The Equilibrium Impacts of Broker Incentives in the Real Estate Market

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Abstract

Over 90% of housing transactions in the United States involve brokers, despite the unusually high commissions compared to those in other developed countries. One possible reason behind the high fees is the customary practice of sellers offering buyers' brokers a commission, incentivizing these brokers to steer buyers toward properties with higher commissions. This paper examines the equilibrium impacts of a widely speculated policy called "*decoupling*," requiring buyers and sellers to each pay their brokers, on commission rates, house prices, and welfare. I develop and estimate a structural model integrating buyers, sellers, and brokers to characterize the equilibrium house prices and commissions. I find that decoupling reduces commissions paid by 53%, as sellers no longer have to offer high commissions to attract buyers, and brokers compete for price-sensitive buyers. Sellers and buyers experience a surplus gain of 4.1% of the total transaction value from having higher net proceeds than the status quo. Despite widespread concerns that decoupling could harm home buyers, I find notable surplus gains for buyers, including low-income buyers, as sellers pass through part of their commission savings to house prices.

Keywords: intermediaries, real estate, competition policy

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1 Introduction

Consumer protection and concerns about conflicts of interest are crucial when consumers rely on intermediaries (Inderst and Ottaviani, 2012), as they are often found in high-stake settings such as financial services or healthcare. I study the residential brokerage industry in the United States, where commission rates are more than double those in other developed countries, with annual commission fees adding up to \$160 billion in 2022.[1] It is customary for sellers to offer and pay commissions to buyers' brokers, and this practice has raised concerns about steered buyers and inflated commission rates.[2] While empirical research has documented the causal impacts of broker incentives on consumer outcomes (Barwick et al., 2017; Barry et al., 2023), little is known about what would happen if this practice were to be banned.

In response to recent lawsuits alleging consumer harm due to sellers compensating buyers' brokers, The Department of Justice proposed "*decoupling*," whereby buyers and sellers pay their respective brokers.[3] Proponents argue that decoupling can reduce commission fees since sellers no longer need to offer high commissions to attract buyers' brokers, and brokers need to compete for buyers on commissions. Others argue that regulations dictating who is responsible for statutory commissions seem unnecessary because of the independence of physical and economic incidence. There also have been concerns that the policy could disproportionately harm low-income buyers who cannot afford brokerage services.[4] All of these are a priori unclear and ultimately an empirical question.

In this paper, I fill the gap by quantitatively assessing the equilibrium effects of decoupling on house prices, commissions, and the welfare of buyers, sellers, and brokers. I develop and estimate a model that characterizes the demand and supply for houses and brokerage competition, linked in equilibrium through house prices and commission rates. Using the estimated model, I simulate a market in which sellers no longer compensate buyers' brokers, and brokers compete on commissions to attract buyers.

The demand side features a discrete choice model of houses that are differentiated by prices, property characteristics, and quality (Bayer et al., 2007). The model for intermediation features brokers steering associated with their incentives and buyers

[1] Smith (2024), Federal Reserve Bank of St. Louis (2024).

[2] See Section C, Chapter IV in Federal Trade Commission, U.S. Department of Justice (2007).

[3] Nosalek vs. MLS Property Information Network (2024).

[4] Schnare et al. (2022).

choosing among differentiated brokers to maximize expected utility (Robles-Garcia, 2019; Grennan et al., 2024). On the supply side, brokers set commissions to maximize profits, and sellers choose house prices and brokers as they trade-off preferences for greater sales proceeds (house prices net of commission fees) versus their desire for a greater likelihood of selling.

The theoretical framework delivers a key insight that sellers may exhibit puzzlingly inelastic demand with respect to commission fees because of the practice of sellers offering half of the commissions to buyers' brokers. In effect, brokers set commissions accounting for the direct commission elasticity, coming from sellers' dis-preference for commission fees for the services provided. However, the steering motive of buyers' brokers reduces sellers' elasticity with respect to commissions, as offering a greater commission rate increases the seller's likelihood of sale. This indirect channel increases the markup of brokers. I provide a novel decomposition that quantifies the relative importance of the direct and indirect channels in determining commission fees.

