previous agent's experience is remarkably predictive of the listing agent's experience. In contrast, for homeowners whose buying agent has exited the market, the line is almost flat, reflecting the mean reversion in the market. This means that buying agent's experience does not predict the subsequent listing agent experience, implying that in choosing a new agent, homeowners tend to draw one with an average experience. In addition to giving us an identification approach, it also gives us confidence that our assumption of conditional random assignment of agent experience in our OLS estimation is reasonable.

Figure 2: Instrumental variable strategy with buyer's agent experience & exit

(A) First stage: effect on listing agent experience

(B) Exclusion restriction: effect on predictable agent experience



Note: This figure illustrates the validity of our quasi-experimental design. In Panel A, we plot listing agent experience against the most recent experience of a buyer agent who worked with the seller in the original purchase of the property. In Panel B we do a similar analysis where instead of the actual listing agent experience we plot the predicted experience based on observable housing characteristics. Data in both panels are split by whether the original buying agent is still active at the time of the listing.

[11]If the agent has exited, we use their last observed experience.

Our identification approach exploits the difference in the slopes of the two lines in Panel A of Figure 2(A). Specifically, we define our instrument as $Z_{i,t} = X_{i,t} \times T_{i,t}$, and control for the direct effect of X_{it} and T_{it}. Intuitively, we control for the direct differences across listings driven by differences in initial buyer agent's experience, and difference across listings where the buyer's agent exits or stays in the market prior to sale. The instrument exploits the interaction of the two effects to isolate variation in the listing agent experience. This is analogous to a difference-in-differences approach, where the identification is driven by the interaction, after controlling for the baseline marginal effects.

As in Equation 1, we are interested in the period-by-period effect of experience on different listing outcomes. Since we have three time periods, we have three endogeneous variables, which requires three instruments. We will mimic the setup of Equation 1, and interact our instrument $Z_{i,t}$ and direct controls $X_{i,t}$ and $T_{i,t}$ with time period fixed effects. Formally, this will give us three first stage equations, and one second-stage. For simplicity, as the first stages are symmetric, we present a representative first stage equation and the second stage below:

$$\log(1 + \text{experience}_{i,t}) \times 1_{t\in p} = \tilde{\alpha}_{i,t} + \sum_{s\in\text{periods}} \pi_{0,s} Z_{i,t} \times 1_{t\in s} \qquad (2)$$

$$+ \pi_{1,s} X_{i,t} \times 1_{t\in s} + \delta_{2,s} T_{i,t} \times 1_{t\in s} + \delta_3 W_{i,t} + u_{i,t}$$

$$y_{i,t} = \alpha_{i,t} + \sum_{p\in\text{periods}} \beta_p \log(1 + \text{experience}_{i,t}) \times 1_{t\in p} \qquad (3)$$

$$+ \delta_{1,p} X_{i,t} \times 1_{t\in p} + \delta_{2,p} T_{i,t} \times 1_{t\in p} + \delta_3 W_{i,t} + \epsilon_{i,t},$$

Note that we directly control for $X_{i,t}$ (experience of the agent that the homeowner purchased the home with) and T_{it} (whether that agent exited) in both the first and second stage equations. The excluded variable, $Z_{i,t}$, provides our identifying variation. We include purchase-year-by-listing-year-by-zipcode fixed effects, such that we are comparing two homeowners who have purchased and subsequently listed in the same years, with similar housing market dynamics. The remaining controls, $W_{i,t}$, are similar to Equation 1.

As with all IV regressions, the necessary assumptions are relevance — the instrument predicts experience — and exclusion — this process only affects housing market outcomes through agent experience. Our approach, as shown in Figure 2(A) clearly satisfies the relevance assumption. We formally report the first stage coefficients for Equation 2 in Appendix Table H1, which has a first-stage F-statistic of 130, 112 and 131 for each of the endogeneous variables, satisfying formal cut-offs for a strong first stage set of instruments (Lee et al., 2020; Staiger and Stock, 1994). While it is fundamentally impossible to prove the exclusion restriction, we provide a test of the assumption in Figure 2(B) by examining whether listing characteristics correlate with our instrument. We regress the experience of listing agents on housing characteristics, and take the fitted value. We then replicate Figure 2(A), but replace the listing agent experience with the predicted values of the experience (excluding the housing controls from the right-hand side for this regression). If we found systematic differences between the fitted values and our instrument, we would be concerned that there may be other, additional unobservable characteristics that are unbalanced across our instrument. Instead, the plot shows that the predictable component of liquidity for these listings does not differ systematically with our instrument, lending support to the exclusion restriction assumption.

4.2 Effect of experience on listing liquidity

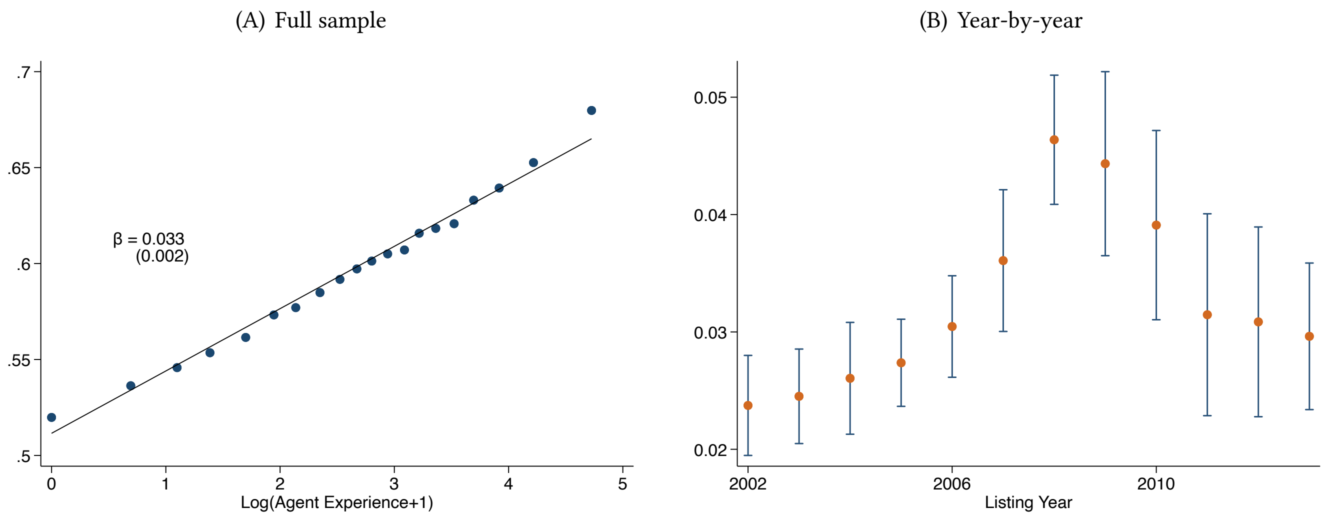
We begin by examining the effect of experience on the probability of sale within 365 days of listing. In Figure 3(A), we present a binned scatterplot of the relationship between listing liquidity and agent experience over our full sample period. The y-axis is the probability that a listing sells within 365 days, and the x-axis is our measure of agent experience, $\log(1 + \text{experience})$. This figure represents the pooled effect of experience on sale probability over the full sample. The relationship is strikingly linear and positive. A one log point increase in agent experience corresponds to approximately a 3.3 pp difference in the probability of sale within a year, or 5.4 percent of the average probability of sale. This corresponds to approximately 10 pp difference in the probability of sale between listings whose agents were in the 10th percentile of the experience (0 clients in the past year) and those of agents in the 90th percentile (21 clients in the past year).

In Figure 3(B), we let the effect of experience vary by listing year, using the same set of zip-code-by-list-year-month fixed effects as in Figure 3(A), and plot the corresponding coefficients with 95 percent confidence intervals. There are large changes in the effect of experience on listing liquidity, with an initial smallest effect of 2.4 pps (standard error (se) = 0.2 pps) in 2002, the largest coefficient of 4.6 pps (se = 0.3 pps) in 2008, falling again to 3 pps (se = 0.3 pps) in 2013.

We formally present estimates results from Equation 1 in Table 1. In each column, we report the effect of experience on the probability of a listing's sale within 365 days. We have two sets of analyses: our main sample in Columns 1–3 in Panel A, where we use all observations, and our IV sample in Columns 4–5 in Panel B, where we implement and evaluate the IV strategy outlined in Section 4.1.

We first focus on the full sample in Panel A. In Column 1, we report the overall pooled effect of experience with zip-code-by-list-year-month fixed effects, corresponding to the estimated effect from Figure 3(A). In Column 2, we repeat the same exercise but allow the effect to vary by our three aggregate time periods, with the base period of the housing boom. In Column 3, our preferred specification, we add the following housing

Figure 3: Agent experience and listing's probability of sale in 365 days



Note: Panel A plots a binned scatterplot (with 20 bins) of the probability that a listing sells within 365 days against the listing agent's experience (measured as $\log(1+\text{experience})$). The binned values and fitted line are residualized for zipcode-by-list-year-month fixed effects (the same controls as Column 1 in Table 1). The slope of the fitted line (the reported coefficient) corresponds to the coefficient on β of Equation 1, holding β fixed across time periods. Panel B plots the year-by-year effect of agent experience (measured as $\log(1+\text{experience})$) on whether a listing sells within 365 days. The reported coefficients correspond to β of Equation 1, allowing β to vary by listing year. The bands correspond to the 95% confidence interval for each coefficient. The regression controls for zipcode-by-list-year-month fixed effects (the same controls as Column 1 in Table 1). Standard errors are clustered at the MLS-level. See Section 3 for more details on the data sample and definition of experience.

controls to capture property-level characteristics: number of bedrooms, bathrooms, garages, living area, and type of cooling system and indicators for waterfront property, view, and fireplaces.[12]

Our baseline results show a strong positive effect of experience on listing liquidity. Split out by time period in Column 2, the effect is 2.65 pps (se of 0.19 pp) during the boom periods, 3.06 pps in the medium house price growth periods, and 3.96 pps during the housing bust periods. After adding housing controls in Column 3 the effect sizes remains similar.

In terms of the overall distribution of experience, listings of an agent in the 90th percentile (corresponding to an experience measure of 21) sold with a 8.2 pp higher probability than listings of agents in the 10th percentile (corresponding to an experience of 0) during the boom period. In the bust period, this gap increased to 12.0 pps. Compared to the average probability of sale of 69.1 percent during the boom period and 50.1 percent during the bust, this implies an increase of 11.9 percent of the mean during the boom and 24.0 percent of the mean during the bust. Thus, not only is agent experience an important factor in whether a listing sells, but the importance grows as the housing market contracts.

In Panel B, we report the estimates from our IV approach. In Column 4, we find that the largest effects come

[12]For each discrete characteristic, we dummy out the values to nonparametrically control for their effect. We censor the top 1 percent of values in our controls to account for outliers.

Table 1: Effect of experience on probability of sale in 365 days

	Panel A: Main Sample			Panel B: IV Sample	
	(1)	(2)	(3)	(4)	(5)
Log(Exp + 1)	0.0327***	0.0265***	0.0273***	0.0160**	0.0299***
	(0.0021)	(0.0019)	(0.0018)	(0.0065)	(0.0021)
Bust × Log(Exp + 1)		0.0132***	0.0128***	0.0183**	0.0202***
		(0.0016)	(0.0016)	(0.0084)	(0.0021)
Medium × Log(Exp + 1)		0.0041***	0.0040***	0.0104	0.0045**
		(0.0015)	(0.0015)	(0.0094)	(0.0021)
Time-by-Zipcode FE	Yes	Yes	Yes	Yes	Yes
House Char.	No	No	Yes	Yes	Yes
Bust Effect		0.0396	0.0402	0.0343	0.0501
Bust p-value		0.0000	0.0000	0.0000	0.0000
Medium Effect		0.0306	0.0313	0.0264	0.0344
Medium p-value		0.0000	0.0000	0.0008	0.0000
Observations	8457206	8457206	8457206	1217705	1217705
Estimation Method	OLS	OLS	OLS	IV	OLS

Note: This table reports estimates of the effect of listing agent's experience (using the $\log(1 + \text{experience})$) on a listings' probability of sale in 365 days. All five columns use different versions of the specifications outlined in Equation 1 and 3. All columns include zipcode-by-listing-year-month fixed effects, and Columns 3-5 add controls for house characteristics. Columns 4 and 5 include purchase-year-by-listing-year-by-zipcode fixed effects. Panel A reports results using the main sample of listings. Panel B uses the IV sample of listings, restricted to observations where we observe the initial purchase of the listing. Column 4 shows results from the IV estimation while Column 5 repeats the specification in Column 3 using the IV sample. Details of the IV estimation are discussed in Section 4. Standard errors are clustered at the MLS level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

during the bust (3.31 pps) and medium (2.63 pps) periods, and the smallest effect during the boom periods of 1.51 pps. Since the IV sample is substantially smaller (due to the restriction of observing the initial purchase), we rerun our OLS specification from Column 3 in Column 5, restricted to the IV sample. We find very comparable (and slightly larger) estimates to Column 3.

Qualitatively, our OLS and IV estimates imply the same relationship between agent experience and listing sale probability – there is a significant effect of experience in all three periods, with a substantially higher effect during the bust periods. However, the IV point estimates are smaller, with the test statistic comparing the two sets of estimates rejecting the null of no difference at the 10% level (p-val = 0.069).[13] We consider two potential explanations for the difference between the IV and OLS estimates in Columns 4 and 5 of Table 1.

The first is omitted variable bias in our OLS regression; that selection between high and low experience agents is correlated with features that make it easier to sell a property. This suggests some amount sorting between agents and listings, and may explain part of the difference between the OLS and IV results since

[13]This test is done using a Sargan-Hansen test in Stata's `ivreg2`.

the IV approach will account for this sorting by exploiting the exit of the agents. In Section 4.5, we explore additional tests that examine different potential selection mechanisms, but find limited evidence on what those mechanisms might be.

The second possible explanation is heterogeneity in the effect of experience on listing outcomes. With heterogeneity in treatment effects, the IV approach will capture the Local Average Treatment Effect (LATE) of the sample of *compliers* induced by the empirical strategy (Imbens and Angrist, 1994), and this estimate may different from the average effect of experience in the whole population.[14] We explore this possibility by following Bhuller et al. (2020) and characterizing compliers based on time period and predicted probability of sale conditional on observable characteristics. We split our sample into twelve mutually exclusive subgroups based on time period (boom, bust and medium) and the predicted probability of sale (four quartiles). We then re-estimate our first-stage regression in each subgroup, using an indicator variable of listing agent experience above the listing-weighted median value (roughly experience equal to 10) as the dependent variable.[15] Using each first stage estimate, we construct the share of compliers within each subgroup, and reweight the subgroups so that the proportion of compliers in a given subgroup matches the share of the estimation sample, and reestimate our OLS regressions. We report these estimates in Appendix Table H2, and note that for the sale probability within 365 days, this reweighting has a negligible effect. As a result, we do not find conclusive evidence that heterogeneous treatment effects is driving our effects.

In sum, the larger magnitude in OLS estimates suggests that there is some selection between agents and listings, but the relative magnitude between the boom and bust period is nearly identical across estimates.

4.3 Agent experience and listing prices

So far, we have focused on the overall effect of experience on sale probability but not on the mechanisms by which experience increases the match probability. There are many mechanisms by which an experienced agent could improve the chances of a listing selling. For example, agents with more experience are likely more connected to other agents and also former clients. Thus, they can attract more matches for a listing by reaching out to potential buyers, or by tapping into their network of buyer agents. Additionally, an experienced agent may more effectively market a property to attract viewings and increase desirability for buyers who view the house.

One channel that is of more ambiguous value to clients is that experienced agents could set lower list prices for their properties, both attracting more buyers and making the purchase more likely. While the seller

[14] An additional assumption, like monotonicity, is necessary when there are heterogeneous effects of experience, in order to ensure that the IV estimate is a properly weighted average of the effects (Imbens and Angrist, 1994).

[15] We use this binary variable, rather than the full continuous value, to ensure that we can construct complier shares.

will benefit from their agent's network and expertise in the selling process, they face an important trade-off when it comes to the property price. Since properties with lower list prices are more likely to sell, ceterus paribus, if experienced agents list properties at lower prices, then that will lead to higher listing liquidity. We note here that the relevant trade-off for the seller is in the sales price and not the list price *per se*.

In this section, we explore whether agents' choice of list price drives the liquidity advantage of experience. We first consider how experience affects the liquidity of a property *conditional* on the initial list price decision. Then, we examine how the listing agent's experience correlates with the initial list price decision. Finally, we explore the sale price difference across experience levels. To compare list prices across properties, we construct a measure of the inferred home value. We do this by taking the last sale price of the property, and appreciating the price of the property forward to the current list date using the Zillow zipcode and tier-level house price index.[16]

In Figure 4, we plot the estimated average probability of sale in 365 days against binned values of the list price, scaled by the inferred value of the home, controlling for zip-code-by-list-year-month fixed effects and our housing controls. We plot two relationships on this plot. First, in solid triangles, we plot the overall relationship for all agents, which comes from pooling all agents together in a single regression. As expected, this relationship is negative. Listing for a higher price decreases chance of sale and vice versa. We find an approximate elasticity of -0.55 for sale probability from changes in the normalized list price, with a change from -0.114 to 0.114 in the log normalized list price leading to a decline of 12.6 percent in the probability of sale.[17]

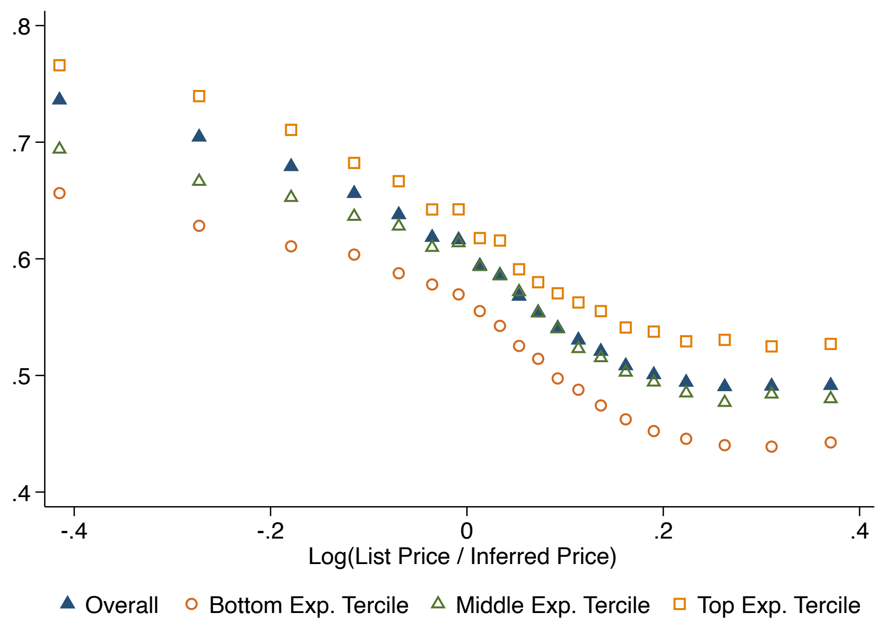
We then split our estimates by agent experience terciles (weighted by listings) and show that there is a stark level difference in the probability of sale across experience levels, holding fixed the value of the list price markup. For all experience levels, a lower list price corresponds to a higher probability of sale, with a similar estimated elasticity for each experience tercile of around -0.5. Additionally, there is also an upward shift in the probability of sale for different experience levels across all levels of normalized list price. For a markup of zero, the difference in sale probability between the top and bottom tercile is 7.3 percentage points. These results imply a large experience effect holding fixed the pricing decisions, potentially due to the channels mentioned previously.

Next, in Table 2 we consider the impact of real estate agent experience on several price measures. In

[16] A note on our sample: each observation requires not only a previous sale observation for the current listing, but also the Zillow price index for the corresponding zip code over that time period in order to estimate the inferred price. As a result, our sample is slightly smaller due to limited coverage of zipcodes at the beginning of our sample.

[17] Our version of this relationship is much more monotonic compared to the ordinary least squares (OLS) figures in Guren (2018). We discuss the difference in Appendix D.

Figure 4: Pricing and sale probability



Note: This graph plots coefficients from a regression of the expected sale probability against twenty equally sized bins of the log of normalized list price – list price scaled by our measure of inferred price. The regression is run both pooled and split by tercile of agent experience. We compute the inferred price as the last historical price that the property has sold for, appreciated to current list date using the Zillow zipcode and tier-level house price index. The regression controls for zipcode-by-year-month fixed effects and housing controls (the same controls as Column 3 in Table 1). See Section 3 for more details on the data sample and definition of experience.

Panel A we use the preferred empirical specification from Column 3 of Table 1 while in Panel B we report the estimates using our quasi-experimental IV approach. In all cases, we consider log outcomes.

In Column 1 of Table 2, we find that that a one log point increase in real estate agent experience is associated with approximately a 0.9 percent decline in list prices during boom periods and a 1.2 percent decline during busts. In Column 2, we see that these declines in list prices correspond to decline (although much smaller) in sale prices. During boom periods, a one log point increase in experience corresponds to a 0.8 percent decline in sale prices and in busts, a 0.7 percent decline. In Column 3, we show that experience does not have a significant effect on the "discount" taken off of list prices, by estimating the effect of experience on the ratio of list price to sale price (e.g. the gap between the initial list price and the subsequent sale price). This indicates that inexperienced agents are not adjusting list prices downwards any more than the experienced agents. Note that for both Column 2 and 3, this sale price is *conditional* on a successful sale.

In Panel B, we report the analogous estimates of Panel A using the quasi-experimental IV design outlined in section 4.1. While these estimates are much noisier, the coefficients on the regressions are comparable to those in the OLS specification in Panel A.

These results let us consider a simple back-of-the-envelope calculation. The effect of one log point increase

Table 2: Experience and prices

	Panel A: OLS Approach			Panel B: IV Approach		
	List / Infer.	Sale / Infer	List / Sale	List / Infer.	Sale / Infer	List / Sale
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Exp + 1)	-0.0092***	-0.0084***	0.0002	-0.0055	-0.0057	-0.0015
	(0.0021)	(0.0032)	(0.0009)	(0.0060)	(0.0064)	(0.0025)
Bust × Log(Exp + 1)	-0.0031*	0.0012	-0.0014	0.0064	0.0110	-0.0012
	(0.0017)	(0.0030)	(0.0009)	(0.0044)	(0.0076)	(0.0045)
Medium × Log(Exp + 1)	0.0001	0.0018	-0.0003	-0.0098	-0.0078	0.0008
	(0.0009)	(0.0012)	(0.0006)	(0.0078)	(0.0092)	(0.0048)
Time-by-Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
House Char.	Yes	Yes	Yes	Yes	Yes	Yes
Bust Effect	-0.0122	-0.0072	-0.0012	0.0009	0.0053	-0.0027
Bust p-value	0.0000	0.0496	0.3473	0.8164	0.5905	0.4834
Medium Effect	-0.0090	-0.0066	-0.0002	-0.0152	-0.0134	-0.0006
Medium p-value	0.0002	0.0477	0.8644	0.0006	0.1534	0.8780
Observations	2203873	1318037	1291305	740336	454836	447586
Estimation Method	OLS	OLS	OLS	IV	IV	IV

Note: This table reports estimates of the effect of listing agent's experience (using the $\log(1 + \text{experience})$) on listings' price outcomes. The first three columns use the specification outlined in Equation 1, and include zipcode-by-listing-year-month fixed effects and controls for house characteristics. Column 1 reports the effect of agent experience on list price normalized to inferred price (measured using the previous sale price, appreciated using zipcode- and price-tier-specific Zillow house price appreciation) for all listings. Column 2 reports the effect on sale prices normalized to inferred price. Column 3 reports the discount that a property sells at relative to its list price. Columns 4,5 and 6 report the analogues of Columns 1,2, and 3 using the IV strategy outlined in section 4.1. All measures are in logs (after taking ratios), and censored (ratios at the 1st and 99th percentile, levels at the 99th percentile). Standard errors are clustered at the MLS level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

in experience is a reduction on markups of roughly 1 percent, suggesting that the effect of list price differences would lead to an increase in the probability of sale by about 0.5 percent, given the elasticities outlined above in Figure 4. Since the effect of experience on sale probability is roughly 2.7 pps during the boom and 4 pps during the bust in Column 3 of Table 1, the listing price effect is between 13 to 19 percent of the overall impact of experience on listing liquidity, depending on the period.[18] This suggests that listing prices, while important, play a limited role in the effect of agent experience on listing liquidity. Thus, for the rest of the paper and in the model, we abstract from differing pricing strategies and focus on the overall effect of experience on liquidity.

4.4 Foreclosure consequences of illiquidity

We have shown that real estate agent experience significantly affects the probability of sale. Why does the ability to sell a home matter? First, many people change homes to accommodate the size of their household and to be closer to a job, friends, or family. Inability to sell the current house thus impedes the purchase of a

[18]Compared to our IV estimates in Column 4 of Table 1, it would be between 14 and 33 percent.

home that better serves their needs. This channel is valuable across all time periods. Second, listing liquidity can be important in the ability to reallocate financial resources from housing to more pressing needs, which can be particularly valuable during a recession. During the recent housing crisis, many households found themselves with expensive mortgages that they could not refinance due to tightening credit. Many attempted to sell their properties but could not do so, and some ended up in foreclosure.

Foreclosures result in a significant financial burden for people who lose their homes. A likely outcome is a substantially lower credit score that limits borrowing ability for years to come. Foreclosures are also socially inefficient because vacant properties tend to depreciate faster, either due to lack of upkeep or through a higher chance of looting and crime, which reduces the value of the property and puts downward pressure on prices for all houses in the neighboring areas.[19]

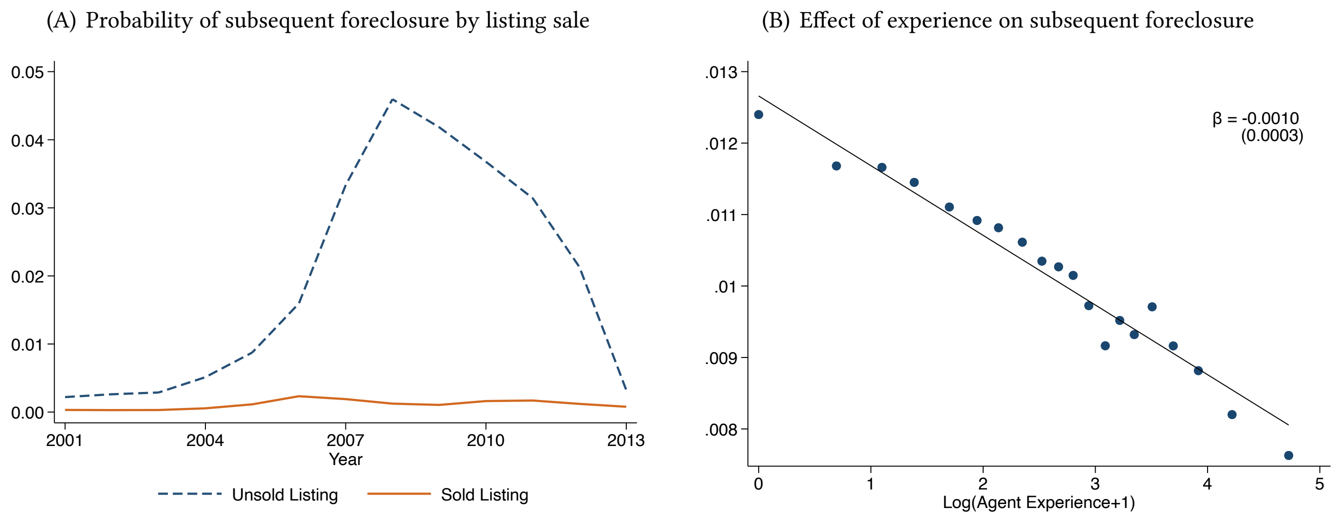
In our listings data, we observe properties that enter foreclosure after being listed for sale as non-foreclosure or non-REO properties. We focus on the outcome of whether a non-foreclosure and non-REO listing is associated with a future foreclosure sometime in the next two years. As one might expect, listings that successfully sold did not experience subsequent foreclosure; however, as we show in Figure 5(A), listings that *failed* to sell in 2008 had a 4.5 pp chance of subsequent foreclosure. Hence, an increased probability of sale for a given listing could play an important role in avoiding foreclosures.

We examine the effect of agent experience on foreclosure probability using the same specifications in Figure 5(B) and Table 3. In Figure 5(B), we plot the binscatter of subsequent foreclosure in the next two years against the log of listing agent's experience. We see a negative and significant effect of agent experience; a one log point increase in an agent's experience leads to a 0.10 pp reduction in the subsequent foreclosure probability (this probability was roughly 2.5 pps at the peak in 2008 in our sample). In Table 3, we estimate the effect of experience on foreclosure across periods. In Column 3 of Panel A, we see that the effect of experience is economically significant during the housing bust, with a one log point increase in experience leading to a reduction in the probability of subsequent foreclosure by 0.2 pps, or almost 10 percent of the average rate of subsequent foreclosure during the bust. This result is even larger in the IV approach in Panel B, but we cannot reject the null that the OLS and IV estimates are the same. This suggests that the effect of experience on foreclosure is not a selection effect by agents into certain homes or sellers, but instead an important channel for real estate agent experience's effect in alleviating foreclosures.

Note that while substantial, this fraction is likely a lower bound on the actual foreclosure outcome of properties. First, we only observe listings that are marked as foreclosure, meaning that the preceding legal

[19] Some examples of papers examining foreclosure externalities include Lin, Rosenblatt, and Yao (2009), Campbell, Giglio, and Pathak (2011), Mian, Sufi, and Trebbi (2015), Gupta (2016), and Guren and McQuade (2019).

Figure 5: Listing sale, subsequent foreclosure, and agent experience



Note: Panel A plots the fraction of listed properties that we observe going into foreclosure in the next two years. The sample is split into listings that did not sell within a year versus those that did. The sample is restricted to non-REOs and non-foreclosure listings. Panel B plots a binned scatterplot (with 20 bins) of the probability that a listing goes into foreclosure in the subsequent two years against the listing agent's experience (measured as $\log(1+\text{experience})$). The binned values and fitted line include controls for zipcode-by-list-year-month fixed effects (the same controls as Column 1 in Table 1). The slope of the fitted line corresponds to the coefficient on β of Equation 1, holding β fixed across time periods. Standard errors are clustered at the MLS-level. See Section 3 for more details on the data sample and definition of experience.

procedures had already been completed. It could very well be that the foreclosure process was initiated within two years but the property has not been put on the market due to a backlog (Mian, Sufi, and Trebbi, 2015). Second, if the lender takes ownership of the property, they might not necessarily put it up for sale right away, again excluding a foreclosure observation from our data.

4.5 Additional robustness checks

While the quasi-experimental design outlined in Section 4.1 is our main approach to addressing selection issues in the OLS specification, another approach is to rule out alternative theories through robustness tests. We do so by examining subsamples of the data where the specific selection concerns are not likely to play a role. We briefly outline the main theories we tested here, and defer a broader discussion to Appendix Section B.

We first consider the alternative mechanism that agents with higher experience choose to work with properties that look observably similar but have unobserved qualities that make them of higher value and, as a result, easier to sell. We test this in two ways: controlling for a proxy of the inferred value of the home in our main specification, and restricting our analysis to a housing market where houses are nearly identical. We next consider whether agents with higher experience choose to work with clients whose properties are easier to sell. We test this in two ways: first, we control for the clients' home equity at the time of the listing, as proxied by the amount of house price appreciation experienced by the seller since the house was last transacted (Guren,

Table 3: Effect of experience on foreclosure in next two years

	Panel A: Main Sample			Panel B: IV Sample	
	(1)	(2)	(3)	(4)	(5)
Log(Exp + 1)	-0.0010***	-0.0002**	-0.0001**	0.0007	-0.0000
	(0.0003)	(0.0001)	(0.0001)	(0.0006)	(0.0001)
Bust × Log(Exp + 1)		-0.0019***	-0.0019***	-0.0055**	-0.0034***
		(0.0006)	(0.0006)	(0.0027)	(0.0009)
Medium × Log(Exp + 1)		-0.0004**	-0.0004**	-0.0043	-0.0010***
		(0.0002)	(0.0002)	(0.0027)	(0.0004)
Time-by-Zipcode FE	Yes	Yes	Yes	Yes	Yes
House Char.	No	No	Yes	Yes	Yes
Bust Effect		-0.0020	-0.0020	-0.0049	-0.0034
Bust p-value		0.0008	0.0008	0.0578	0.0003
Medium Effect		-0.0006	-0.0006	-0.0037	-0.0010
Medium p-value		0.0262	0.0289	0.1567	0.0267
Observations	8013855	8013855	8013855	1140228	1140228
Estimation Method	OLS	OLS	OLS	IV	OLS

Note: This table reports estimates of the effect of listing agent's experience (using the $\log(1 + \text{experience})$) on a listings' probability of foreclosure in the next two years. All columns include zipcode-by-listing-year-month fixed effects, and Columns 3-5 add controls for house characteristics. Panel A reports results using the main sample of listings. Panel B uses the IV sample of listings, restricted to observations where we observe the initial purchase of the listing. Column 4 shows results from the IV estimation while Column 5 repeats the specification in Column 3 using the IV sample. Details of the IV estimation are discussed in Section 4. Standard errors are clustered at the MLS level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

2018). Second, we examine a subsample of listings that followed a deed transfer that we assume proxies for a life-changing event (Kurlat and Stroebel, 2015). Finally, we consider how our results change if we include listing agent fixed effects. However, we note that these results are likely biased: those agents who were unsuccessful in selling properties when they had low experience are less likely to continue as agents and build experience, which will bias our within-agent effect of experience downwards.

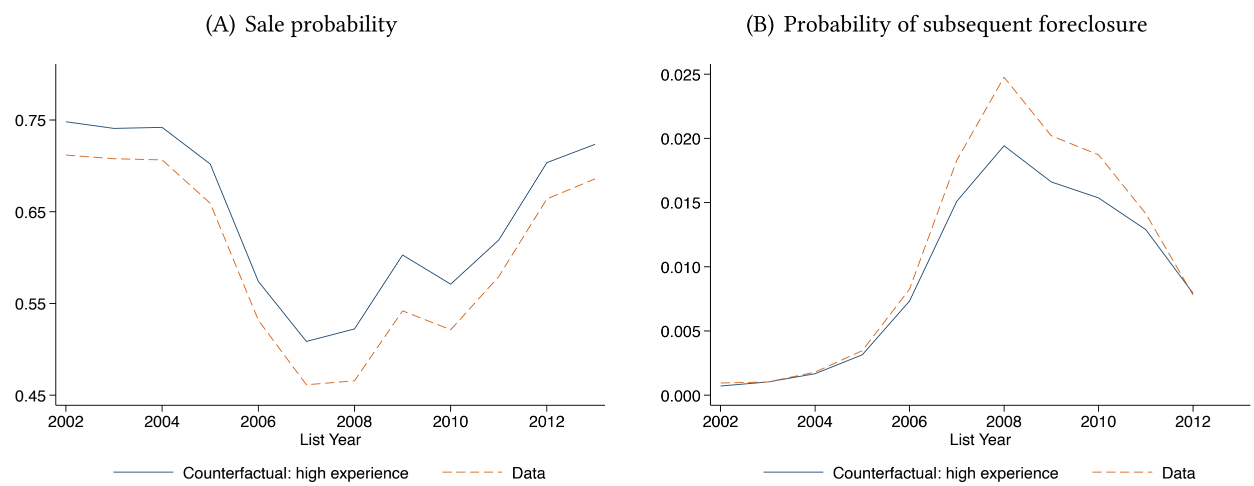
In sum, we find that our estimated effect of experience on listing outcomes is remarkably robust across different analyses. Moreover, we are unable to identify a particular channel that explains the small gap between our OLS and IV estimates in Table 1.

4.6 Naive counterfactual and entry and exit patterns

Given our estimates, can we say how much real estate agent experience contributed to the drop in listing liquidity in the recent housing bust? One naive approach to this question is to use our regression model from Section 4.2 and compute the predicted sale probability for the counterfactual, where all variables are fixed except for the experience of the listing agent. For the counterfactual, we split all agents in terciles according to their experience (listings weighted) and compute the average experience within each tercile. For all agents whose experience is below the average of the top tercile, we replace experience with that average. We then calculate the predicted probability of sale and subsequent foreclosure using our preferred specification (e.g., including house controls and zip-by-year-month) and allowing the effect of experience to vary by year.

Figure 6(A) plots the observed average yearly probability of sale and the predicted counterfactual. We see a stark jump in the probability of sale for all years. In Appendix Table H4, we report the year-by-year numbers, which show that the effect is highest in the bust. In 2008, the naive counterfactual leads to a 12.2 percent increase in the probability of sale, and in 2004 it improves liquidity by only 5.0 percent. A similar exercise for our measure of subsequent foreclosure probability (illustrated in Figure 6(B)) suggests that roughly 20 percent of listings that subsequently foreclosed could have avoided foreclosure between years 2004 and 2010.

Figure 6: Naive counterfactuals



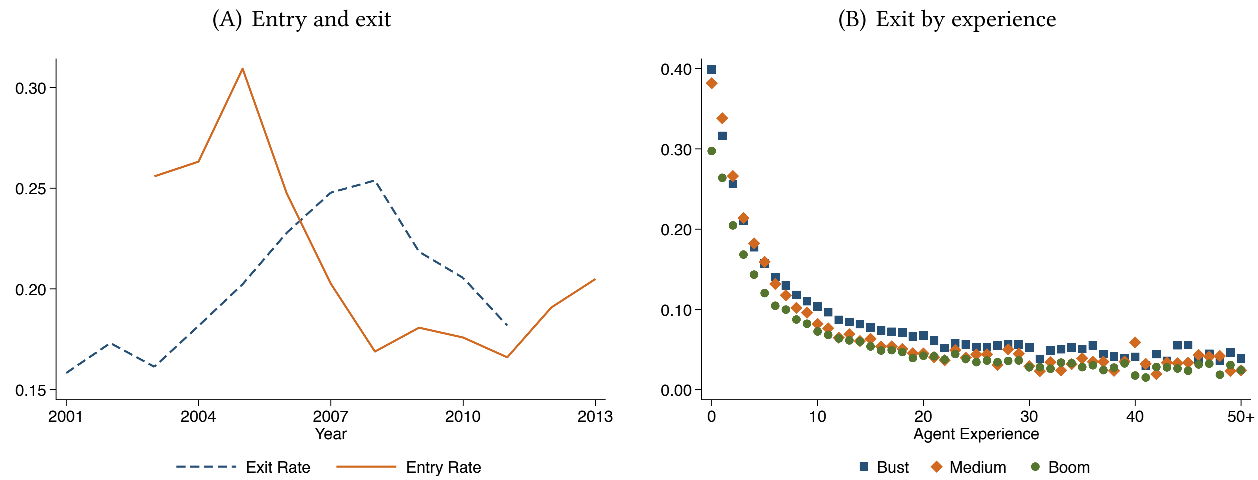
Note: This figure plots the results of the naive counterfactual discussed in Section 4.6. In Panel A, we consider the probability of sale in 365 days as the outcome. In Panel B, we consider the probability of a listing subsequently going into foreclosure in the next two years. In each panel, the empirical time series is plotted in the orange dashed line. We then regress the outcome on housing controls, zipcode-list-year-month fixed effects, as well as listing agent experience agent interacted with each calendar year. Using the coefficients of this regression, we then predict sale probability for a counterfactual where all agents are in the top experience tercile. The blue solid line plots the average counterfactual outcome using the predicted values.

However, this counterfactual is not achievable in practice. Agent experience is endogenous and depends on agents' entry and exit decisions as well as on their opportunities to accrue experience. The churn for low experience agents in this market is substantial, making it difficult for newly entered agents to become experienced. In Figure 7(A), we plot the aggregate entry and exit rates for real estate agents in the US, where the entry rate is the share of currently active agents who had zero activity in the previous two years and exit rate is the share of currently active agents who we do not observe as active in the following two years.[20] In the

[20]See Appendix C for a discussion on alternative definitions of entry and exit.

boom years of 2003 to 2006, more than a quarter of all active agents were brand-new and between 15 percent and 22 percent of all agents subsequently exited each year. Starting in 2008, the share of new entrants had plunged from its previous peak of 30 percent but remained as high as 17 percent. As the entry of agents fell, the exit rate of agents grew steadily, peaking in 2008.[21]

Figure 7: Entry and exit rates



Note: Panel A plots entry and exit rates among currently active agents. An active agent is someone who has at least one listing originating in the current year or is marked as a buyer agent for at least one sale in the current year. We define entrant to be agents who are active in the current year, but were not active in the previous two calendar years. Similarly, exiting agents are those we observe active in the current year and inactive in the following two calendar years. Panel B plots average exit rates by each experience level, with experience greater than 50 pooled with agents who have experience of 50.

The high exit rates are concentrated among inexperienced agents. In Figure 7(B), we plot the exit rates at each experience level, broken out by time periods. In all settings, inexperienced agents have far higher exit rates, near 30 percent, while the exit rates for agents with experience above 30 dip below 5 percent. During the bust periods, inexperienced agents have the highest exit rates, but all agents' exit rates shift upwards.