I estimate the model using a sample of housing transactions from Riverside, California, from 2009 to 2015. The transaction-level data from CoreLogic include properties listed on the market, their list prices, property characteristics, brokers and agents involved, and commission offers made to buy-side brokers. Additionally, using supplemental data, I observe the financial characteristics of both sellers and buyers.

On the demand side, the main object of interest is the elasticity with respect to house prices and commissions. A potential threat is that house prices and commissions may be correlated with unobserved property and broker quality. I use a seller's predetermined loan characteristics at the time of the seller's purchase, such as loan-to-value and loan term, as instruments. Intuitively, sellers with a greater mortgage burden at sale are more likely to desire higher house prices and lower commissions (Genesove and Mayer, 1997; Anenberg, 2011; Andersen et al., 2022). The conclusions are robust to controlling for market conditions at purchase and sale.

On the supply side, I estimate sellers' preference for greater house prices against the likelihood of a sale within a quarter, which I call "patience," and their sensitivity to commission rates paid to brokers. A potential threat to identification is that patient sellers have houses that are difficult to sell for unobserved reasons. To isolate exogenous variation in the likelihood of a sale, I use the differentiation instruments (Gandhi and Houde, 2019) that build on the notion that the likelihood of sale for a house depends on both the characteristics of the house and the characteristics of *other* properties listed in the same market. With the recovered seller pricing functions, I estimate seller sensitivity to commissions from the variation in observed commissions across brokers, following the procedure for estimating a discrete game with incomplete information with the Bayesian-Nash equilibrium concept (Bajari et al., 2010; Ellickson and Misra, 2012). The demand- and supply-side estimates are comparable to the literature. Buyers are sensitive to house prices, and buy-side brokers are sensitive to commission revenues. The estimates imply that buyers have an own-price elasticity of -7.7 on average, comparable to Guren (2018). Sellers face a significant trade-off between paying higher commissions for a greater probability of sale and retaining more sales proceeds. The estimates imply that offering one percentage point (pp) less commission to buy-side brokers leads to -7% drop in the probability of sale within a quarter, consistent with Barwick et al. (2017). Lastly, sellers, on average, are willing to trade 16 days on the market for 1% of the direct sale proceeds, similar to Genesove and Mayer (1997) that finds 21 days for the most patient sellers. There is also meaningful heterogeneity across quantiles by buyers' income and sellers' house prices.

The estimates shed light on why sellers appear to exhibit inelastic demand for brokerage services. On average, brokers face an elastic demand of sellers with an average of -5, only accounting for the direct commission elasticity. However, incorporating the threat of steering from paying lower commissions decreases the elasticity to -2.9, providing significant market power to the brokers. The estimated elasticities tell that the average seller commission of 2.7% (half of the 5.4% total commission) can be decomposed into a marginal cost of 1.0% and a 1.7% markup, with 45% of the markup coming from the current broker incentives.

With the estimates from the structural model, I simulate the counterfactual after decoupling with profit-maximizing buy-side brokers charging a flat fee to buyers. Decoupling reduces the posted commission rates from 5.4pp to 2.0pp for sellers, and buy-side brokers charge a flat fee equivalent to 1.0% of house prices to buyers, leading to a 53% decrease in the total commissions paid by both buyers and sellers. The significant drop in commissions is driven by sell-side brokers pricing only to the direct channel of sellers' sensitivity to commissions and by buy-side brokers competing for buyers who are assumed to have become as sensitive to commissions as sellers.

The equilibrium prices drop by 3% because sellers pass commission savings onto the prices, and buyers pass their statutory commissions onto the prices. However, sellers still retain greater proceeds from the sale, and buyers pay less for a house (inclusive commissions) than before, amounting to a significant consumer welfare gain of 4.1% of the total transaction value. The lower house prices bring additional buyer demand, increasing the number of transactions by 1.9%, leading to an increase in total welfare by 1.5% of the transaction value.

The policy has significant distributional impacts across consumers. Among consumers, buyers gain 2.8%, and sellers gain 1.3% of the transaction value. In terms of a *percentage change* in surplus compared to the status quo, buyers in the lowest income quantile experience a 16.9% increase. This reflects a sorting pattern whereby low-income buyers who are price elastic tend to purchase in neighborhoods with low house prices. Indeed, houses in the bottom price quantile experience the largest price drop, generating significant surplus gains for low-income, price-sensitive buyers.

For sellers, low-patience ones gain the least (1.3%) because the decoupled structure removes a mechanism for impatient sellers to increase the probability of sale through compensating buy-side brokers. Conversely, high-patience sellers benefit from the lower commissions with a 1.9% increase in surplus. Sellers in the lowest house price quantile experience a small surplus increase (0.22%) compared to those in the highest quantile (3.3%). The lowest price quantile attracts price-sensitive buyers and experiences the largest drop in house prices.

The conclusions are robust to other counterfactuals. First, the welfare implications are similar if buy-side brokers charge a percentage-based fee instead of a flat fee. Second, the conclusions are similar in a counterfactual that accounts for potential credit constraints faced by buyers, especially low-income ones who lack cash in hand to pay commissions. Even under this scenario, buyers gain 3.6% of the total transaction value, driven by many buyers choosing not to use a broker and being able to pass more of their commissions onto the house prices.

The debate around decoupling broker incentives has centered on whether it will effectively lower commissions and whether it could harm home buyers in the process. I develop a model that quantitatively assesses the main channels that matter when comparing the status quo and the decoupled counterfactual. I find that decoupling significantly reduces commissions. It matters who pays the statutory commissions because decoupling lowers the commissions by shutting down the steering motives of brokers and encouraging more competition. The lowered transaction costs result in more transactions, increasing overall welfare.[5] The results highlight the importance

[5]Buchak et al. (2024) and Grochulski and Wang (2024) also evaluate the potential impact of decoupling on house prices but with exogenously determined commissions. Buchak et al. (2024) finds that lowered commission fees can lead to an *increase* in the future value of home ownership, resulting in higher house prices.

of accounting for linkages between the housing markets and intermediation markets. In my setting, buyers capture a larger share of savings than sellers, and the concern that low-income buyers will be harmed may not hold due to adjustments in equilibrium house prices. These findings underscore the importance of accounting for the equilibrium effects across housing segments and demographics, offering insights into designing broker incentive structures and their interaction with the housing market.

Related Literature This paper contributes to the large, established body of literature on real estate brokers in the United States.[6] I complement reduced form evidence on the impacts of broker incentives, including steering by buy-side brokers in Boston (Barwick et al., 2017) and across the United States (Barry et al., 2023), in-house transactions in Canada (Han and Hong, 2016), and selling without brokers (Hendel et al., 2009). I contribute by providing a structural model to characterize the equilibrium implications of decoupling on house prices and commission fees. My model also characterizes welfare and distributional implications for buyers, sellers, and brokers.

I also contribute to the literature on the equilibrium effects of broker or expert advisor incentives.[7] Recent work has focused on the mortgage market in the United Kingdom (Robles-Garcia, 2019), the auto loan market in the United States (Grunewald et al., 2023), and the pharmaceutical market in the United States (Grennan et al., 2024). My paper adds to this body of work by studying the real estate market, one of the largest brokerage industries. I implement credible identification strategies to address confounders of house prices and commissions due to unobserved property and agent quality.

Lastly, the model contributes to the broader literature on house price formation. I augment standard discrete choice models of the housing market (Bayer et al., 2007; Calder-Wang, 2021) with models of intermediation and conflicts of interest (Robles-Garcia, 2019; Grennan et al., 2024). In doing so, my model deepens our understanding of how intermediaries and platforms influence liquidity and price formation throughout the housing cycle (Buchak et al., 2022; Gilbukh and Goldsmith-Pinkham, 2023;

[6] Hsieh and Moretti (2003); Han and Hong (2011); Barwick and Pathak (2015) study broker entry; Gilbukh and Goldsmith-Pinkham (2023) study broker role across the macro housing cycle; Levitt and Syverson (2008); Hendel et al. (2009) study heterogeneous sellers; Aiello et al. (2022) study their role as intermediaries; Hatfield et al. (2019) study collusion.