This churn is heavily driven by market conditions. Since commissions paid to listing agents tend to be a fixed percentage of the sale price, this creates tremendous incentives to enter (and exit) the market as the house prices change.[22] In addition, agent earnings are directly related to listing volume (the opportunity to make a sale) and the ease with which transactions are made (whether the sale occurs). We now show that housing market conditions also influence the *distribution* of agent experience.

To examine how the real estate agent's entry, exit, and experience shifts in response to market conditions,

[21] For comparison, according to the US Census Bureau's Business Dynamics Statistics, the entry and exit rates of the establishments in the US range between 8 percent to 12 percent in the same time period (2000–2015), where exit is defined as the fraction of establishments with positive employment who had/will have zero employment in the previous/following year. A similar definition for agents (one-year window) delivers an even larger churn than is described in this section (see Appendix C).

[22] The influence of housing market conditions on real estate agent entry has been documented previously in Hsieh and Moretti (2003).

we assign each agent to a home market (as measured by the county in which they have the largest share of activity). We define entry rate in a particular county as the fraction of corresponding agents currently active who we have not observed in our data (including in other counties) in the previous two years. Similarly, exit rate is the share of agents who are currently active in the county who we do not observe in the following two years. Appendix Table H3 summarizes the number of counties in the data as well as the mean and standard deviation of the number of active agents, exit rates, and entry rates in each county. We observe from 663 to 869 distinct counties per year.

We estimate county-level regressions of the following form:

$$Y_{it} = \alpha_i + \text{Sales / Listings}_{it}\gamma_1 + \Delta\text{Sales Price}_{it}\gamma_2 + \Delta\text{Listing Volume}_{it}\gamma_3 + \epsilon_{it}, \tag{4}$$

where Sales / Listings$_{it}$ measures the market tightness in county i and year t, ΔSales Price$_{it}$ measures the percentage change in average sale price, and ΔListing Volume$_{it}$ measures the percentage change in the number listings. Y_{it} corresponds to several measures of agent entry and exit within the market as well as measures of the experience distribution. α_i controls for county fixed effects to allow for county-specific time-invariant heterogeneity. We weight these regressions by the number of listings in a county in a given year.

In Table 4, we report the estimates of the effect of market conditions on agents' entry, exit, and experience. In Column 1, we see that easier markets (high sales relative to listings), increase in prices, and increase in listings volume all lead to higher real estate agent entry. In fact, the change in listing volume is a larger predictor of agent entry than changes in sale price or market tightness. On the other hand, in Column 2, we see that market tightness is the only statistically significant predictor of exit. Conditional on Sales / Listings, neither the change in prices nor the change in listings leads to an increase in exit rates. In Column 3–7, we examine how market conditions affect the distribution of experience. Interestingly, with easier markets, the average experience in the market increases, but the average log experience declines. This occurs because the experience distribution skew increases, with the 25th and 50th percentile decreasing and the 75th percentile increasing. In contrast, with an increase in listing volume, the experience distribution shifts leftward and both the average experience and log experience fall. The distribution is not affected in a statistically significant way due to shifts in the average price, suggesting that the change in listing volume and, to a lesser extent, sale/listings capture the main effect on experience.

A policymaker interested in influencing listing liquidity cannot directly manipulate the experience of agents. However, our results suggest that economic incentives play an important role in the accrual of ex-

Table 4: Turnover rates and market conditions

	Probability of		Experience Summary Statistic				
	Entry	Exit	Mean	Mean (Log)	25th perc.	50th perc.	75th perc.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sales / Listings	0.12***	-0.19***	0.65*	-0.11***	-0.77***	-0.70**	0.87*
	(0.02)	(0.02)	(0.33)	(0.04)	(0.17)	(0.30)	(0.45)
Δ Sales Price	0.07***	-0.04	0.43	0.03	-0.23	0.32	0.72
	(0.02)	(0.04)	(0.41)	(0.05)	(0.23)	(0.31)	(0.59)
Δ Listing Volume	0.24***	-0.02	-3.33***	-0.50***	-1.73***	-2.75***	-3.75***
	(0.02)	(0.01)	(0.35)	(0.04)	(0.13)	(0.24)	(0.42)
R^2	0.5819	0.6881	0.8953	0.8469	0.6361	0.8153	0.8679
FIPS Code F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5364	4694	5751	5751	5751	5751	5751

Note: In this table, we report how agent entry and exit, along with the distribution of experience, varies with county-level housing market conditions. We assign each active agent in the data to a fips code in which they have the most activity. We report the estimated coefficients from Equation 4 in each column for different outcomes, where Sales / Listings$_{it}$ measures the market tightness in county i and year t, ΔSales Price$_{it}$ measures the percentage change in average sale price and ΔListing Volume$_{it}$ measure the percentage change in the number listings. In Column 1, we report the effects for agent entry rates. For Column 2, we report the effects for agent exit rates. In Columns 3-6, we report the effects on different components of the agent experience distribution at the county level. In all regressions, we control for county-level fixed effects, and weight by the number of listings in a county in a given year. Standard errors are clustered at the county-level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

perience. Thus, by changing the incentives of the agents through realistic policies, such as increasing the certification cost to become an agent, a policymaker might hope to affect the experience distribution. To accurately assess the impact of these policies on the overall market, we develop a structural model of real estate intermediaries that will capture the effect of policies on the distribution of experience as well as on the aggregate listing liquidity in the housing market.

5 Theoretical model of real estate agents

This section first describes the setup for our structural dynamic model of real estate agents. We then characterize the dynamic equilibrium. Finally, we numerically calibrate the model and evaluate the fit to the data.

5.1 Model setup

There are three types of agents in the model: buyers, sellers, and real estate agents. All the houses in the economy are identical, and there is no heterogeneity in buyers or sellers. However, agents differ by their market experience, e. Consistent with our empirical analysis, an agent's experience is defined as the number of their listings in the previous year plus the number of successful transactions they facilitated when representing a buyer. We revisit the formal definition when we describe how experience is updated.

Time is discrete $t \in \mathbf{N}(\mathbf{N} = \{0, 1, 2, ...\})$, and all agents are assigned a unique index i so that the experience level of an agent i at time t is $e_{i,t} \in \mathbf{N}$. We define a competition state n_t^a to be a vector over experience levels that specifies the number of all active agents of experience e. For a particular agent i, the set of competitors can be described as $n^a_{-i,t}$, where $n^a_{-i,t}(e) = n_t^a(e) - 1$ if $e = e_{it}$ and $n^a_{-i,t}(e) = n_t^a(e)$ otherwise. In addition to competition level, each period is also characterized by an industry state $z_t = (n_t^s, v_t)$ that is common across all agents and has two components: a time-specific number of sellers that are looking to sell their property, n_t^s, and the valuation, v_t, at which the buyers value a home. We assume that the industry state evolves according to a Markov process with transition probabilities P and takes on three values $z_t \in \{z_1, z_2, z_3\}$ representing bust, medium, and boom activity in the housing market. Finally, we denote n_t^b as the total number of buyers (determined endogenously) that search for a house in period t.

In the beginning of each period t, the industry state $z_t = (n_t^s, v_t)$ is realized and competition level n_t^a is observed. There is an infinite pool of potential real estate agents who have an option to pay an entry cost c_e to get licensed and enter in the current period with experience level $e = 0$. Following agent entry decisions, an infinite pool of potential buyers decide whether to pay a search cost c_b and enter the market.

Next, all buyers and sellers are paired with an agent. We assume that a fraction ϕ of clients contact an agent at random and the remaining fraction gets a referral and is matched with an agent with a probability proportional to the agent's experience share. The number of seller and buyer clients are Poisson random variables with means and variances both equal to $s(e, n_t^s; n_t^a)$ and $b(e; n^a, n_t^b)$, respectively, where the average number of sellers an agent with experience e is expected to work with is

$$s(e, n_t^s; n_t^a) = \phi n_t^s \frac{1}{\sum_{\tilde{e}} n_t^a(\tilde{e})} + (1 - \phi) n_t^s \frac{e}{\sum_{\tilde{e}} n_t^a(\tilde{e})\tilde{e}}. \tag{5}$$

Similarly, the number of buyers that an agent with experience e is expected to work with is

$$b(e; n^a, n_t^b) = \phi n_t^b \frac{1}{\sum_{\tilde{e}} n_t^a(\tilde{e})} + (1 - \phi) n_t^b \frac{e}{\sum_{\tilde{e}} n_t^a(\tilde{e})\tilde{e}}. \tag{6}$$

An experienced agent can then expect to have more clients on both the seller and buyer side. While a linear relationship between experience and number of listings might seem ad hoc, it is a surprisingly accurate representation of what we observe in the data. Appendix Figure H3 plots the median and the 25th and 75th percentiles of the number of clients we observe in the data (this includes all listings and successful buyers) at each value of agent experience (recall that this measure uses *historical* information, so the linear relationship is not mechanical). Appendix Table H5 explores this relationship more formally in a regression. The coefficient on agent experience is one of the moments matched in the calibration exercise.

Clients fully delegate the housing search process to their agents and thus have no further role in the model. We further assume that all client-agent pairs can be treated as independent of other links that the two parties might have. That is, an agent who is working with both a seller and a buyer cannot easily pair the two clients for a transaction. Instead, the search market operates as if each client was represented by their own individual agent. We now describe the search market in more detail.

We model the housing market using the directed search framework, a standard setting in the labor, finance, and industrial organization literature. In this setting, buyer agents can direct their search toward houses whose listing agents have a particular experience. This effectively creates different submarkets that are indexed by the experience of selling agents operating in that submarket.[23]

In each submarket, j with s seller agents and b buyer agents, $s(1-e^{-b\nu(e_j)/s})$ matches are realized, where e_j is experience level of listing agents in that market.[24] The function $\nu(e)$ captures the overall experience advantage of attracting clients to a property and making the match more likely. We impose ν to have the following functional form: $\nu(e) = \nu_1 e^{\nu_2}$. Power functions are useful in this setting, as they allow for a decreasing returns to scale, meaning faster "learning" by inexperienced agents observed in the data.[25]

Then, the match probability for a buyer and a seller is a function of listing agents experience e and the market tightness, $\theta = b/s$:

$$\eta(e,\theta) = \frac{1}{\theta}\left(1 - e^{-\nu(e)\theta}\right) \qquad \text{Buyer Match Probability}$$

$$\mu(e,\theta) = 1 - e^{-\nu(e)\theta} = \theta\eta(e,\theta) \qquad \text{Seller Match Probability}$$

Once a meeting occurs, prices are determined via Nash bargaining with bargaining parameter γ for the buyer. We assume that a seller of an unsold house, and a buyer of a house, identically value the future changes in resale price. As a result, the total surplus of a transaction will not be affected by the continuation value of holding on to the property and is simply ν_t. The prices will then be the same in each submarket and is equal

[23] While our model's setup and solution method echoes the standard directed search model (see Moen (1997) and Shimer (1996)), it differs in a significant way. The standard directed search model involves both optimal price setting on one side and the ability to direct search to particular prices on the other (each market only differing in prices). Instead, markets in our model differ in their matching function, so home buyers direct their search to a particular technology, while the prices are determined upon meeting. The ability for buyers to select into different technologies combined with certain class of matching functions makes the equilibrium block recursive, one of the main appeals of the directed search framework.

[24] This matching function is an approximation of an urn-and-ball matching function for a large number of agents. The formulation is convenient because it restricts the probability of match to be between zero and one. In addition, match probabilities for each side exhibit constant return to scale, which allows us to keep track of the market tightness only rather than the number of counterparties on each side of the market. For a more detailed discussion, refer to Rogerson, Shimer, and Wright (2005).

[25] Some recent papers that use power functions to describe experience effect on production include Benkard (2000), Kellogg (2011), and Levitt, List, and Syverson (2013).

to

$$p(v_t) = \gamma v_t. \tag{7}$$

Buyer agents choose the submarket to enter to maximize buyer valuation:

$$V^B = -c_b + \max_j \eta(e_j, \theta_{j,t})(v_t - p_t). \tag{8}$$

Since prices do not differ by submarket, it must be that the probability of purchase, $\eta(e_j, \theta_{j,t})$, is also constant in equilibrium. Otherwise, only markets with highest $\eta(e_j, \theta_{j,t})$ would attract buyers. Intuitively, this means that while some markets have a better technology, they also attract longer lines, equalizing the overall probability of match for each buyer. The buyer free entry condition implies that buyers will enter until $V^B = 0$. The free entry condition, combined with the equilibrium result of equal match rates, determines the technology queue trade-off for the buyers:

$$\eta(e_j, \theta_{j,t}) \equiv \frac{1}{\theta_{j,t}}(1 - e^{-\nu(e)\theta_{j,t}}) = \frac{c_b}{(1-\gamma)v_t} = \eta(v_t). \tag{9}$$

The left-hand side is decreasing in θ, while the right-hand side is constant in θ. Thus, there is a unique $\theta_{j,t}$ for each market that satisfies the equilibrium conditions for free entry and submarket indifference. Solving for $\theta_{j,t} = \theta(e_j, v_t)$ allows us to compute the equilibrium match probabilities for the seller side

$$\mu(e_j, \theta_{j,t}) = 1 - e^{-\nu(e_j)\theta(e_j, v_t)} = \mu(e_j, v_t). \tag{10}$$

While in equilibrium $\eta(v_t)$ is constant across markets, $\mu(e_j, v_t)$ is increasing in the experience of a listing agent operating in submarket j through the $\nu(e_j)$ function. Thus, the experience of an agent only affects outcomes of sellers and does not improve outcomes for the buyers. This is a simplifying assumption that allows us to abstract from heterogeneity on both sides of the search market, but we think it is quite realistic. While the marketing effort and expertise is often crucial in whether a house finds a buyer, the buyer agent mainly engages in scheduling viewings for existing homes for sale, which arguably requires less know-how. For simplicity, we subsequently drop the j subscripts from equilibrium equations since every submarket j is uniquely identified by the experience e of listing agents of that submarket.

After the matches are realized, buyers pay p_t, of which 3 percent goes toward the buyer agent earnings, 3 percent goes toward the seller agent earnings, and the remaining 94 percent is taken by the seller. In reality, agents only get to keep a percentage of the commission, while the remaining share is taken by the office where they work. Moreover, more experienced agents, who bring in more business to the office, get to keep a higher fraction of their earnings, while new agents have a less favorable split. While we do not explicitly model real estate offices, we assume that agents in the model get to keep a fraction of their commission as a function of their earnings. We parameterize this function to be consistent with survey evidence on commission splits: $f(x) = 0.1498x^{0.1455}$ so that an agent who receives x dollars in commissions takes $f(x)x$ in profits.[26]

Next, for a particular distribution n_t^a of experience across agents, we compute the total number of buyers n_t^b in equilibrium:

$$n_t^b = \sum_e n_t^a(e) s(e, n_t^s; n_t^a)\theta(e, \nu_t). \tag{11}$$

This equation aggregates the buyers who are present in each market, using the equilibrium market tightness multiplied by the number of listings (sellers) allocated to the corresponding experience group.

We can now construct the per-period expected profit function for each agent of experience e:

$$E[\pi(e)|z_t, n_t^a, n_t^b] = E\left[0.1498\left(s(e, n_t^s; n_t^a)\mu(e, \nu_t)\psi p(\nu_t) + b(e; n_t^b, n_t^a)\eta(\nu_t)\psi p(\nu_t)\right)^{1.1455}\right], \tag{12}$$

where agents expect to get $s(e, n_t^s; n_t^a)$ listings that will sell with probability $\mu(e, \nu_t)$ as well as $b(e; n_t^b, n_t^a)$ buyers who buy with probability $\eta(\nu_t)$. All transacted properties will earn the agent a fraction of the total commission ψ = 3 percent on the sale price $p(\nu_t)$.

At the end of the period, experience of all agents is updated. Consistent with the empirical analysis, we assume that all listings contribute to experience equally, no matter if they are sold, while only successful buyers count toward experience. Then the expected experience level of an agent entering time t with experience e_t is

$$E[e_{t+1}|e_t, z_t; n_t^b, n_t^a] = s(e, n_t^s; n_t^a) + b(e; n_t^b, n_t^a)\eta(\nu_t). \tag{13}$$

At the end of the period, but before the next aggregate state is realized, all agents draw an idiosyncratic cost of operating $c_{i,t}$ from a log-normal distribution, with $\log(c_{i,t}) \sim N(\mu_{fc}, \sigma_{fc})$. If the drawn cost exceeds the agents' expected value of staying in the business, they choose to exit the market.

The expected value of an agent i of experience e entering time t is then

$$V_t(e_{i,t}, z_t; n_t^b, n_t^a) = E[\pi(e_{i,t})|z_t, n_t^a, n_t^b] + \beta E_t[\max\{0, -c_{i,t} + V_{t+1}(e_{i,t+1}, z_{t+1}; n_{t+1}^b, n_{t+1}^a)\}]. \tag{14}$$

[26] Appendix F describes the survey evidence.

A value of an entrant entering time t is similarly

$$V_t(0, z_t; n_t^b, n_t^a) = -c_e + E[\pi(0)|z_t, n_t^a, n_t^b] + \beta E_t[\max\{0, -c_{i,t} + V_{t+1}(e_{i,t+1}, z_{t+1}; n_{t+1}^b, n_{t+1}^a)\}]. \quad (15)$$

Since both the number of clients and the probability of sale is increasing with experience, V is strictly increasing with experience as well. Then the optimal exit strategy $\rho_t(e_{i,t+1}, c_{i,t}))$ follows a cut-off rule:

$$\rho_t(e_{i,t+1}, c_{i,t})) = \begin{cases} 1 & \text{if } c_{i,t} > E_t[V_t(e_{i,t+1}, z_{t+1}; n_{t+1}^b, n_{t+1}^a)] \\ 0 & \text{otherwise.} \end{cases} \quad (16)$$

The free entry condition for real estate agents implies that if any agents find it profitable to enter, agents will keep entering until the value of entry is driven down to zero. If, however, no entry happens, then the value of entry must be negative. Formally, if λ_t is the entry rate at time t, then $\lambda_t V_t(0, z_t; n_t^b, n_t^a) = 0$.[27]

5.2 Model equilibrium

We allow the exogenous aggregate state $z_t = (n_t^s, v_t)$ to take on three different pairs of values corresponding to boom, bust, and medium periods of the housing market, as in our empirical analysis. The endogenous measure of buyers n_t^b is a function of v_t, n_t^s, and n_t^a, as described in Equation 11, so it is not a distinct state variable. The main challenge is n_t^a, the distribution of agents across all experience groups. Allowing agents to keep track of n_t^a makes the state space essentially infinite since each value of the function $n_t^a(e)$ is a state variable itself. While in a static setting, this distribution might reduce to one profit-relevant value that affects competition (such as the overall experience level in the market), in a dynamic setting, the entire distribution is needed to project how competition will evolve over time.

To simplify the problem, we adopt the extended oblivious equilibrium concept described in Weintraub, Benkard, and Van Roy (2010). In this equilibrium, agents approximate the distribution n_t^a using its long-run average value corresponding to a recent history of aggregate states z_t. Adopting the notation of the original paper, let $\{w_t = (z_t, z_{t-1})\}$ be a Markov chain adopted to the filtration generated by $\{z_t : t \geqslant 0\}$. Let $\lambda(w_t)$ be the entry rate and $\rho(e, w_t)$ be the exit policy at state w_t. We define $\tilde{n}_{\lambda,\rho}^a(w_t)$ to be the predicted distribution of agents at state w_t, which corresponds to the long-run average distribution under entry rates λ and policy function ρ. We now define agent's value function $\tilde{V}(e, w|\rho', \rho, \lambda)$ as the expected present value for an agent of experience e in aggregate state w given that they follow an exit strategy ρ', while the competitors follow a

[27] While we match the aggregate state n_t^s (number of sellers) to the actual number of listings we observe in the data, we abstract from issues of discreteness for other measures and allow for non-integer values of n_t^b, n_t^a, and the entry rate λ_t.

common strategy ρ and enter at rate λ [28]:

$$\tilde{V}(e, w|\rho', \rho, \lambda) = E[\pi(e, w)] + \beta E[\max\{0, -c + \tilde{V}(e', w')|e, w, \rho', \rho, \lambda]. \tag{17}$$

Similarly, an entrant's value is

$$\tilde{V}(0, w|\rho', \rho, \lambda) = -c_e + E[\pi(0, w)] + \beta E[\max\{0, -c + \tilde{V}(e', w')|0, w, \rho', \rho, \lambda]. \tag{18}$$

In both,

$$E[\pi(e)|w, \tilde{n}^a_{\lambda,\rho}, n^b] = E\left[0.1498\left(s(e, n^s; \tilde{n}^a_{\lambda,\rho})\mu(e, v)\psi p(v) + b(e; n^b, \tilde{n}^a_{\lambda,\rho})\eta(v)\psi p(v)\right)^{1.1455}\right], \tag{19}$$

Where n^s and v are defined by the state z (i.e., are a function of w); total buyers for each state are defined in Equation 11; functions s and b defining the distribution of clients are defined by Equations 5 and 6; match probabilities η and μ are defined in Equations 9 and 10; and price $p(v)$ is defined in Equation 7. Finally, the w is updated via adopting the Markov process for aggregate state z and agent experience updates according to Equation 13.