[7] For example, see Christoffersen et al. (2013); Anagol et al. (2017); Egan (2019); Robles-Garcia (2019); Chalmers and Reuter (2020); Egan et al. (2022); Grunewald et al. (2023) for financial products; and Ho and Pakes (2014); Clemens and Gottlieb (2014); Grennan et al. (2024) for healthcare.

Calder-Wang and Kim, 2024). I also develop a novel model of price formation by sellers, building upon insights from related literature with heterogeneous home sellers actively setting prices (Genesove and Mayer, 1997; Anenberg, 2011; Guren, 2018; Andersen et al., 2022).

2 Background and Data

2.1 Real Estate Brokers in the U.S.

In the U.S. real estate market, over 90% of home buyers and sellers use brokers (Kasper et al., 2023). In a typical transaction, there are two brokers involved: one representing the buyer, or "buy-side broker," and one representing the seller, or "sell-side broker." Buyers rely on their brokers to help find suitable homes and guide them through the purchasing process. Sellers depend on their brokers to market their properties, attract buyers, and secure higher sale proceeds within a desired timeframe.

A distinctive feature of the market is that it is customary for sellers to pay the commission fees for both brokers involved in the transaction. The commission fees for buy-side brokers, often also as a percentage of the transaction price, are decided between sellers and their brokers prior to posting properties on the local Multiple Listings Service (MLS) – a shared database of listed properties for local real estate professionals. Once set, the commission rate offered to buy-side brokers is posted on the MLS along with the property listing for all brokers to see. The posted commissions act as a "bounty" for other brokers, incentivizing them to show the property to buyers and claim the commission once the sale closes.

While sellers, in theory, have the freedom to negotiate commission rates with their brokers, they often feel pressure to meet a "standard" rate for buy-side brokers to ensure adequate buyer interest and timely sales. The commission rate offered to buy-side brokers becomes the reference point for the sell-side broker's rate, as both brokers typically expect to get paid equally (Brobeck, 2021).[8] As a result, brokers are often reluctant to negotiate their rates, as higher commissions offered by sellers incentivize other brokers to prioritize these listings, which increases the sell-side broker's profitability and sellers' sales probability (Brobeck, 2019).

Buyers are not expected to pay their brokers directly because sellers have already

[8]This norm dates back to 1913. The 1913 Code of Ethics says "...always be ready and willing to divide the regular commission *equally* with any member of the Association who can produce a buyer for any client."

committed to pay for buy-side brokers upon listing. In fact, brokers had marketed their services as "free" to home buyers before this practice was made illegal in 2020.[9] Sophisticated buyers sometimes approach sellers without a buy-side broker to reduce the purchase price by the amount of the commission that would otherwise go to a buy-side broker. However, the pre-determined contract between the seller and the sell-side broker often binds sellers to pay the full commission *regardless* of the involvement of a buy-side broker in the transaction. This system effectively removes price sensitivity of buyers from the buy-side brokers perspective, as they are rewarded based on sellers offers rather than buyers preferences for lower fees.

Numerous antitrust complaints regarding steering and exclusionary practices have prompted a series of lawsuits, culminating in a settlement announced on March 15th, 2024.[10] While the settlement aims to discourage buy-side brokers' steering based on commissions, it primarily restricts sell-side brokers from posting commission offers to buy-side brokers on the MLS, leaving several loopholes. For example, buy-side brokers can contact sellers to inquire about the compensation offered. Additionally, buy-side brokers can still suggest to buyers that they are not responsible for the fee by showing properties listed by sellers willing to cover the buy-side broker's commission.