Definition An *extended oblivious equilibrium* consists of

1. An exit strategy $\rho(e, w)$ and entry rate $\lambda(w)$ that satisfy the following conditions:

   (a) Agents optimize their exit strategy using the extended oblivious value function:

   $$\sup_{\rho'} \tilde{V}(e, w|\rho', \rho, \lambda) = \tilde{V}(e, w|\rho, \rho, \lambda).$$

   (b) Either the oblivious expected value of an entering agent is zero or the optimal entry rate is zero (or both):

   $$\lambda(w)\tilde{V}(0, w|\rho', \rho, \lambda) = 0,$$
   $$\tilde{V}(0, w|\rho', \rho, \lambda) \leqslant 0,$$
   $$\lambda(w) \geqslant 0, \forall w \in Z \times Z.$$

[28] Equations 17 and 19 are slightly abusing notation since ρ' is built in the value function, as we already showed that all firms will follow a cut-off strategy. This is, however, an equilibrium result, so we choose to stay consistent with the original formulation of the problem.

2. $n^b(w)$, entry rate of buyers such that the value of entry is zero (there are always some entrants as long as $v_t \gg c_b$).

3. A belief $\tilde{n}^a(w)$ over the distribution of agents that corresponds to the long-run average distribution of agents across experience.

We adopt a slightly modified version of the solution method described in Weintraub, Benkard, and Van Roy (2010). The full algorithm is described in detail in Appendix G.[29]

5.3 Calibration

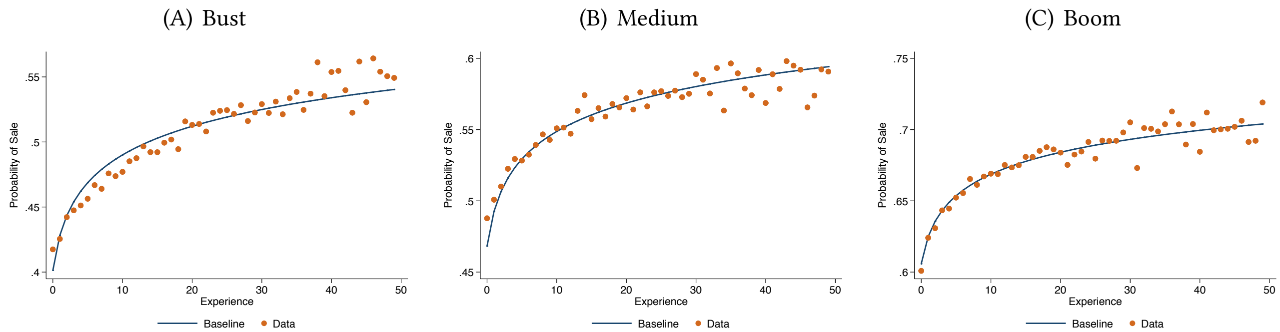
Calibrating the model to the data involves three nested steps. First, we define the stochastic behavior of z_t and fit the behavior of the common aggregate states for each $z_t = (v_t, n_t^s)$ to match prices (that directly correspond to the housing valuation) and the overall number of sellers looking to sell their property that we see in the data. Next, for a given state z_t, we calibrate the directed search model to match the sale probabilities for each agent experience group. Finally, given the parameters from the previous two steps, we fit the entry and exit parameters to match the observed entry and exit rates for every state $w_t = \{z_t, z_{t-1}\}$ and agent experience level.

For the first step, we define three states for z_t using the historical series of the Case-Shiller house price index for years 1940–2017 in the same way as we did in the empirical section. We first deflate the index by the Consumer Price Index (less shelter) and then compute the annual average of the 12-month growth rate. We define years with growth rates in the bottom and top quartile of the data to be bust and boom years, respectively. The remaining years correspond to the medium state. Figure (H2) plots the adjusted growth rates together with our approximation for the state process. The evolution of states in this dataset allows us to compute a Markov transition probability matrix P for the aggregate state z_t (in step three, we use P to infer the transition probability matrix for recent state history, w_t).

Given these three states, we use the data to compute the observed number of sellers, $n^{s,obs}(z_t)$, and the observed average price levels, $p^{obs}(z_t)$, in each state in the data. For a given price, the parameters of interest, $(v(z_t), \gamma)$, are not separately identified, as they always enter in our model as multiples of each other. Hence,

[29] The intractability of a distribution as a state variable could also be tackled by a commonly used algorithm introduced in Krusell and Smith (1998). There, agents' decisions are allowed to depend on a finite set of moments that describe the underlying distribution. These moments evolve according to a parameterized law of motion that is approximated to best fit the model generating process. While this approach solves a similar problem, the oblivious equilibrium concept differs in an important way. It allows agents to internalize an entire approximate distribution (rather than estimated moments of the distribution). Thus, instead of keeping track of several moments to base their decisions on, the agent keeps track of past few realizations of some aggregate state and bases their decisions on the approximate distribution implied by the corresponding history. If the distribution in question has a nonregular shape (and thus is difficult to summarize by a few moments), the oblivious equilibrium approach might be a better way to address the issue of high dimensionality.

Figure 8: Sale probability: calibrated model vs. data



Note: This figure plots the sale probability for each agent experience level from the model and the data counterpart. In the model, these values vary only by aggregate state z, corresponding to housing boom, a medium state and the housing bust. The empirical counterpart plots the coefficients semiparametric estimates of the effect of experience on sale probability, from a regression of sale outcome variable on housing controls, zip-by-year-month fixed effects, and a separate dummy for each experience level of the listing agent (relative to experience of zero). The reported estimates are the estimated coefficient, plus the overall average sale probability for experience level at zero.

we normalize the Nash bargaining parameter, $\gamma = 0.5$, and fit $v(z_t)$ to match the observed average prices: $p^{obs}(z_t) = \gamma v(z_t)$.

Next, we use the observed sale probabilities for each experience group and aggregate state to calibrate the parameters of the housing search markets. Since the probability of sale does not depend on the distribution of experience, we can calibrate the search parameters without computing the equilibrium of the model. We match the probability of sale for each experience value, e, in different aggregate states, $z_t \in (bust, medium, boom)$, to their counterparts in the model $\mu(e, z_t) = 1 - e^{-\nu_1(z_t)e^{\nu_2}\theta(e,z_t)}$. In equilibrium, $\theta(e, z_t)$ is a function of $c_b, v(z_t)$ and γ due to free entry of the buyers (Equation (9)). Since the cost of entry for the buyer, c_b, identifies the overall level of sale probabilities across all states, we normalize $\nu_1(bust) = 1$ such that $\nu_1(medium)$ and $\nu_1(boom)$ measure the differences in sale probabilities across aggregate states. Finally, ν_2 governs the differences in sale probability across experience levels within states. Formally, let $\Theta_1 = (c_b, \nu_1(medium), \nu_1(bust), \nu_2)$ be the parameters of interest, while the set of moments are $g(e, z, \Theta) = (\tilde{\mu}^{obs}(e, z_t) - \mu_{model}(e, z_t, \Theta))$, the vector of differences between observed and model predicted sale probabilities by each state and experience level. The chosen parameters $\hat{\Theta}_1$ are then

$$\hat{\Theta}_1 = argmin_{\Theta_1} \sum_{e,z} g(e, z, \Theta_1)^2. \tag{20}$$

Finally, we estimate the remaining parameters, c_e, μ_{fc}, and σ_{fc}, governing the entry and exit rates of real estate agents. Computing the entry and exit rates implied by these parameters involves a computation of the equilibrium that also uses the calibrated aggregate states $z_t = (n^s(z_t), v(z_t))$, P, and the parameters from the previous step, $\hat{\Theta}_1$. We choose c_e, μ_{fc}, and σ_{fc} to minimize the difference between the observed entry and exit rates corresponding to each experience and state history $w_t = (z_t, z_{t-1})$, $\Lambda(e, w_t)$, and $\rho^{obs}(e, w_t)$ and their counterparts in the model. Formally, let $\Theta_2 = (c_e, \mu_{fc}, \sigma_{fc})$, $g_1(e, w, \Theta) = (\tilde{\rho}^{obs}(e, w_t) - \rho_{model}(e, w_t, \Theta))$, and $g_2(w, \Theta) = (\tilde{\Lambda}^{obs}(w_t) - \Lambda_{model}(w_t, \Theta))$. Then,

$$\hat{\Theta}_2 = \text{argmin}_{\Theta_2} \sum_{e,w} \left(g_1(e, w, \Theta)^2 + g_2(w, \Theta)^2 \right). \tag{21}$$

While there are a total of nine values for w_t in the model (corresponding to pairwise combinations of the three values for z_t), we can match them with only six in the data. In addition, for two of the six states, we cannot identify exit rates because they appear late in the sample, and so we do not know if the agent enters back in the sample in the following two years or not. We summarize the parameter values and the calibration strategy in Table 5.

Table 5: Model calibration

Parameter	Value	Identifying Moment
P	$\begin{array}{c} \\ \text{Bust} \\ \text{Medium} \\ \text{Boom} \end{array} \begin{bmatrix} \text{Bust} & \text{Medium} & \text{Boom} \\ 0.65 & 0.16 & 0.19 \\ 0.23 & 0.58 & 0.19 \\ 0.12 & 0.25 & 0.63 \end{bmatrix}$	historical price data
$n^s(z)$	$\begin{bmatrix} 221,193 & 195,023 & 240,191 \end{bmatrix}$	number of listings
ν	$\begin{bmatrix} \$342,540 & \$367,810 & \$381,710 \end{bmatrix}$	price level
γ	0.5	-
$\nu_1(z)$	$\begin{bmatrix} 1 & 0.97 & 1.08 \end{bmatrix}$	norm / average sale probability by state
ν_2	0.03	sale probability by experience
c_b	\$13,547	overall sale probability
c_e	\$2,160	entry rates
μ_c σ_c	8.26 2.54	exit rates across experience groups
ϕ	0.23	experience accumulation

Note: This table reports the calibrated parameter values for the model, together with the description of the identifying moment in the data. See Section 5.3 for more details on the calibration procedure.

5.4 Model fit

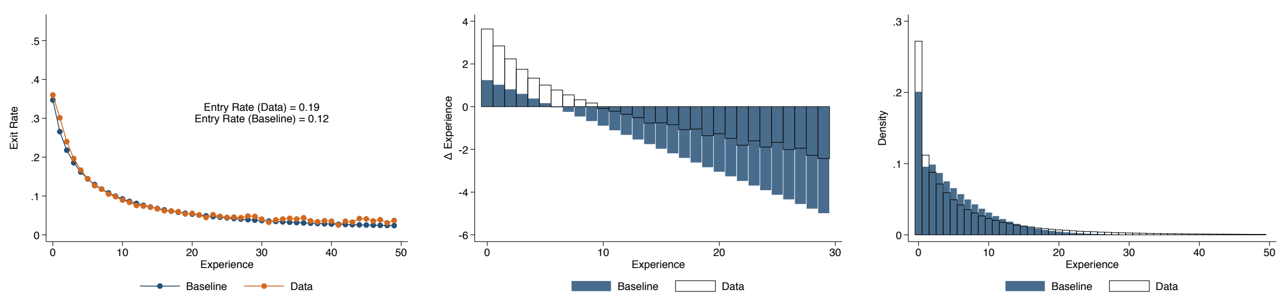
We next evaluate how well the model fits key aspects of the real estate intermediation industry. To do so, we compare several moments in the model, both explicitly targeted in the calibration exercise and those not targeted, to their counterparts in the data.

The first set of moments identify four parameters to target the probability of sale in each state z_t for each experience group e. Figure 8 plots the values predicted by the model and the equivalent counterpart in the data. The model captures these rates quite well.

The next set of moments identify three parameters that govern the entry and exit rates of real estate agents for every state and experience level. Entry and exit, together with experience accumulation, are the three key dynamic features that shape the experience distribution of real estate agents. To see how well our model fares against data, we first compare model fit by averaging all values across aggregate states observed in our sample. Panel A of Figure 9 plots the average empirical and model exit rates at each level of experience. Next, Panel B plots compares the average changes in experience at each level of experience conditional on staying in the market (i.e., the experience accumulation). Last, Panel C plots the empirical and model distributions of experience. We see that the distribution of experience fits reasonably well but underfits the rate of entry (agents with experience of zero). The model captures the shape of the experience accumulation but predicts larger decay in experience than in the data. Finally, the exit rates by experience match closely.

Figure 9: Entry, exit, experience accumulation and distribution: calibrated model vs. data

(A) Exit Rates by Experience (B) Experience Accumulation (C) Distribution of Experience



Note: This figure plots the baseline model fit against the observed data. Panel A plots the aggregate exit rates across different experience bins in the equilibrium of the model and as observed in the data. It also reports the average entry rates for the model and the data. Panel B plots average experience accumulation conditional on staying in the market the following year. Panel C plots the average distribution of agents across experience levels, comparing the predicted model distribution against the observed experience distribution. As discussed in the calibration section, we do not observe states bust-boom, medium-medium, and boom-bust. In addition, we only observe bust-medium and medium-boom in the last two years, so it is not possible to identify exit probability for agents in those states, since we can not rule out them coming back to the market in the following two years.

Recall that under our equilibrium concept, agents make their entry and exit decisions based on the recent history, namely the last two values, of aggregate states. In Table H6, we report the model fit for entry and exit rates as well as the experience accumulation and distribution in each realization of the aggregate state history that we observe in the data and for various experience levels. Interestingly, the model predicts no entry in periods that follow big spikes in entry in the previous period. The model can, however, match exit rates fairly well. To capture how fast agents accumulate experience, we compute the change in experience of agents conditional on staying in the market and present the experience change for different experience points. To capture the distribution of agents, we compute the 25th, 50th, and 75th percentile of agent experience. With our calibrated model in hand, we can now consider various counterfactual changes to the model policy parameters and evaluate the change in market equilibrium.

6 Counterfactual policies

In this section, we evaluate various policy interventions using the calibrated model. We consider three policies. With the rest of the structural parameters fixed, the equilibrium of the model is recomputed with 1) lower commission rates; 2) more informed clients, meaning a lower fraction of buyers and sellers who go to a random agent; and 3) increased entry costs.

We are interested in how those policies change the composition of experience, both overall and in the bust state following the boom, when nonsale outcomes may be most costly (as highlighted in Section 4.4). The shift in the experience distribution comes from three different channels: entry, exit, and experience accumulation. We estimate how each channel is affected by different policies and how the overall change in the distribution is translated into the aggregate probability of sale.

In the last section, we discuss how the three policies might be compared by policymakers. All three counterfactual policies that we consider qualitatively improve the overall match rate between sellers and buyers through an increase in the amount of experience in the market across aggregate states. In addition to buyer and sellers matching with higher probability, a market with improved efficiency will attract more buyers through the free entry condition. This will further increase liquidity for listings.

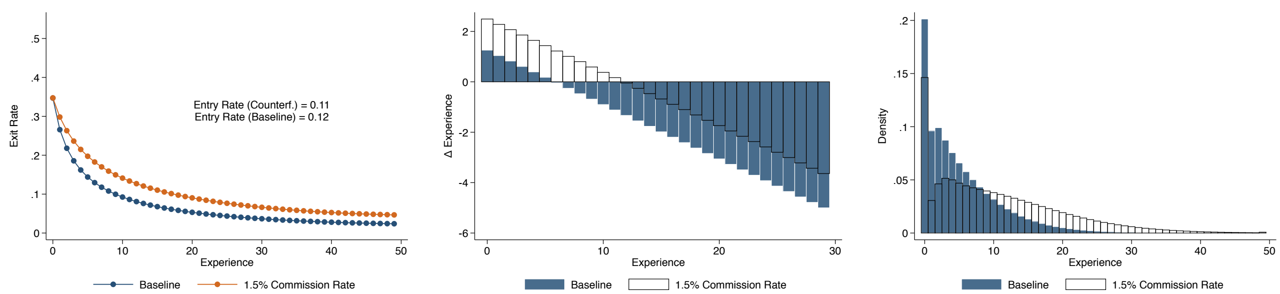
A usual approach to choosing among available policies is be a cost-benefit analysis. However estimating the cost of the implementation is outside of the scope of this paper. For example, imposing a cap on commission rates might be a legislative initiative, while informing clients on the important of experience would involve a marketing campaign, and finally, changing the implicit cost of entry would have both legislative challenges at the state level and an impact on revenue from state licensing. Instead, our approach is to choose a magnitude for each of the policies that leads to the *same* impact on liquidity and examine how each deferentially affects welfare. In addition, we offer detailed analysis on how the policies affect employment, an important consideration to policymakers. While foreclosures are not part of the model, a back of the envelope calculation using our empirical analysis suggests that the reduction in liquidity in the policies considered would lead to a 3.5

percent reduction in foreclosure rates.[30]

Counterfactual 1: lower commission rates The first counterfactual exercise is to vary commission rates. Qualitatively, reduced commission rates make entry less profitable and reduce the overall entry rates. They also lower the profitability of *all* agents in the market, thus increasing exit rates for all levels of experience. In general, increased exit rates are not desirable, as exit leads to loss of knowledge in the market. However, this loss is compensated by much faster accumulation of knowledge among existing agents, as these agents compensate for fixed and entry costs by working with more listings. Figure 10 illustrates the effect by contrasting the baseline equilibrium with one where the commission rate is cut by half to $\psi = 1.5$ percent. Panel A shows that while entry rate decreases, exit rates increase for all experience levels. In Panel B, the expected change in experience, conditional on remaining active, is higher for all experience agents. Finally, Panel C plots the overall effect on the distribution.

Figure 10: Counterfactual experiment: 1.5% commission rates

(A) Exit rates by experience (B) Experience accumulation (C) Distribution of experience



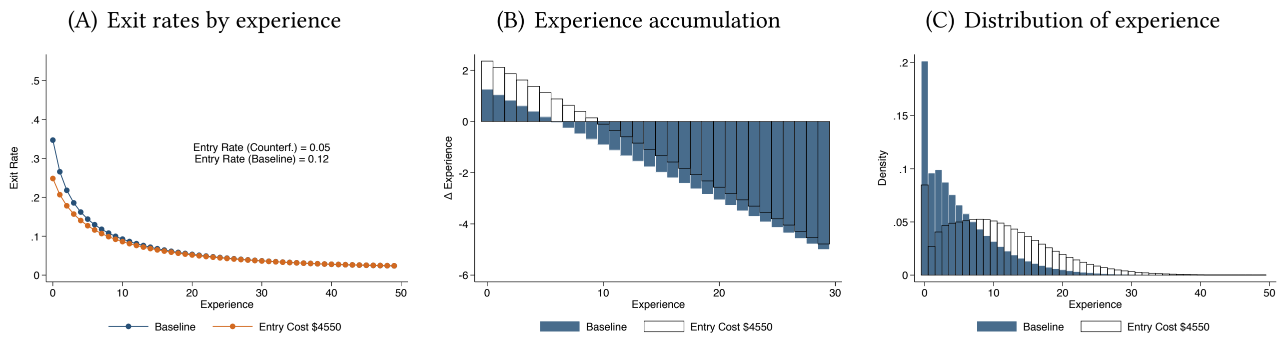
Note: This figure plots the baseline model fit against the counterfactual of reduced commission rates. Panel A plots the aggregate exit rates across different experience bins in the baseline and counterfactual equilibrium of the model. It also reports the average entry rates for the baseline and counterfactual model. Panel B plots average experience accumulation conditional on staying in the market the following year. Panel C plots the average distribution of agents across experience levels, comparing the baseline model distribution against the counterfactual distribution.

Counterfactual 2: increasing entry costs The second counterfactual examines the effect of changing entry costs directly. This policy is perhaps the most straightforward to implement, as states can simply raise the licensing costs of real estate agents. However, increasing entry costs has a negative effect on entry rates. Free entry condition implies that to compensate for increased entry costs, new agents would have to work with more agents to earn more profits. As a result, entrants learn faster, while the more experienced agents learn slower, as their experience share is reduced with the overall level of experience increasing in the market. Figure

[30] 1.8pp improvement in sale probability would lead to a 1.8pp*5.5pp =.1pp improvement in foreclosure rate. This would bring down the overall foreclosure rate of 2.7pp in 2008 by about 3.5 percent.

11 illustrates these channels for an increased entry cost of $4,550.

Figure 11: Counterfactual experiment: increase of entry cost to $4,550 dollars



Note: This figure plots the baseline model fit against the counterfactual of setting entry costs to $4,550 dollars. Panel A plots the aggregate exit rates across different experience bins in the baseline and counterfactual equilibrium of the model. Panel A also reports the average entry rates for the baseline and counterfactual model. Panel B plots average experience accumulation conditional on staying in the market the following year. Panel C plots the average distribution of agents across experience levels, comparing the baseline model distribution against the counterfactual distribution.

Counterfactual 3: informing clients The third and last counterfactual speaks to policies that improve client awareness on the importance of experience. If sellers knew the extent to which the outcome of their listing depends on the agent they choose, they would seek references or evidence of past experience when hiring an intermediary. In the model, this policy would reduce the fraction of clients ϕ who look for an agent at random and would increase the complementary fraction who match with agents through referrals.

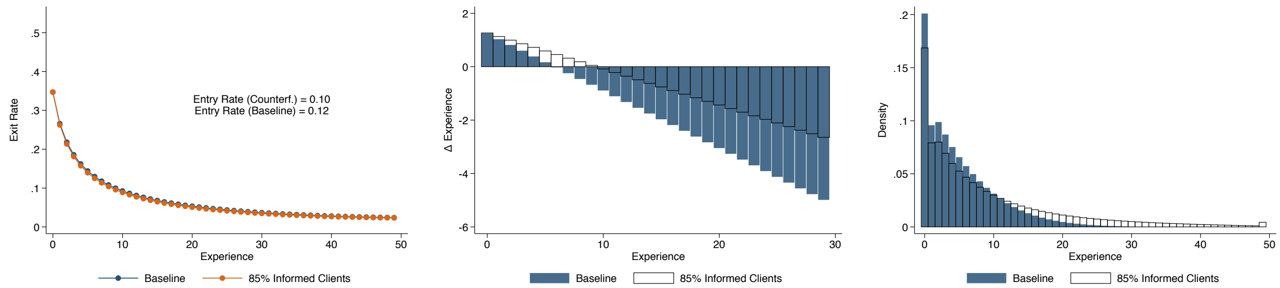
This policy essentially shifts the industry profits from low experience agents toward more experienced ones. This shift greatly reduces the incentives to enter the market and results in much lower entry rates than those we see in the baseline model. With fewer agents remaining and higher expected returns to experience, exit rates in this counterfactual fall for most experience groups, allowing for more knowledge to remain in the market. However, knowledge accumulation is slow for the entrants who can actually increase exit rates for the lowest experience groups. Figure 12 illustrates these channels for ϕ = 15 percent.

6.1 Policy selection

By increasing the overall experience level of real estate agents, each policy leads to an improvement in liquidity. How should the policymakers choose which one might be most effective? We assume that improved liquidity is the primary goal of the policymakers and choose a magnitude for each of the policies that leads to the *same* impact on liquidity. Table 6 shows the detailed liquidity consequences from each of the three policies that we consider in this exercise. We then examine how these policies affect seller welfare and shape the real estate agent labor market.

Figure 12: Counterfactual experiment: increase of informed clients to 85%

(A) Exit rates by experience (B) Experience accumulation (C) Distribution of experience



Note: This figure plots the baseline model fit against the counterfactual equilibrium where clients are more informed, that is only 15% of all clients seek out a random agent, while the remaining 85% ask for a referral and are assigned to agents with probability proportional to agent experience. Panel A plots the aggregate exit rates across different experience bins in the baseline and counterfactual equilibrium of the model. Panel A also reports the average entry rates for the baseline and counterfactual model. Panel B plots average experience accumulation conditional on staying in the market the following year. Panel C the average distribution of agents across experience levels, comparing the baseline model distribution against the counterfactual distribution.

To evaluate welfare, we examine consequences of each policy for sellers, as buyers and agents have free entry, and so have zero relative welfare value independent of parameter values. While sellers are not modeled as dynamic agents, we can assume that sellers who do not sell their home return to the market the next period and repeat the effort to sell. Their ex-ante value is computed as

$$V^s(w) = \sum_{\tilde{e}} \underbrace{\left(\phi \frac{n^a(w,\tilde{e})}{\sum_e n^a(w,e)} + (1-\phi)\frac{\tilde{e} n^a(w,\tilde{e})}{\sum_e n^a(w,e)e}\right)}_{\text{Match prob. with exp. } e} \times \left(\underbrace{\mu(\tilde{e}, v(w))(1-\psi)p(v(w))}_{\text{Sell this period}} + \underbrace{(1-\mu(\tilde{e}, v(w)))\beta E[V^S(w')|w]}_{\text{Unsold home}}\right).$$

The seller value has two parts: in the first, it measures the expected value of selling a home in the current period (including the cost of the commission), conditional on matching with an agent of a given experience; the second part is the value of moving into the next period with an unsold house, which is scaled by the probability of *not* selling the home this period with an agent of a given experience. These values are then integrated over the relative probability of matching with an agent of experience e. Table 7 shows the effect of each policy on seller welfare for each of the aggregate states. In all the policies, the welfare improves more when the housing market is currently in a bust state. This is unsurprising because we know that experience affects liquidity most in that state. In addition, bust is likely to be followed by another period of bust, so the option value of future resale is less valuable then as well. Comparing the policies, the biggest welfare gains unambiguously come from lowering commissions. This is because the reduction in commission is entirely

Table 6: Aggregate liquidity

		Data	Basel.	$\psi = 1.5\%$		c_e = \$4550		$\phi = 15\%$	
		Mean	Mean	Mean	%Δ	Mean	%Δ	Mean	%Δ
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bust_{t-1}	Bust_t	0.482	0.482	0.500	3.8	0.499	3.5	0.501	3.9
Bust_{t-1}	Medium_t	0.546	0.539	0.555	3.0	0.553	2.6	0.556	3.3
Bust_{t-1}	Boom_t	.	0.660	0.672	1.8	0.670	1.6	0.674	2.1
Medium_{t-1}	Bust_t	0.480	0.482	0.501	3.9	0.498	3.2	0.501	3.8
Medium_{t-1}	Medium_t	.	0.540	0.556	3.0	0.554	2.7	0.557	3.3
Medium_{t-1}	Boom_t	0.664	0.660	0.673	1.9	0.671	1.7	0.674	2.1
Boom_{t-1}	Bust_t	.	0.479	0.497	3.8	0.494	3.1	0.498	4.0
Boom_{t-1}	Medium_t	0.543	0.538	0.555	3.0	0.552	2.6	0.556	3.3
Boom_{t-1}	Boom_t	0.660	0.659	0.672	1.9	0.670	1.7	0.673	2.1
Bust_t		0.482	0.482	0.500	3.8	0.498	3.4	0.500	3.9
Medium_t		0.544	0.539	0.555	3.0	0.554	2.7	0.557	3.3
Boom_t		0.661	0.660	0.672	1.9	0.670	1.6	0.674	2.1
Overall		0.563	0.561	0.576	2.9	0.574	2.6	0.577	3.1

Note: This table reports the average probability of sale in each of the nine aggregate states, as well as in each of the three periods and the overall value (weighted by their ergodic probability) for each policy. Column 1 reports the average sale probability observed in the data. Column 2 reports the sale probability for our baseline calibration of the model. The next six columns correspond to the counterfactual equilibria and the percentage difference of those values from the baseline. Columns 3 and 4 correspond to lowering commission rates to 1.5% of the transaction price. Columns 5 and 6 correspond to raising the entry costs directly to \$4,550. Finally, Columns 7 and 8 correspond to having more informed clients by lowering the percentage of buyers and sellers that randomly match to an agent to 15%, thereby increasing the chance of referrals. See Section 6 for more details on the counterfactual policies.

pocketed by sellers in our model; thus a change from 3 percent to 1.5 percent on each side of the transaction leads to a total of 3 percent savings. While in our model we do not allow for adjustments in price, realistically, these saving could potentially be passed on to buyers, attracting even more of them to the market and further improving liquidity.

We next turn to the real estate agent labor market. Table 8 computes the total number of agents who operate in each state under different policies. All three policies lead to a lower number of agents in the real estate intermediation sector, but informing clients of the importance of experience results in significantly more agents participating in the housing market than under the other two policies. This is because under this policy, the distribution of agents remains skewed toward less experience—more agents participate and are likely to be in the medium experience range. The other two policies result in more experts and more of a bimodal distribution—agents are either highly experienced and deal with multiple listings or have no experience—which allows for fewer agents to operate in the market.

Policymakers might care about the dues collected on real estate agent licenses. As we can see from Table 8,

Table 7: Seller valuation

		Basel.	$\psi = 1.5\%$		c_e = \$4550		$\phi = 15\%$	
		Mean	Mean	%Δ	Mean	%Δ	Mean	%Δ
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bust_{t-1}	Bust_t	151,340	156,940	3.70	152,020	0.45	152,110	0.51
Bust_{t-1}	Medium_t	161,190	167,170	3.71	161,910	0.45	162,070	0.55
Bust_{t-1}	Boom_t	169,790	175,810	3.55	170,300	0.30	170,460	0.39
Medium_{t-1}	Bust_t	151,360	156,950	3.69	152,000	0.42	152,120	0.50
Medium_{t-1}	Medium_t	161,220	167,210	3.72	161,950	0.45	162,100	0.55
Medium_{t-1}	Boom_t	169,800	175,840	3.56	170,330	0.31	170,470	0.39
Boom_{t-1}	Bust_t	151,280	156,870	3.70	151,920	0.42	152,060	0.52
Boom_{t-1}	Medium_t	161,180	167,170	3.72	161,890	0.44	162,060	0.55
Boom_{t-1}	Boom_t	169,770	175,800	3.55	170,300	0.31	170,440	0.39
Bust_t		151,337	156,933	3.70	152,003	0.44	152,106	0.51
Medium_t		161,205	167,193	3.71	161,928	0.45	162,085	0.55
Boom_t		169,779	175,809	3.55	170,305	0.31	170,449	0.39
Overall		160,773	166,643	3.65	161,411	0.40	161,545	0.48

Note: This table reports the seller value in each of the nine aggregate states, as well as in each of the three periods and the overall value (weighted by their ergodic probability) for each policy. Column 1 reports the seller valuation calculated in our baseline calibration of the model. The next six columns correspond to the counterfactual equilibria and the percentage difference of those values from the baseline. Columns 2 and 3 correspond to lowering commission rates to 1.5% of the transaction price. Columns 4 and 5 correspond to raising the entry costs directly to \$4,550 dollars. Finally, Columns 6 and 7 correspond to an increase in fraction of informed clients to 85% by lowering the percentage of buyers and sellers that randomly match to an agent, thereby increasing the chance of referrals. See Section 6 for more details on the counterfactual policies.

each policy leads to fewer licenses issued. However with an increased entry costs policy, the state can recoup the loss of licensing fees through the extensive margin of higher fees per agent. Both reducing commissions and informing clients leads to a reduction of total fees but less so with the informed clients, as this policy leads to more agents participating in the market.

Table 8: Employment

		Basel.	$\psi = 1.5\%$		c_e = \$4550		$\phi = 15\%$	
		Mean	Mean	$\%\Delta$	Mean	$\%\Delta$	Mean	$\%\Delta$
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bust_{t-1}	Bust_t	186,944	95,218	-49.07	99,090	-46.99	125,781	-32.72
Bust_{t-1}	Medium_t	235,640	119,383	-49.34	124,287	-47.26	157,517	-33.15
Bust_{t-1}	Boom_t	272,949	137,548	-49.61	143,254	-47.52	181,240	-33.60
Medium_{t-1}	Bust_t	196,752	101,332	-48.50	113,811	-42.16	135,305	-31.23
Medium_{t-1}	Medium_t	235,819	119,521	-49.32	124,438	-47.23	157,659	-33.14
Medium_{t-1}	Boom_t	273,048	137,612	-49.60	143,342	-47.50	181,335	-33.59
Boom_{t-1}	Bust_t	224,666	115,041	-48.79	128,782	-42.68	153,181	-31.82
Boom_{t-1}	Medium_t	235,553	119,879	-49.11	128,783	-45.33	157,496	-33.14
Boom_{t-1}	Boom_t	272,853	137,550	-49.59	143,242	-47.50	181,220	-33.58
Bust_t		193,846	99,057	-48.91	106,075	-45.38	131,326	-32.28
Medium_t		235,720	119,592	-49.27	125,553	-46.74	157,593	-33.14
Boom_t		272,907	137,561	-49.59	143,263	-47.50	181,245	-33.59
Overall		234,161	118,737	-49.26	124,967	-46.54	156,725	-33.00

Note: This table reports the total employment of listing agents in each of the nine aggregate states, as well as in each of the three periods and the overall value (weighted by their ergodic probability) for each policy. Column 1 reports the seller valuation calculated in our baseline calibration of the model. The next six columns correspond to the counterfactual equilibria and the percentage difference of those values from the baseline. Columns 2 and 3 correspond to lowering commission rates to 1.5% of the transaction price. Columns 4 and 5 correspond to raising the entry costs directly to \$4,550 dollars. Finally, Columns 6 and 7 correspond to an increase in fraction of informed clients to 85% by lowering the percentage of buyers and sellers that randomly match to an agent, thereby increasing the chance of referrals. See Section 6 for more details on the counterfactual policies.

7 Conclusion

The experience of real estate agents affects the sale probability of homes listed for sale, and this effect aggregates to influence housing liquidity over the housing cycle through the distribution of experience. Downturns are particularly affected for two reasons: first, not only are inexperienced agents worse at selling listings, but they are especially bad during housing busts. Second, due to low barriers to entry and fixed commission rates, the housing boom attracts many new agents into the profession, intensifying competition for clients and thus hindering experience accumulation. These new agents remain in the market for the onset of the downturn, resulting in a distribution skewed toward lower experience.

Using a structural model of entry and exit, we estimate counterfactuals that incorporate the dynamic decisions of the real estate agents. Several policies are considered: 1) increased entry costs, 2) lower commission rates, and 3) more informed clients. Relative to the baseline, all three policies lead to an increase in average liquidity, with the largest effect during the bust. While the policies have comparable effects of aggregate liquidity, the three policies have different effects on seller valuations and on the level of employment of real estate agents. Reducing commission rates has the largest positive effect on seller valuations, while decreasing the share of clients who look for an agent at random has the smallest negative impact on the level of employment. Interestingly, doubling entry costs is least effective along both margins but may be the easiest policy to implement.

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Online Appendix for

Heterogeneous Real Estate Agents and the Housing Cycle

Sonia Gilbukh Paul Goldsmith-Pinkham

Table of Contents

A Measuring experience

Explored here are different measures of experience available in the data. For each agent, we observe their activity in every year - the number of listings they originated in that year, a fraction of those listings that sold, and the number of buyers that they have represented in a sale closed in that year.[31] We are interested in constructing a measure that is most predictive of our variables of interest: the number of clients that each agent gets each year, and the outcomes of the listings. In addition, we are interested in a measure that makes most use of the data available.

Table A1 illustrates an exercise where we regress the number of clients that an agent has in a particular year on several measures of experience. First column represents out preferred specification, which measure experience as the number of clients that an agent had in the previous year. In Column 2 we explore whether it matters that some of these clients were buyer and some sellers. While seller activity seems to weigh more in predicting the number of clients in the subsequent year, the coefficients are similar, and the fit does not improve

[31] All of these statistics can be computed by location and property characteristics as well. This suggests that to assess an outcome for a particular property, one might weight the relevant experience (in same neighborhood or same type of property) more than other. We address this by exploring a neighborhood where all houses are near identical (priced within 10% of each other) in Appendix B. Agents operating in this neighborhood have experience almost exclusively with these homogeneous properties, thus our baseline experience measure is equivalent to the location- and type- specific measure.

much from our preferred specification. We next consider whether it is important to differentiate sellers into those who successfully sold their home and those who didn't. Regression in Column 3 suggests that unsold properties seem to influence current activity less than successful sales. However, again, the predictive power of this regression does not improve enough to justify considering unsold listings separately. In Columns 4 and 5 we test whether activity prior to last year has predictive power for current activity. The results suggest that both clients in the past year and in the past two and three years have predictive power, however the coefficients on second and third lag variables are small and the explanatory power of this regressions is almost identical to the preferred specification. Another measure of experience we could explore for a subsample of the data is the number of years since entry. Excluded in this subsample would be agents that we do not observe entering in the data. We add this measure to our comparison analysis in Column 6 and for a fair comparison re-do out preferred specification on the same subsample in Column 7[32]. Years since entry does not capture nearly as much variation as the baseline specification.

To see how the choice of experience measure affects our prediction for probability of sale, we construct different measures of experience and repeat the baseline regression on probability of sale. Appendix Table A2 presents the results. We regress sale probability on the log of experience measure plus one, controlling for housing characteristics, and adding zip-by-list-month fixed effects. Eight experience measures are as follows: 1) baseline measure, sum of all clients in the previous year, 2) sum of all clients in the previous two years, 3) sum of all clients in the previous three years, 4) discounted sum of clients in the previous two years (discount factor 0.5), 5) discounted sum of clients in the previous three years (discount factor 0.5), 6) number of listings in the previous year, 7) number of sales in the previous year, 8) number of active years since entry in our data. Using the subsample of data used in Column 8, we re-run our preferred specification in Column 9.

All of the measures have almost identical explanatory power (R^2 in Column 8 is best comparable to one in Column 9). Since the baseline specification allows us to use the most of our data and is easy to implement in the model, we consider it the best choice of experience measure for our analysis.

[32]We also tried exploring non linear relationship between current clients and years since entry. For that we treated years since entry as a categorical variable. It did not change the results or the conclusion

Table A1: Experience measures and number of clients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Clients (t-1)	0.77***						0.75***
	(0.00)						(0.00)
Buyers (t-1)		0.70***	0.72***	0.64***	0.64***		
		(0.00)	(0.00)	(0.00)	(0.00)		
Sellers (t-1)		0.80***	0.88***	0.76***	0.76***		
		(0.00)	(0.00)	(0.00)	(0.00)		
Failed Sellers (t-1)			-0.12***				
			(0.00)				
Buyers (t-2)				0.10***	0.09***		
				(0.00)	(0.00)		
Sellers (t-2)				0.04***	0.02***		
				(0.00)	(0.00)		
Buyers (t-3)					0.01***		
					(0.00)		
Sellers (t-3)					0.03***		
					(0.00)		
Years Active						0.78***	
						(0.00)	
R^2	0.5155	0.5161	0.5213	0.5172	0.5173	0.1336	0.4438
Fips Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows regressions of number of listings (successful or not) and successful purchases an agent has in the current period on several measures of prior activity. In Column 1, the right hand side variable is the sum of all clients (both buyers and sellers) in the previous year. In Column 2, the regression splits on lagged buyer and seller client count separately. Column 3 adds unsuccessful sales. In Columns 4 and 5 we add additional lags of buyers and sellers. In Column 6, we instead look at how many years the agent has been active since entry in our data. Column 7 repeats Column 1 with a subsample of data used in Column 6.

Table A2: Experience measures and sale probability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log (Exp1 + 1)	0.029***								0.025***
	(0.002)								(0.002)
Log (Exp2 + 1)		0.026***							
		(0.001)							
Log (Exp3 + 1)			0.025***						
			(0.001)						
Log (Exp4 + 1)				0.028***					
				(0.001)					
Log (Exp5 + 1)					0.028***				
					(0.001)				
Log (Exp6 + 1)						0.062***			
						(0.003)			
Log (Exp7 + 1)							0.029***		
							(0.002)		
Log(Years Active +1)								0.030***	
								(0.004)	
R^2	0.3433	0.3434	0.3434	0.3434	0.3434	0.3503	0.3432	0.4436	0.4448
Time X Zip Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
House Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: In Column 1, we regress sale probability on the log of experience measure plus one, controlling for housing characteristics, and adding zip code by list month fixed effects. The next columns correspond to the same analysis for different experience measures: 2) sum of all clients in the previous two years, 3) sum of all clients in the previous three years, 4) discounted sum of clients in the previous two years (discount factor 0.5), 5) discounted sum of clients in the previous three years (discount factor 0.5), 6) number of listings in the previous year, 7) number of sales in the previous year, 8) number of active years since entry in our data. Using the subsample of data used in Column 8, we re-run our preferred specification in Column 9.

B Additional robustness analysis

In this section, we elaborate on the additional robustness tests that we use to rule out alternative theories of selection between listings and agents.