Given these ongoing concerns, the Department of Justice (DOJ) has reopened the case against the National Association of Realtors (NAR) to pursue full "*decoupling*" of the compensation structure. It aims to shift broker incentives and increase buyers' price sensitivity to commissions by requiring each party to pay their own broker. The heightened buyers' sensitivity to commission costs would encourage brokers to compete on price and service quality, leading potentially to a lower overall commission rates. However, critics caution that requiring buyers to pay their brokers directly could disproportionately impact first-time and lower-income buyers, as this group may struggle with the upfront costs, potentially limiting their access to homeownership (Schnare et al., 2022).

2.2 Data

I use the CoreLogic MLS data as the primary dataset and supplement it with CoreLogic Mortgage and Transfer, Loan-level Market Analytics (LLMA), and the public Home Mortgage Disclosure Act (HMDA) data. The primary dataset, CoreLogic MLS, contains detailed transaction-level outcomes for properties listed through local MLS

[9] US DOJ v. The Nat'l Ass'n of Realtors (2020).

[10] See Nadel (2021) for extensive treatment of legal issues surrounding the compensation practice.

systems. The supplementary datasets obtain financial and demographic information for the sellers and buyers involved in the observed transactions.

CoreLogic Multiple Listings Service (MLS) MLS databases are maintained by local real estate professionals as a centralized platform where sell-side agents post detailed information about properties, including list prices, addresses and attributes of the properties, seller brokerage office and agent information, and commissions offered to buy-side brokers. Upon a property's sale, sell-side agents update this information with the closing price, contract date, closed date, and buy-side agent and broker office details. Access to MLS often requires a real estate agent license and a paid subscription. CoreLogic, a real estate data company, aggregates the MLS data across states into a standardized format. The cleaned dataset includes nearly 600 variables per listing. While extensive, I make the following assumptions for variables not observed in this dataset.

One limitation of the data is that I do not observe the net compensation paid by sellers to sell-side brokers net of the shares offered to buy-side brokers. This information is generally recorded only on the HUD-1 form at closing. However, as discussed previously, sell-side brokers are typically paid the same amount as buy-side brokers, so I assume that sellers paid twice the observed buy-side broker commission rate throughout the analysis.

A second limitation is that MLS transactions necessarily involve brokers on the sellers side, meaning the dataset excludes transactions by sellers who opted for the for-sale-by-owner (FSBO) channel. However, buyers without broker representation may still be recorded in the dataset, though it is not possible to identify them directly. To address this, I assume that transactions involving the same agent on both sides likely represent cases where the buyer did not have a broker. When buyers approach listings without a broker, the sell-side broker becomes a "dual agent." In California, where this analysis is set, dual agency is permitted with mandatory disclosure to buyers. This likely means that unrepresented buyers consciously choose not to bring their broker into the transaction.

Lastly, I distinguish between "broker" and "agent." Real estate agents are salespeople working under licensed brokers or brokerage firms and cannot close a transaction independently (Kenney, 2024). Although experienced agents may set their commission rates, the brokerage often sets standard rates for its agents (Barwick et al., 2017). Brokerage offices are affiliated with larger brands, such as Coldwell Banker, RE/MAX, and Keller-Williams. Most of these brands operate as franchises, offering brand recognition to local offices for a fee. Throughout this paper, I focus on competition among local brokerage offices rather than individual agents or overarching brands.

CoreLogic Transfer and Mortgage The CoreLogic Mortgage and Transfer data are gathered from the public deed transfer records. When a property transaction occurs, local authorities record the transfer, which includes the property address, transaction price, buyer and seller identities, and financing details. Additional information is recorded if a mortgage is involved, such as the origination date, loan amount, initial interest rate, interest rate type (fixed vs. adjustable), loan term, and loan type (e.g., conventional vs. FHA).

Transfer and mortgage data are merged with the MLS data using property addresses, transaction prices, and transaction dates. Through this merge, I obtain a panel of owners for each property, capturing the buyer's and seller's financial characteristics at the time of their respective transactions. For instance, I observe initial loan characteristics from when a seller first financed the property, which may have occurred several years before listing on the MLS.