We first consider the alternative mechanism that agents with higher experience work with properties that have unobserved (to the econometrician) qualities that make them of higher value and, as a result, easier to sell. To address this issue, we control for the inferred price of each home and rerun our main specification in Column 3 of Table 1. We measure the inferred price using the previous observed sale price (as measured using deeds data) for the property and appreciating the value of the home using Zillow zip-code- and tier-level house price appreciation indexes. We report these estimates for each of our main outcomes in Appendix Table B3, and find very similar results to our main specification.

Table B3: Effect of experience on outcomes controlling for inferred price

	Sale Pr.	Will Foreclose	List / Inferred	Sale/Infer	List / Sale
	(1)	(2)	(3)	(4)	(5)
Log(Exp + 1)	0.0343***	-0.0003**	-0.0096***	-0.0088***	0.0002
	(0.0030)	(0.0001)	(0.0022)	(0.0032)	(0.0009)
Bust × Log(Exp + 1)	0.0132***	-0.0030***	-0.0051***	-0.0008	-0.0014
	(0.0030)	(0.0010)	(0.0016)	(0.0028)	(0.0009)
Medium × Log(Exp + 1)	0.0028	-0.0008**	-0.0006	0.0010	-0.0004
	(0.0026)	(0.0003)	(0.0010)	(0.0014)	(0.0006)
Time-by-Zipcode FE	Yes	Yes	Yes	Yes	Yes
House Char.	Yes	Yes	Yes	Yes	Yes
Inferred House Price	Yes	Yes	Yes	Yes	Yes
Bust Effect	0.0475	-0.0034	-0.0147	-0.0096	-0.0013
Bust p-value	0.0000	0.0028	0.0000	0.0084	0.3158
Medium Effect	0.0371	-0.0011	-0.0102	-0.0078	-0.0002
Medium p-value	0.0000	0.0148	0.0000	0.0206	0.8394
Observations	2752700	2465337	2203873	1318037	1291305

Note: This table reports estimates for our outcomes using our main specification from Equation 1 with an additional control for inferred price. We measure the inferred price using the previous observed sale price (as measured using deeds data) for the property and appreciating the value of the home using Zillow zip-code- and tier-level house price appreciation indexes. Displayed are our preferred specification of regression outcomes in equation 1 for several variables: sale probability, future foreclosures, relative list price, relative sale price and the discount from the original list price. The regressions include zipcode-by-year-month fixed effects and housing controls (the same controls as Column 3 in Table 1). In Column 1, we report the effect of experience on the probability of sale in 365 days. In Column 2, we report the effect on subsequent foreclosures. Column 3 reports the effect of agent experience on list price normalized to inferred price (measured using the previous sale price, appreciated using zipcode- and price-tier-specific Zillow house price appreciation) for all listings. Column 4 reports the effect on sale prices normalized to inferred price. Column 5 reports the discount that a property sells at relative to its list price. Standard errors are clustered at the MLS-level. See Section 3 for more details on the data sample and definition of experience.

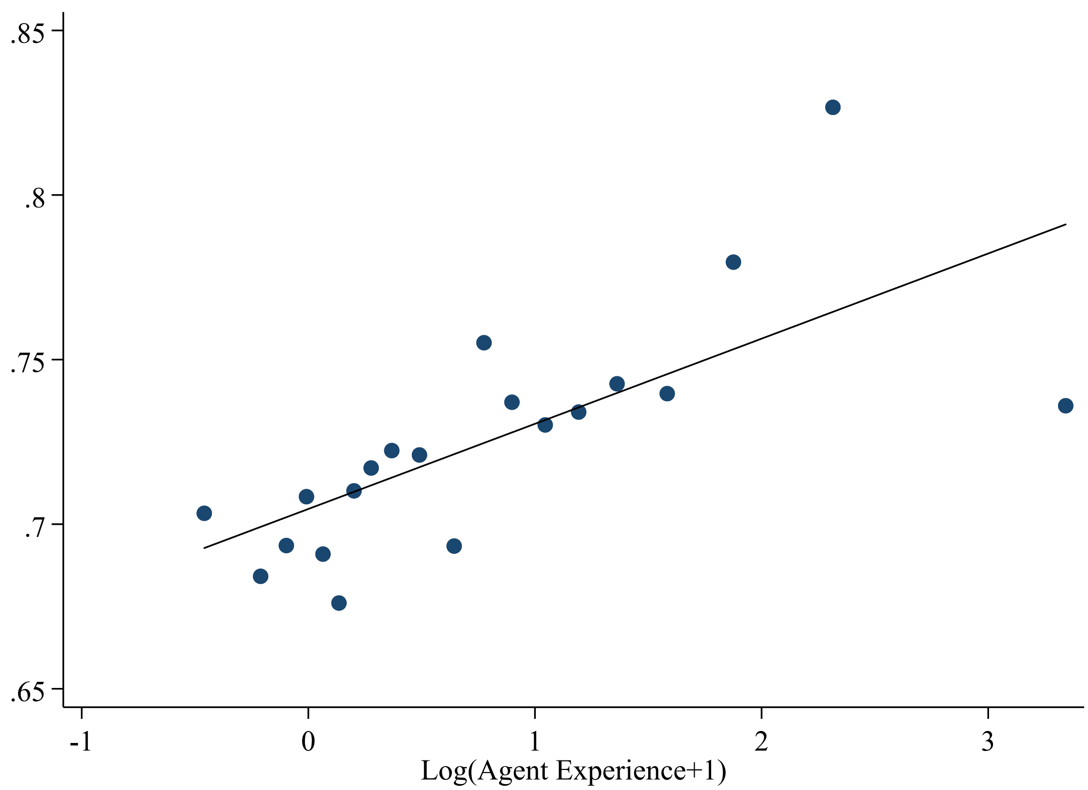
As an additional check for selection-on-properties by agents, we restrict our analysis to a homogeneous suburb of San Diego, Chula Vista, where houses are nearly identical. In this market, the standard deviation of prices for listings is less than 20 percent, and as a result, there is limited range for agents of differing experience to select into different types of home. Appendix Figure B1 shows the satellite view of this area, illustrating the homogeneity of properties.

Figure B1: Satellite view of Chula Vista, CA

Note: A satellite view of Chula Vista, CA from Google Maps.

Appendix Figure B2 repeats our main empirical results from Section 4.2 and find the same linear and monotonic relationship between agent experience and the probability of sale in Chula Vista. In Column 1 of Appendix Table B4, using our preferred regression specification from Column 3 of Table 1, we find that the effect of experience on the probability of sale is still positive but is smaller in magnitude during the boom period. However, the effect of experience in the medium and bust periods are large and significant, similar to what we find in Table 1. We report the estimates for our other outcomes in Columns 2-5 and find similar results to the main analysis.

Figure B2: Agent experience and probability of sale in Chula Vista, CA



Note: This figure focuses on the subsample of listings in Chula Vista, CA. This figure plots a binned scatterplot (with 20 bins) of the probability that a listing sells within 365 days against the listing agent's experience (using the $\log(1 + \text{agent experience})$). This plot and fitted line account for zipcode-by-year-month fixed effects and housing controls (the same controls as Column 3 in Table 1). The fitted line, average bin values, and the reported coefficient correspond to the coefficient on β of Equation 1, not allowing β to vary by time period. Standard errors are clustered at the zipcode-level. See Section 3 for more details on the data sample and definition of experience.

Table B4: Effect of experience on outcomes in Chula Vista, CA

			Log Prices		
	Sale Pr.	Will Foreclose	List / Inferred	List / Sale	Sale/Infer
	(1)	(2)	(3)	(4)	(5)
Log(Exp + 1)	0.0047	-0.0001	0.0074*	0.0057*	0.0015
	(0.0054)	(0.0002)	(0.0030)	(0.0024)	(0.0016)
Bust × Log(Exp + 1)	0.0376**	-0.0167**	0.0003	0.0117*	-0.0107**
	(0.0138)	(0.0051)	(0.0050)	(0.0051)	(0.0029)
Medium × Log(Exp + 1)	0.0470***	-0.0018	-0.0036	0.0022	0.0003
	(0.0093)	(0.0014)	(0.0042)	(0.0040)	(0.0016)
Time-by-Zipcode FE	Yes	Yes	Yes	Yes	Yes
House Char.	Yes	Yes	Yes	Yes	Yes
Bust Effect	0.0424	-0.0167	0.0077	0.0174	-0.0092
Bust p-value	0.0376	0.0150	0.0956	0.0212	0.0052
Medium Effect	0.0517	-0.0019	0.0038	0.0079	0.0017
Medium p-value	0.0010	0.1615	0.2845	0.0314	0.3801
Observations	11128	10258	5740	4114	4104

Note: This table reports estimates for our outcomes using our main specification from Equation 1, focusing on the homogeneous subsample of listings in Chula Vista, CA. The regressions include zipcode-by-year-month fixed effects and housing controls (the same controls as Column 3 in Table 1) In Column 1, we report the effect of experience on the probability of sale in 365 days. In Column 2, we report the effect on subsequent foreclosures. Column 3 reports the effect of agent experience on list price normalized to inferred price (measured using the previous sale price, appreciated using zipcode- and price-tier-specific Zillow house price appreciation) for all listings. Column 4 reports the effect on sale prices normalized to inferred price. Column 5 reports the discount that a property sells at relative to its list price. Standard errors are clustered at the zipcode-level. See Section 3 for more details on the data sample and definition of experience.

We next consider whether agents with higher experience choose to work with clients whose properties are easier to sell. To test this, we control for the client equity at the time of the listing, as proxied by the amount of house price appreciation experienced by the seller since the house was last transacted. As argued in Guren (2018), there are two reasons why clients with lower equity are likely to be less flexible in the selling process. First, low equity sellers are likely to be cash constrained, especially if they are looking into purchasing another property and need money for down payment. Second, sellers who have a higher equity in the property are less likely to experience loss aversion from selling at a lower price than what they initially paid. We control for this house price appreciation and report the estimates in Appendix Table B5. Again, we find similar results to our main estimates.

As an additional check for selection-on-clients by agents, we examine a subsample of listings that followed a deed transfer that we assume proxies for a life-changing event (Kurlat and Stroebel, 2015). Specifically, we look at listings that occur within two years of a previous transaction where both parties have the same last name but have a different first name. These transactions likely capture a transfer of property from a married couple to one partner, which likely happens in a case of divorce or death of one of the spouses. Sellers in this sample are likely more motivated in getting rid of the property than an average seller because they either cannot afford maintaining it or do not have use for it altogether. Due to a smaller sample size across locations, we are unable to control for zip-code-by-list-year-month fixed effects and instead include county-by-list-year-month fixed effects. We first replicate our main figure and find the same linear and monotonic relationship

Table B5: Effect of experience on outcomes controlling for equity stake

	Sale Pr.	Will Foreclose	List / Inferred	Sale/Infer	List / Sale
	(1)	(2)	(3)	(4)	(5)
Log(Exp + 1)	0.0342***	-0.0003**	-0.0092***	-0.0085***	0.0001
	(0.0030)	(0.0001)	(0.0021)	(0.0031)	(0.0009)
Bust × Log(Exp + 1)	0.0131***	-0.0031***	-0.0030*	0.0012	-0.0014
	(0.0030)	(0.0010)	(0.0017)	(0.0030)	(0.0009)
Medium × Log(Exp + 1)	0.0024	-0.0007**	0.0003	0.0020	-0.0003
	(0.0026)	(0.0003)	(0.0009)	(0.0012)	(0.0006)
Time-by-Zipcode FE	Yes	Yes	Yes	Yes	Yes
House Char.	Yes	Yes	Yes	Yes	Yes
Equity Stake	Yes	Yes	Yes	Yes	Yes
Bust Effect	0.0473	-0.0033	-0.0122	-0.0073	-0.0012
Bust p-value	0.0000	0.0027	0.0000	0.0497	0.3274
Medium Effect	0.0366	-0.0010	-0.0089	-0.0065	-0.0001
Medium p-value	0.0000	0.0130	0.0003	0.0501	0.8898
Observations	2752700	2465337	2203873	1318037	1291305

Note: This table reports estimates for our outcomes using our main specification from Equation 1 with an additional control for seller equity stake. We proxy equity stake by house price appreciation since the previous sale.
Displayed are our preferred specification of regression outcomes in equation 1 for several variables: sale probability, future foreclosures, relative list price, relative sale price and the discount from the original list price. The regressions include zipcode-by-year-month fixed effects and housing controls (the same controls as Column 3 in Table 1). In Column 1, we report the effect of experience on the probability of sale in 365 days. In Column 2, we report the effect on subsequent foreclosures. Column 3 reports the effect of agent experience on list price normalized to inferred price (measured using the previous sale price, appreciated using zipcode- and price-tier-specific Zillow house price appreciation) for all listings. Column 4 reports the effect on sale prices normalized to inferred price. Column 5 reports the discount that a property sells at relative to its list price. Standard errors are clustered at the MLS-level. See Section 3 for more details on the data sample and definition of experience.

between agent experience and the probability of sale in Figure B3.

We then reestimate our main specification in Appendix Table B6 and find a significant and positive effect of experience on sale probability in Column 1, with a similar magnitude to our main estimates. However, we do not find significant differences in the effect of experience across boom and bust periods. We replicate our main outcomes in the remaining tables.

Next, we address the concern that agents may differ by more than their measured experience level. We test this in two ways. We first consider the most natural approach to this in Appendix Table B7, where we rerun our preferred regression specification from Column 3 of Table 1 and include listing agent fixed effects. In Column 1, one log point increase in listing agent's experience increases the probability of sale by 0.8 pps during the boom period, and 1.1 and 1.8 pp during the medium and bust periods, respectively. These effects are smaller in magnitude than in Table 1 but the relative value of experience in the bust is much higher.

However, including agent fixed effects creates bias in our estimates of experience. Examining the effect of experience *within-agent* is complicated by the fact that agents who continue to work (and build experience) were more likely to be successful early on. Those agents who were unsuccessful in selling properties when they had low experience are less likely to continue as agents and build experience. As a result, the *within-agent* effect of experience on listing liquidity will be flattened, as those agents who continue on will have been most

Table B6: Effect of experience on outcomes in motivated seller sample

			Log Prices		
	Sale Pr.	Will Foreclose	List / Inferred	Sale/Infer	List / Sale
	(1)	(2)	(3)	(4)	(5)
Log(Exp + 1)	0.0327*	0.0000	-0.0040	-0.0012	0.0051
	(0.0163)	(0.0001)	(0.0125)	(0.0173)	(0.0062)
Bust $\times$ Log(Exp + 1)	0.0066	-0.0044**	-0.0201*	-0.0458*	0.0015
	(0.0220)	(0.0017)	(0.0114)	(0.0236)	(0.0170)
Medium $\times$ Log(Exp + 1)	0.0087	-0.0007	-0.0100	-0.0345	0.0022
	(0.0228)	(0.0027)	(0.0154)	(0.0288)	(0.0192)
Time-by-Zipcode FE	Yes	Yes	Yes	Yes	Yes
House Char.	Yes	Yes	Yes	Yes	Yes
Bust Effect	0.0393	-0.0044	-0.0241	-0.0471	0.0066
Bust p-value	0.0000	0.0134	0.0010	0.0507	0.6963
Medium Effect	0.0415	-0.0007	-0.0140	-0.0358	0.0074
Medium p-value	0.0007	0.7831	0.2123	0.3718	0.7267
Observations	12196	11957	2794	1305	1305

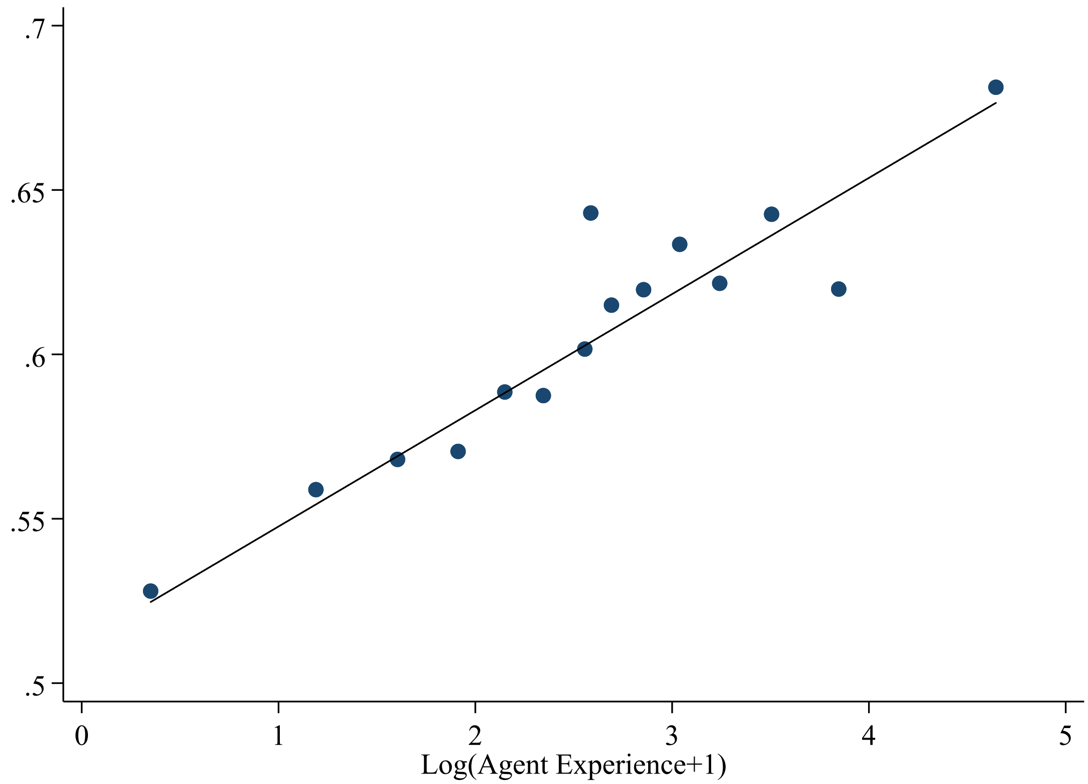
Note: This table reports estimates for our outcomes using our main specification from Equation 1, focusing on a subsample of motivated sellers who have likely inherited the property or gone through a divorce. Specifically, these listings occur within two years after a deeds record of a transaction between two people who have the same last name, but a different first name. Displayed are our preferred specification of regression outcomes in equation 1 for several variables: sale probability, days on market, and days to sale. The regressions include county-by-year-month fixed effects and housing controls (the same controls as Column 3 in Table 1). In Column 1, we report the effect of experience on the probability of sale in 365 days. In Column 2, we report the effect on subsequent foreclosures. Column 3 reports the effect of agent experience on list price normalized to inferred price (measured using the previous sale price, appreciated using zipcode- and price-tier-specific Zillow house price appreciation) for all listings. Column 4 reports the effect on sale prices normalized to inferred price. Column 5 reports the discount that a property sells at relative to its list price. Standard errors are clustered at the MLS-level. See Section 3 for more details on the data sample and definition of experience.

Table B7: Effect of experience on outcomes with agent fixed effects

			Log Prices		
	Sale Pr.	Will Foreclose	List / Inferred	Sale/Infer	List / Sale
	(1)	(2)	(3)	(4)	(5)
Log(Exp + 1)	0.0082***	0.0008***	-0.0030***	-0.0020***	-0.0005**
	(0.0004)	(0.0001)	(0.0004)	(0.0005)	(0.0002)
Bust $\times$ Log(Exp + 1)	0.0100***	-0.0017***	-0.0025***	0.0034***	-0.0027***
	(0.0005)	(0.0001)	(0.0005)	(0.0007)	(0.0003)
Medium $\times$ Log(Exp + 1)	0.0032***	-0.0003***	-0.0007	0.0015**	-0.0006**
	(0.0005)	(0.0001)	(0.0005)	(0.0007)	(0.0003)
Time-by-Zipcode FE	Yes	Yes	Yes	Yes	Yes
House Char.	Yes	Yes	Yes	Yes	Yes
Agent FE	Yes	Yes	Yes	Yes	Yes
Bust Effect	0.0182	-0.0009	-0.0055	0.0013	-0.0032
Bust p-value	0.0000	0.0000	0.0000	0.0184	0.0000
Medium Effect	0.0114	0.0005	-0.0037	-0.0005	-0.0011
Medium p-value	0.0000	0.0000	0.0000	0.4102	0.0002
Observations	8399120	7955319	2146647	1263059	1236183

Note: This table reports estimates for our outcomes using our main specification from Equation 1, with the addition of listing agent fixed effects. The regressions include zipcode-by-year-month fixed effects and housing controls (the same controls as Column 3 in Table 1). In Column 1, we report the effect of experience on the probability of sale in 365 days. In Column 2, we report the effect on subsequent foreclosures. Column 3 reports the effect of agent experience on list price normalized to inferred price (measured using the previous sale price, appreciated using zipcode- and price-tier-specific Zillow house price appreciation) for all listings. Column 4 reports the effect on sale prices normalized to inferred price. Column 5 reports the discount that a property sells at relative to its list price. Standard errors are clustered at the zipcode-level. See Section 3 for more details on the data sample and definition of experience.

Figure B3: Effect of experience on outcomes in motivated seller sample

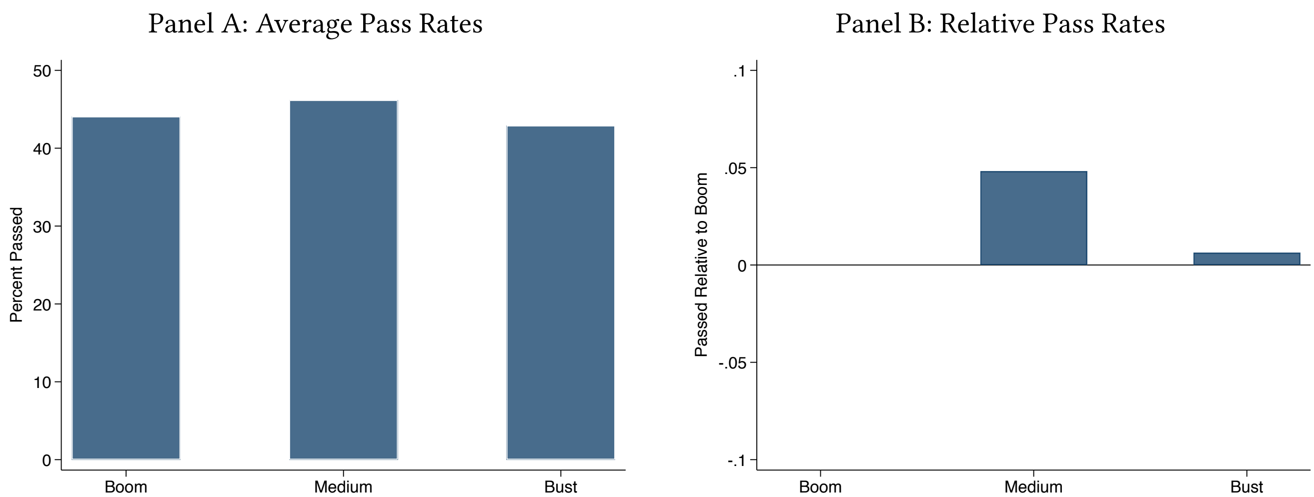


Note: This figure focuses on the subsample of listings where we can identify a recent death or divorce prior to the listing. This figure plots a binned scatterplot (with 20 bins) of the probability that a listing sells within 365 days against the listing agent's experience (using the $\log(1 + \text{agent experience})$). This plot and fitted line account for for county-by-year-month fixed effects and housing controls (the same housing controls as Column 3 in Table 1). The fitted line, average bin values, and the reported coefficient correspond to the coefficient on β of Equation 1, not allowing β_e to vary by time period. Standard errors are clustered at the MLS-level. See Section 3 for more details on the data sample and definition of experience.

successful in selling properties with less experience. Thus these estimates are best viewed as a lower bound of our effects, and reassuring evidence that even after controlling for time-invariant agent characteristics, there are strong positive effects on listing liquidity.

A related concern is that during the bust periods, the new (and inexperienced) agents that select into the real estate market are worse at selling properties in unobservable ways. If the quality of people entering the profession changes over the cycle, it would presumably be reflected in the pass rates for real estate license exams. In Appendix Figure B4, we show that exam pass rates are nearly identical across the cycle, with similar pass rates in boom and bust periods. This suggests that the incoming pool of interested agents is similar across time.

Figure B4: Exam pass rates across the cycle



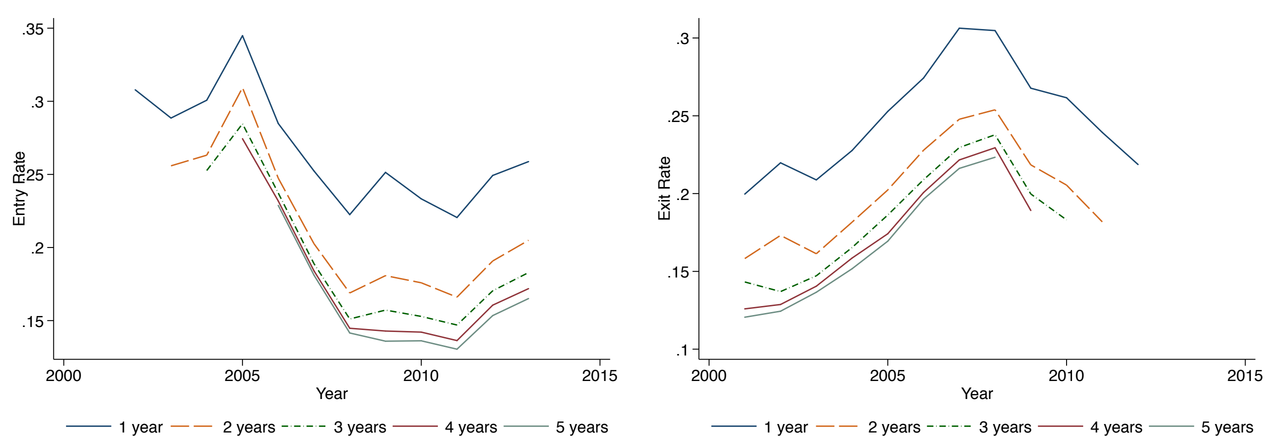
Note: This plot uses collected data on real estate salespersons exam statistics in each state from Arello, a data provider. In the first panel, we show the average of all pass rates in the United States corresponding to each period as defined in the model. The second plot we take the pass rate for each time period in each state and normalize it to the boom period in that state. We report the U.S. average of these relative pass rates weighted by the number of exams given in the corresponding state.

C Entry and exit rates

Our data lets us observe selected activity of agents (listings on the seller side and successfully purchased homes on the buyer side) and we do not directly know whether an "inactive" agent has exited the market or was unable to get clients. Some real estate agents might leave the market temporarily and then come back when housing conditions are more favorable for intermediaries. To examine these channels Figures 5(A) and 5(B) plot entry/exit rates defined as a fraction of currently active agents who are not active in the previous/next n years. A wider window lets us more accurately define exit and avoid marking re-entering agents as new. It also limits the amount of data that we can use. Moreover, as discussed in the paper, if there is significant discounting in accumulation of knowledge (such as being familiar with contemporary market conditions, having a client base and being connected to a network of professions), a re-entering agent might not necessarily have an advantage over a newly licensed one. Taking into account the costs and the benefits (both rates change significantly from $n = 1$ to $n = 2$, but change less for larger n's), we settle on choosing a 2 year window for our definition of entry and exit for both our descriptive analysis and model calibration.

Figure C5: Entry and exit at different horizons

(A) Entry (B) Exit

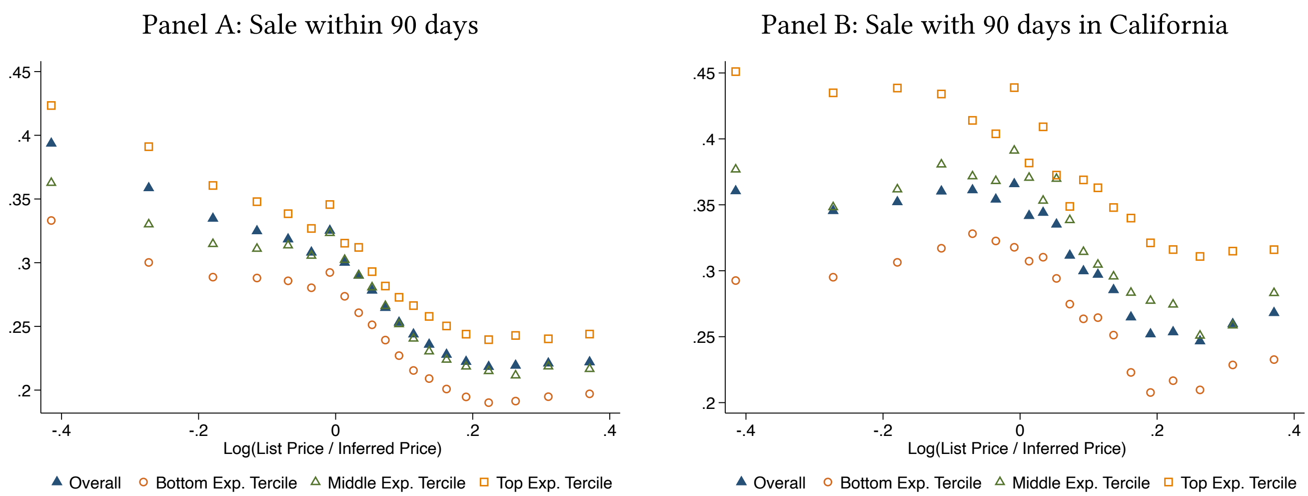


Note: Panels A and B plot entry and exit rates respectively for various definitions of thereof. For, $n \in \{1, 2, .., 5\}$ we define entry/exit rates as a fraction of currently active agents who are not active in the previous/next n years.

D Alternative estimates of sale probability vs. list price / inferred price

These results reconcile Figure 4 with Figure 1 from Guren (2018). Several things differ between our samples. First, in Guren (2018), the outcome focuses on the probability of sale in 13 weeks. In Panel A of Appendix Figure D1, we replicate Figure 4 using probability of sale in 90 days to make it comparable. In Panel B, we additionally limit our sample to listings in the state of California, the same state that Guren (2018) focused on. In this subsample of Panel B, we see shape to the curve as in Figure 1 of Guren (2018).

Figure D1: Pricing and sale probability



Note: This graph plots a binned scatterplot (with 20 bins) of the expected sale probability against the log of normalized list price – list price scaled by our measure of inferred price. We compute the inferred price as the last historical price that the property has sold, appreciated to current list date using the Zillow zipcode and tier-level house price index. The regression controls for zipcode-by-year-month fixed effects and housing controls (the same controls as Column 3 in Table 1), and we plot this relationship split by tercile of agent experience. See Section 3 for more details on the data sample and definition of experience.

E Microfoundation of the theoretical matching function

Suppose there are s houses for sale and b buyers who each decide to view one house at random. The probability that any particular house is visited by at least one buyer is $1-\left(1-\frac{1}{s}\right)^{b}$ - the complimentary probability to that of an outcome where every buyer chooses to view another house. An approximation of this match probability for large numbers of s and b is $1-e^{-\theta}$, where $\theta = b/s$. The number of total matches that will be made, or match function, is $m(b,s) = s(1-e^{-\theta})$. As $\theta \to \infty$ or $\theta \to 0$, this function approaches a Leontief formulation. Intuitively, if there are very few houses relative to the number of buyers, most houses will be visited and s matches will be made. Similarly, if there are very few buyers relative to the number of houses, each buyer is likely to visit a distinct house, so the number of matches will be b. For θ's outside the extreme range however, there are inefficiencies associated with the lack of coordination among the buyers. Since they can not ex-ante agree to each visit a separate house, there will be houses that have multiple buyers and some that will end up with none.

Imagine now that instead of visiting sellers, a buyer visits real estate agents. Then a real estate agent can schedule buyer visits to one house in their inventory. If the inventories consist of one seller per agent, the matching function resulting in this set up is exactly the same as in the buyer - seller matching problem. However if an agent has more than one house, the coordination inefficiency is reduced due to the ability of an agent to perfectly coordinate the buyers within their housing stock. At the extreme, if there is only one agent, the match function is Leontief for any ratio of buyers and sellers: an agent will assign one house per each buyer until either the buyers of houses run out. More generally, if there are b houses and a agents with l listings each, and if b and a is a large number. We can approximate the probability of match for each seller as

$$\begin{aligned}
\mu^{l}(a,b) &= \sum_{i=1}^{l}\left(e^{-b/a}\frac{(b/a)^{i}}{i!}\frac{i}{l}\right)+\left(1-\sum_{i=0}^{l}\left(e^{-b/a}\frac{(b/a)^{i}}{i!}\right)\right)\\
&= 1-\sum_{i=0}^{l}\left(e^{-b/a}\frac{(b/a)^{i}}{i!}\frac{l-i}{l}\right)
\end{aligned}$$

Proposition 1. $m^{1}(a,b) < m^{l}(a/l,b), \forall l > 1$

Proof. We can restate the original problem by considering agents who have l listings each, but buyers who are bypassing the agents and looking at houses directly. Then the probability of each particular house to be visited is as follows:

$$\mu(la,b) = \sum_{i=1}^{\infty} e^{-b/a}\frac{(b/a)^{i}}{i!}\left(1-\left(1-\frac{1}{l}\right)^{i}\right)$$

The arrival of buyers to agents is still a poisson distributed variable. For each realization of it, buyers are randomly landing on each house in the inventory, thus if i buyers arrive for a particular agent, the conditional probability of at least on match is $1-(1-1/l)^{i}$. If however the agents can direct the buyers, they can avoid the congestion of many buyers randomly deciding to visit the same house and instead either assign one buyer for each house or ration the houses among buyers. Thus the conditional probability of match is $\mathrm{min}(i/l, 1)$

$$\mu^l(a,b) = \sum_{i=1}^{\infty} e^{-b/a} \frac{(b/a)^i}{i!} \min\left\{1, \frac{i}{l}\right\}$$

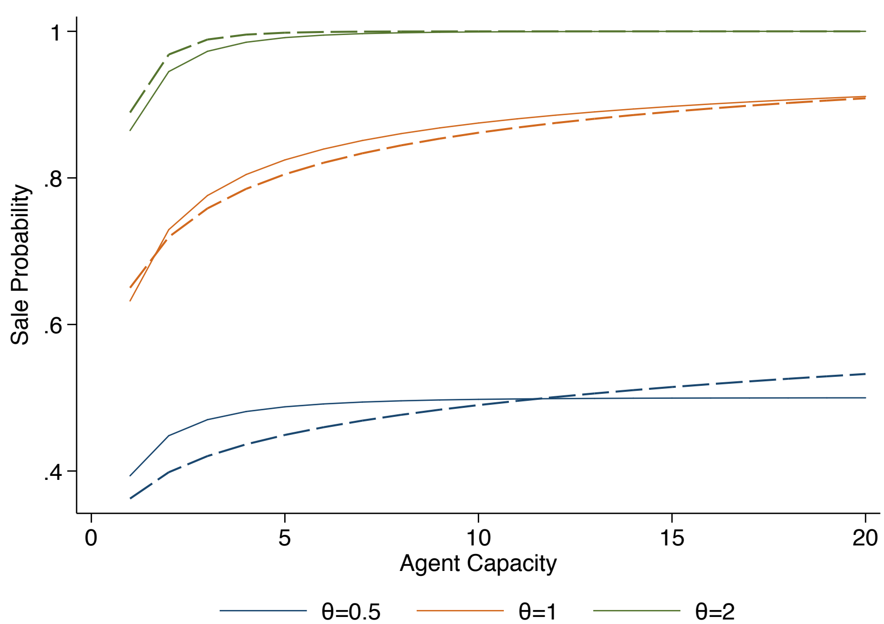
At $i = 0$, the expressions in the sum are the same and equal to 0. However as i increases, $m^l(a,b)$ increases faster than $m(la, b)$. We can see that from computing the slope of the part that differs in the too expressions with respect to i.

$$\frac{d}{di}\left(1-\left(1-\frac{1}{l}\right)^i\right) = -\left(1-\frac{1}{l}\right)^i \log\left(1-\frac{1}{l}\right) <^{33} \left(1-\frac{1}{l}\right)^i \frac{1}{l} < \frac{d}{di}\frac{i}{l} = \frac{1}{l}$$

Note than when $\min\left\{1, \frac{i}{l}\right\}$ reaches 1, it is always larger than $0 < \left(1-\left(1-\frac{1}{l}\right)^i\right) < 1$. Since $m^l(a,b) = la\mu^l(a,b)$ and $m(la,b) = la\mu(la,b)$, the inequality in the proposition holds. $\square$

We have shown that markets where agents have larger networks are thus more efficient at producing matches. Let us now fix the number of sellers s and buyers b and explore how the probability of match $\mu^l(s/l, b)/s$ varies with capacity of agents l. Note first, that the coordination problem that agents solve is more of an issue then s is similar to b, so improvement in efficiency will vary depending on the market tightness. Also, the maximum possible number of matches is the minimum of s and b, so improvement in efficiency is bounded. Figure E1 plots the $\mu^l(s/l, b)/s$ for various values of $\theta = s/b$.

Figure E1: Agent capacity and efficiency improvement



Note: This plot graphs the probability of sale for houses in market with different agent capacity holding market tightness (the ratio of buyers to sellers) fixed. The three solid lines represent different values for buyer to seller ratios θ. The dashed lines represent the matching function set up used in the model. We allow for θ to vary across l, and λ_2 vary across states.

For a fixed θ the probability of sale for each value of agent capacity is a concave function approaching a constant. This relationship can be approximated by the functional form that we assume in the model: $\mu(exp) = 1 - e^{-\lambda_1 exp^{\lambda_2} \theta}$. Since different aggregate states imply different market tightness (ratio of buyers to sellers), we allow the curvature λ_1 to change with the state. Here λ_2 represents the experience advantage. For the illustration above, we can calibrate $\lambda_1(z)$ and λ_2 to match the relationship that is delivered by the micro-founded model. While z represents varying θ in our toy model, in the baseline set up buyers have more incentives to go into markets that are more efficient, so for the overall market tightness n_t^b/n_t^s, each market will have its own ratio of buyers to sellers which will be larger for more efficient agents. In the dashed lines, Figure E1 then plots the model specification where we allow for λ_1 to vary across the three levels, but within each level, θ increases with l. We can see that our model approximates well the micro founded model described above.

F Office commission splits

Real estate agents can not legally sign contracts with clients without being affiliated with a real estate broker. The agents are thus always affiliated with a real estate office (where there is a real estate broker). In return for an opportunity to work and other services, such as advertising and brand recognition, an agent typically gives an office a part of their commission. The commission split is a negotiable part of an agent-office contract and thus varies substantially. Unsurprisingly, agents who bring in more business to the office are able to negotiate a more favorable commission split, while new agents tend to give up about half of their commissions. National Association of Realtors survey conducts a study of real estate professionals (National Association of Realtors (2017a)) and documents the commission splits for each earning bin summarized in Table F1.

Figure F1: Survey evidence on commission splits

Exhibit 3-3 COMPENSATION STRUCTURES FOR REALTORS®, BY GROSS PERSONAL INCOME

(Percentage Distribution)

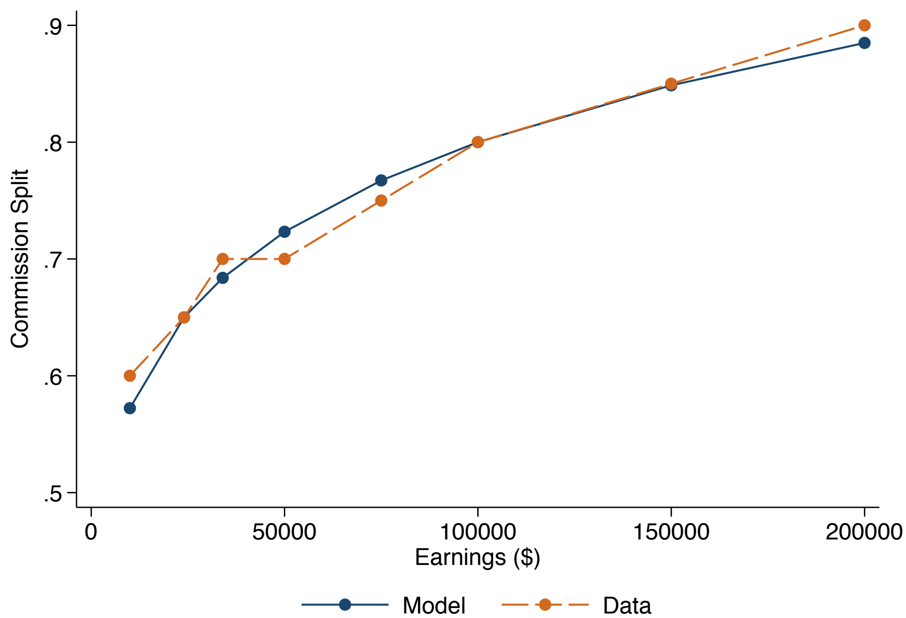
		GROSS PERSONAL INCOME							
	ALL REALTORS®	Less than \$10,000	\$10,000 to \$24,999	\$25,000 to \$34,999	\$35,000 to \$49,999	\$50,000 to \$74,999	\$75,000 to \$99,999	\$100,000 to \$149,999	\$150,000 or more
Percentage commission split	68%	77%	79%	73%	70%	61%	60%	51%	48%
100% Commission	18	15	13	15	15	21	21	26	29
Commission plus share of profits	3	1	2	2	3	3	2	4	6
Salary plus share of profits/ production bonus	3	*	1	2	2	4	5	9	6
Salary only	2	1	1	2	4	2	4	2	1
Share of profits only	1	1	1	*	1	2	1	2	2
Other	6	6	4	6	5	8	8	6	8
Median year-starting percentage commission split	70%	58%	60%	65%	70%	70%	70%	80%	80%
Median year-ending percentage commission split	70%	60%	65%	70%	70%	75%	80%	85%	90%

* *Less than 1 percent*

Note: This table summarizes the compensation structure of real estate professionals based on their income level. The commission split displayed in the first row is the average percent of the earned commission that an agent shares with their office.