Public Home Mortgage Disclosure Act (HMDA) The U.S. Consumer Financial Protection Bureau (CFPB) collects detailed mortgage application-level data from originators, covering the universe of mortgage applications from 2007 to the present at the census tract-year level. Though anonymized, it includes key details such as application outcomes (approved vs. denied), loan amounts, property values, and the census tract of each property. These data points can be linked to transfer instances with mortgages by matching the census tract, year, loan amount, and property value. While some cases may result in fuzzy matching, this process enables access to rich demographic information, including income, debt-to-income ratios, and interest rates for originated mortgages.

The HMDA data provide useful metrics for gauging the size of potential buyers in a given area because they include all loan applications, both approved and denied. Given that approximately 65 to 70% of home purchases are financed by a mortgage, the number of applications serves as an approximate measure of potential home buyer activity.[11]

[11] https://www.redfin.com/news/all-cash-homebuyers-september-2023/.

CoreLogic Loan-Level Market Analytics (LLMA) To further link transfer instances with buyer and seller demographics, I incorporate CoreLogic's LLMA data. Like the public HMDA data, the LLMA contains loan-level data with key characteristics (e.g., interest rates, loan values, debt-to-income ratios) but with less anonymization at the zip-month level, enabling a more precise match with transfer records.

2.3 Empirical Setting and Descriptives

The sample transactions come from the city of Riverside, California, covering the period from 2009 to 2015, with summary statistics shown in Table A1. I focus on California because it exhibits cross-sectional variability in commission rates offered to buy-side brokers, unlike more uniform markets such as Texas.[12] Figure 1 shows the cross-sectional distributions of commission rates offered to buy-side brokers in 2009 and 2014, revealing a bi-modal or tri-modal pattern rather than the degenerate distribution commonly believed.

The city of Riverside is selected as the primary focus due to the computational demands of estimating the structural model and simulating counterfactuals with thousands of heterogeneous sellers, buyers, and brokers, which necessitates a market-by-market approach. For the structural estimation, I restrict the sample to transactions involving brokers with at least 20 listings or five closed transactions.

Within the sample, I empirically examine whether sellers offering lower commissions to buy-side brokers face the threat of steering in a form of lower sales probability. I follow the regression specification used by Barwick et al. (2017):

$$1\{\text{Sold within market}_{ht}\} = \beta \mathbb{1}\{\text{Comm}_{ht} < 2.5\} + X_{ht}\gamma + \epsilon_{ht}, \tag{1}$$

where h denotes house/seller, t denotes the quarter. X_{ht} includes observable characteristics of the house or seller and fixed effects. ϵ_{ht} represents the unobserved factors affecting the sales probability of houses. The coefficient in front of the low-commission indicator, β, is the main coefficient of interest. I run OLS regressions of Equation (1) across various specifications of X_{ht}. This exercise aims to replicate the study by Barwick et al. (2017) and show transparently that the key findings from the literature hold within my empirical setting.

Table 1 presents the results. I find that sellers offering less than 2.5% commissions

[12] Texas is known for its "uniform" commission rates. Over 98% of listings offer a 3% commission across periods and cities, consistent with the findings of Barry et al. (2023).

to buy-side brokers are associated with worse sales outcomes across all specifications. In the most saturated specification, the effect of a low commission is a four percentage point (pp) decrease in sales probability or an 11% decrease. This is consistent with the findings of Barwick et al. (2017), who report a similar impact of -5pp to -8pp in sales probability, corresponding to a -7.6% to 12% decrease, depending on specifications.

3 Theoretical Framework

Building on the qualitative evidence and the empirical findings from Section 2, I present a stylized model of the U.S. real estate market, focusing on the interaction between sellers and sell-side brokers. The model aims to capture the mechanisms through which the current incentive structure leads to higher equilibrium commissions.