In our model, we choose the commission split to be a function of earnings that matches this survey evidence. Using the functional form $f(x) = ax^b$, we find that $a = 0.1498$ and $b = 0.1455$ best approximates the data as shown in Figure F2.

Figure F2: Matching office commission split



Note: This figure plots the reported commission splits corresponding to different earning levels, as reported in the National Association of Realtor survey (National Association of Realtors (2017a)). On top of these survey values, we fit the best approximation of the function $f(x) = ax^b$.

G Solution algorithm for the baseline model

$\lambda(w) = \tilde{\lambda}(w)$ for all w : guess entry rate

$\rho(e, w) = \tilde{\rho}(e, w)$ for all e, w : guess exit policy

$n^a(e, w) = \tilde{n}^a(e, w)$ for all e, w : guess distribution of agents

$\tilde{V}_\rho(e, w)$, for all w, e: compute value functions consistent with ρ

$n = 0$

repeat

repeat

Given $n^a(e, w)$, compute $s(e, w), b(e, w)$ - distribution of clients

Given s, b, ρ, T (transition probability matrix for w) compute transition probabilities over the entire state space P

Compute new distribution $n^{a*}(e, w) = \lambda[P^0 + P^1 + ... + P^{40}]$

$\Delta_1 = ||n^{a*} - n^a||$, update $n^a = n^{a*}$

until $\Delta_1 < \epsilon$

Solve for optimal prices and probabilities of sale

Compute expected profit and $V^*(e, w|\rho, \lambda) = E[\pi] + \beta E[\max\{0, -c + V(e', w'|\rho, \lambda)\}]$

$\lambda^*(w) = \lambda(w)\frac{V(0,w|\rho,\lambda)+c_e}{c_e}$ *for all w*

$\lambda = \lambda + (\lambda^* - \lambda)/(n^{\delta_1} + N_1)$

$$\rho^* = \begin{cases} 1 & \text{if } c > V^*(e, w|\rho, \lambda) \\ 0 & \text{if } c \leqslant V^*(e, w|\rho, \lambda) \end{cases}$$

$\rho = \rho + (\rho^* - \rho)/(n^{\delta_2} + N_2)$

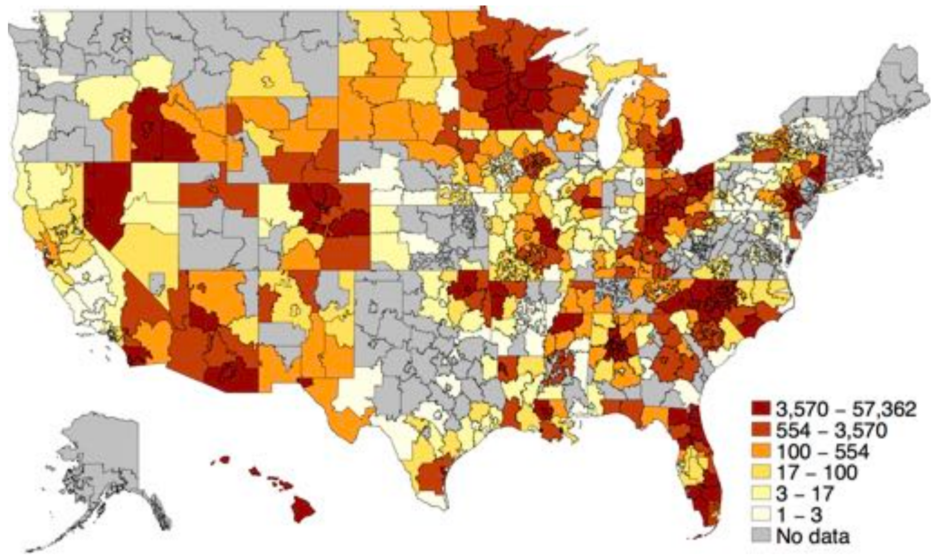
$\Delta_2 = ||\rho - \rho^*||, \Delta_3 = ||\lambda - \lambda^*||$

until $\Delta_2 \leqslant \epsilon_2$ and $\Delta_3 \leqslant \epsilon_3$

We note here that uniqueness of extended oblivious equilibrium has not been proven. It well may be that there are multiple equilibria associated with the same set of parameters. However with multiple different starting points, we were unable to find more than one equilibrium. Furthermore, for our exercise we are only aiming at finding an equilibrium that is closest to the data and are not interested in multiplicity *per se*.

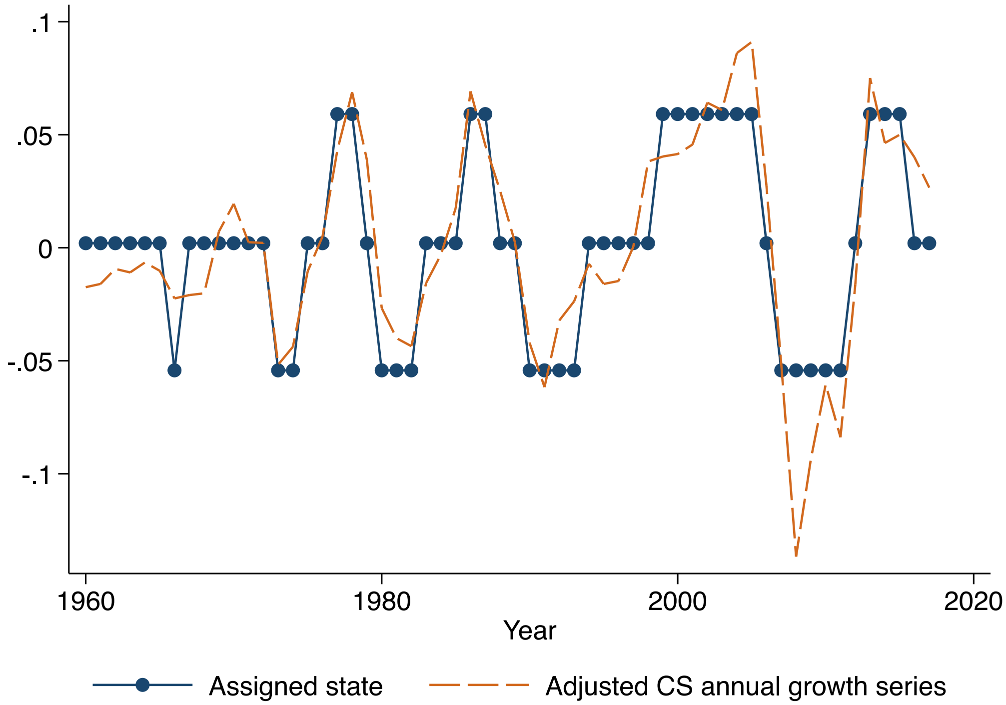
H Additional results

Figure H1: Coverage



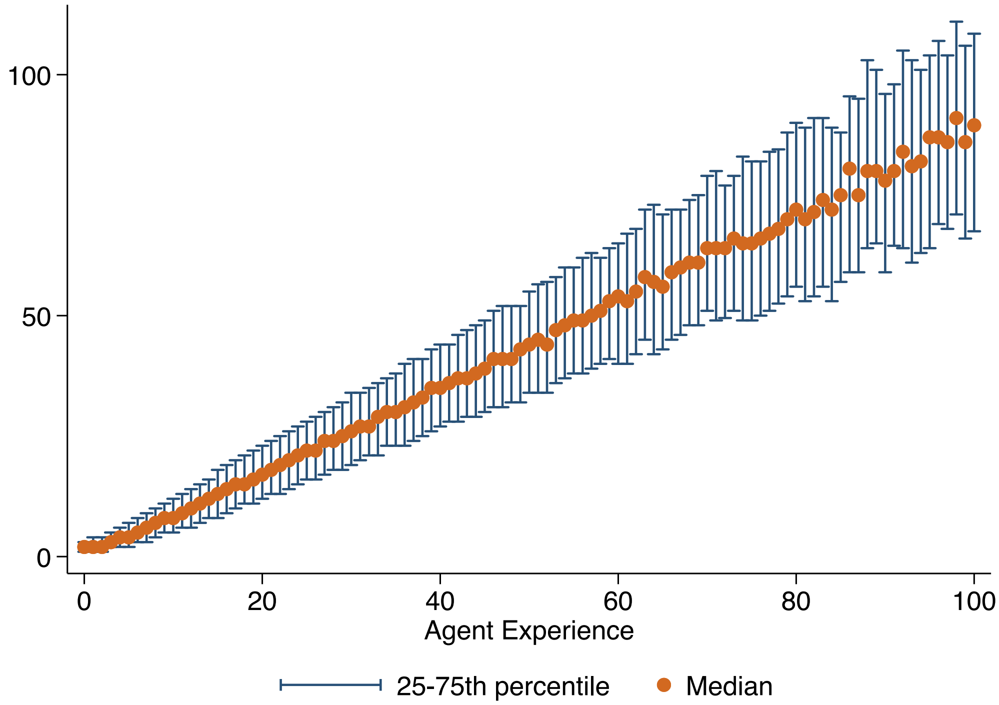
Note: This figure plots a choropleth map of the number of listings per three-digit zip in the main sample.

Figure H2: Construction of aggregate state variables using Case Shiller adjusted series



Note: This figure shows the construction of our three aggregate state variables. The dashed line plots the average annual 12-month growth rates of the Case-Shiller house price index deflated by the overall Consumer Price Index less shelter. The dots represent one of the three states assigned to each year.

Figure H3: Clients and experience



Note: This figure plots the number of clients (all listings and successful buyers) that an agent is observed working with in a given year, based on the experience level of the agent in that year. All listings are attributed to the original list year, and all buyers are counted for the close year of the property they bought, thus there is no overlap between clients across different years. Experience is defined as the number of clients that and agent had in the previous year. See Section 3 for more details on the data sample and definition of experience.

Table H1: First stage of instrumental variables

	Experience	Experience × Bust	Experience × Medium
	(1)	(2)	(3)
Log(Buyer Agent Exp + 1) × Inactive	-0.2658***	0.0002	0.0001
	(0.0165)	(0.0002)	(0.0001)
Bust × Log(Buyer Agent Exp + 1) × Inactive	0.0329***	-0.2335***	-0.0000
	(0.0094)	(0.0162)	(0.0001)
Medium × Log(Buyer Agent Exp + 1) × Inactive	0.0065	-0.0000	-0.2599***
	(0.0128)	(0.0003)	(0.0137)
First-stage F-statistic	130.5841	112.8275	131.9488
Observations	1217738	1217738	1217738

Note: This table reports estimates for our first stage regression from Equation 2. The regressions include zipcode-by-purchase-year-month-by-listing-year-month fixed effects and housing controls (the same controls as Column 3 in Table 1). Standard errors are clustered at the MLS-level. See Section 3 for more details on the data sample and definition of experience.

Table H2: Complier analysis

			Log Prices		
	Sale Pr.	Will Foreclose	List / Inferred	List / Sale	Sale/Infer
	(1)	(2)	(3)	(4)	(5)
Log(Exp + 1)	0.0297***	-0.0000	-0.0076***	-0.0050***	-0.0013***
	(0.0021)	(0.0001)	(0.0009)	(0.0014)	(0.0004)
Bust $\times$ Log(Exp + 1)	0.0207***	-0.0035***	-0.0022	0.0016	-0.0012
	(0.0021)	(0.0009)	(0.0020)	(0.0029)	(0.0009)
Medium $\times$ Log(Exp + 1)	0.0054**	-0.0011**	0.0004	-0.0001	0.0006
	(0.0021)	(0.0004)	(0.0009)	(0.0011)	(0.0005)
Time-by-Zipcode FE	Yes	Yes	Yes	Yes	Yes
House Char.	Yes	Yes	Yes	Yes	Yes
Inferred House Price	Yes	Yes	Yes	Yes	Yes
Bust Effect	0.0504	-0.0035	-0.0099	-0.0033	-0.0025
Bust p-value	0.0000	0.0003	0.0000	0.3192	0.0297
Medium Effect	0.0352	-0.0011	-0.0073	-0.0051	-0.0008
Medium p-value	0.0000	0.0358	0.0000	0.0123	0.2716
Observations	1217705	1140228	740336	454847	447586

Note: This table reports estimates for our outcomes using our main specification from Equation 1, reweighting 12 mutually exclusive subgroups so that the proportion of compliers from our IV analysis in a given subgroup matches the share of the estimation sample. See the text for details on the complier reweighting. The regressions include zipcode-by-year-month fixed effects and housing controls (the same controls as Column 5 in Table 1). In Column 1, we report the effect of experience on the probability of sale in 365 days. In Column 2, we report the effect on subsequent foreclosures. Column 3 reports the effect of agent experience on list price normalized to inferred price (measured using the previous sale price, appreciated using zipcode- and price-tier-specific Zillow house price appreciation) for all listings. Column 4 reports the effect on sale prices normalized to inferred price. Column 5 reports the discount that a property sells at relative to its list price. Standard errors are clustered at the MLS-level. See Section 3 for more details on the data sample and definition of experience.

Table H3: County summary statistics

Year	Unique	Agents		Exit Rates		Entry Rates	
	Counties	Mean	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2002	663	225	(656)	0.18	(0.22)	-	-
2003	713	228	(692)	0.17	(0.20)	0.31	(0.28)
2004	747	246	(762)	0.18	(0.22)	0.32	(0.28)
2005	808	266	(845)	0.20	(0.23)	0.35	(0.28)
2006	851	263	(832)	0.24	(0.26)	0.30	(0.27)
2007	853	254	(772)	0.26	(0.25)	0.27	(0.27)
2008	857	225	(683)	0.26	(0.25)	0.20	(0.24)
2009	858	209	(656)	0.23	(0.25)	0.19	(0.23)
2010	851	201	(637)	0.23	(0.25)	0.20	(0.25)
2011	869	186	(611)	0.21	(0.24)	0.20	(0.25)
2012	861	191	(632)	-	-	0.21	(0.26)

Note: This table presents summary statistics for our data at the county level. For each year, Column 1 counts the number of distinct counties observed in our data. Column 2 and 3 report the mean and standard deviation of number of agents active in the counties. Column 4 and 5 report the mean and standard deviation of exit rates. Columns 6 and 7 report the mean and standard deviation of entry rates.

Table H4: Naive counterfactuals

	Sale Probability			Foreclosure Probability		
	Data	Counterf.	% Δ	Data	Counterf.	% Δ
2002	0.71	0.75	5.1	0.001	0.001	-32.9
2003	0.71	0.74	4.7	0.001	0.001	-0.2
2004	0.71	0.74	5.0	0.002	0.002	-7.4
2005	0.66	0.70	6.5	0.003	0.003	-10.2
2006	0.53	0.57	8.0	0.008	0.007	-12.6
2007	0.46	0.51	10.2	0.018	0.015	-21.1
2008	0.47	0.52	12.2	0.025	0.019	-27.5
2009	0.54	0.60	11.2	0.020	0.017	-21.6
2010	0.52	0.57	9.5	0.019	0.015	-21.9
2011	0.58	0.62	6.9	0.014	0.013	-9.7
2012	0.66	0.70	6.0	0.008	0.008	1.7
2013	0.69	0.72	5.5	.	.	.

Note: This table shows results from partial equilibrium counterfactual exercise. For each outcome y (sale and identifier of future foreclosure), we run the following regression: $y_{i,t} = \alpha_{i,t} + \sum_{p \in \text{periods}} \beta_p \log(1 + \text{experience}_{i,t}) + \delta W_{i,t} + \epsilon_{i,t}$, where $W_{i,t}$ are detailed property characteristics, $\alpha_{i,t}$ are zipcode-by-list-month fixed effects, and the β_p vary by year. For the counterfactual, we split all agents in terciles according to their experience (listings weighted) and compute the average experience within each tercile. For all agents whose experience is below the average of the top tercile, we replace experience with that average. Columns labeled "Counterf." show yearly averages for these predicted values. Columns labeled "Data" show yearly averages of the actual outcome values. Finally "%Δ" columns show the percentage difference between the two.

Table H5: Number of clients

	(1)	(2)
Agent Experience	0.85***	0.91***
	(0.02)	(0.02)
Bust × Experience		-0.14***
		(0.03)
Medium × Experience		-0.03
		(0.03)
R^2	0.7152	0.7195
FIPS Code F.E.	Y	Y
N	1672032	1672032

Note: This table shows a regression of number of clients we observe in the data (this includes all listings and successful buyers) against experience of the agent. Experience here is measured as the number of clients that the agent had in the previous two years. All listings are attributed to the original list year, and all buyers are counted for the close year of the property they bought, thus there is no overlap between clients across different years. To exclude the outliers with unreasonable number of clients, the sample truncates the top 1% of agent by year observations. The first specification controls only for location and time fixed effects, where the county used for each observation is where an agent has the most number of clients in a particular year. The second specification includes three time periods for boom, bust and medium aggregate states interacted the experience measure. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table H6: Model fit

Panel A:		Exit Rates						Entry Rates	
		Experience 0		Experience 10		Experience 40			
		Baseline	Data	Baseline	Data	Baseline	Data	Baseline	Data
Bust_{t-1}	Bust_t	0.35	0.39	0.10	0.10	0.03	0.04	0.13	0.17
Bust_{t-1}	Medium_t	0.35	.	0.08	.	0.03	.	0.31	0.19
Medium_{t-1}	Bust_t	0.35	0.41	0.11	0.11	0.03	0.04	0.00	0.20
Medium_{t-1}	Boom_t	0.35	.	0.08	.	0.02	.	0.28	0.20
Boom_{t-1}	Medium_t	0.35	0.38	0.09	0.08	0.03	0.06	0.05	0.25
Boom_{t-1}	Boom_t	0.35	0.30	0.08	0.07	0.02	0.02	0.18	0.19

Panel B:		Learning							
		Experience 0		Experience 5		Experience 10		Experience 40	
		Baseline	Data	Baseline	Data	Baseline	Data	Baseline	Data
Bust_{t-1}	Bust_t	1.5	3.4	0.5	0.7	-0.5	-0.4	-6.3	-4.1
Bust_{t-1}	Medium_t	1.2	3.4	0.6	1.0	-0.1	0.3	-4.2	-1.3
Medium_{t-1}	Bust_t	1.4	3.6	0.0	0.8	-1.4	-0.6	-9.6	-3.0
Medium_{t-1}	Boom_t	1.0	.	-0.3	.	-1.6	.	-9.4	.
Boom_{t-1}	Medium_t	1.2	3.6	0.2	0.9	-0.8	-0.3	-6.9	0.3
Boom_{t-1}	Boom_t	1.0	4.0	-0.2	1.4	-1.4	0.4	-8.7	-1.4

Panel C:		Distribution							
		25th Percentile		50th Percentile		75th Percentile		95th Percentile	
		Baseline	Data	Baseline	Data	Baseline	Data	Baseline	Data
Bust_{t-1}	Bust_t	2	1	5	3	9	8	17	24
Bust_{t-1}	Medium_t	0	0	3	3	8	8	16	24
Medium_{t-1}	Bust_t	2	0	5	3	9	8	17	23
Medium_{t-1}	Boom_t	0	0	3	3	7	8	16	24
Boom_{t-1}	Medium_t	1	0	3	3	7	8	16	23
Boom_{t-1}	Boom_t	0	0	3	3	7	8	15	23

Note: This table reports the fit of the baseline calibrated model against the observed empirical data. Each panel reports the predicted baseline model values and the observed empirical values for pairs of aggregate states, corresponding to the previous year's aggregate state and the current aggregate state. Panel A reports the exit for different experience levels of agents, as well as the overall entry rates. Panel B reports the change in experience (denoted as the change in the experience level this period less the experience last period) for those individuals who did not exit the market. Panel C characterizes the experience distribution at different points in the distribution.