3.1 Setup

Consider a sell-side broker l with a set of sellers, each with house $h \in \mathcal{H}$, in a single market. The timing of actions proceeds as follows:

1. **Broker sets the commission rate**: The broker sets the commission rates, c_l, to maximize profit, with half of the commission, $\frac{1}{2}c_l$, offered to buy-side brokers.

2. **Seller decides to list:** Given the commission rate, each seller of house h decides whether to list with broker l. This choice depends on the commission charged by the broker, the expected price of the house, and the probability of sale, denoted ϕ_{hl}. Let

$$s^L_{hl}(c_l, p_{hl}, \phi_{hl}),$$

represent seller h's demand for sell-side broker l. This demand increases with the expected price and sales probability, i.e., $\frac{\partial s^L_{hl}}{\partial p_{hl}} > 0$ and $\frac{\partial s^L_{hl}}{\partial \phi_{hl}} > 0$, but decreases with the commission rate, $\frac{\partial s^L_{hl}}{\partial c_l} < 0$.

The sales probability for each house, ϕ_{hl}, depends on the house prices on the market, $\boldsymbol{p} := \{p_{hl}\}_{h \in \mathcal{H}}$, and the commission offered to buy-side brokers:

$$\phi_{hl}(\boldsymbol{p}, \frac{1}{2}c_l).$$

The probability of sale decreases with the house's price, i.e., $\frac{\partial \phi_{hl}}{\partial p_{hl}} < 0$, but increases with the commission offer to buy-side brokers, i.e., $\frac{\partial \phi_{hl}}{\partial \tilde{c}_l} > 0$. I defer a detailed discussion of the buy-side mechanism until the following section.

3.2 Equilibrium commission rates under current incentive structure

Broker l considers the average house price $\overline{p}$ as a state variable and seeks to maximize profit by choosing a commission rate c_l:

$$\Pi_l(c_l;\bar{p}) = \left[\sum_{h\in\mathcal{H}} s^L_{hl}(c_l)\phi_{hl}(\frac{1}{2}c_l)\right]\left(\frac{1}{2}\overline{p}c_l - mc_l\right), \tag{2}$$

where $s^L_{hl}(c_l)\phi_{hl}(\frac{1}{2}c_l)$ represents the joint probability of seller h choosing the broker and successfully selling the house. The broker expects revenue of $\frac{1}{2}\overline{p}c_l$ and incurs a marginal cost of mc_l per transaction.

Taking the first-order condition of Equation (2) with respect to c_l gives the expression for the optimal commission rate:

$$c^*_l = 2\frac{mc_l}{\overline{p}} - \left[\sum_{h\in\mathcal{H}} \phi_{hl}\left(\overbrace{\frac{\partial s^L_{hl}}{\partial c_l}}^{(i)<0} + \overbrace{\frac{\partial s^L_{hl}}{\partial \phi_{hl}}\frac{\partial \phi_{hl}}{\partial c_l}}^{(ii)>0}\right) + \overbrace{s^L_{hl}\frac{\partial \phi_{hl}}{\partial c_l}}^{(iii)>0}\right]^{-1} \sum_{h\in\mathcal{H}} s^L_{hl}\phi_{hl}. \tag{3}$$

Equation (3) highlights the channels through which the current incentive structure allows sell-side brokers to charge higher markups. The term (i) captures *direct* channel – sellers sensitivity to commission rates, holding sales probability fixed. This standard marginal revenue function reflects the broker's natural market power from differentiation.

The last two terms, (ii) and (iii), capture the *indirect* channel. Sellers prefer a higher probability of sale, all else being equal, and the marginal commission offered to buy-side brokers increases this probability. The term (iii) captures that it is also in the sell-side broker's interest to close sales by offering higher commissions to buy-side brokers. The indirect channel is present under the current incentive structure, reducing the elasticity of the marginal revenue curve and thereby increasing brokers' market power.

The model illustrates the effect of decoupling on sell-side commissions: without the influence of offers to buy-side brokers, both (ii) and (iii) in Equation (3) drop out:

$$c_l^{*,CF} = \frac{mc_l}{\overline{p}^{CF}} - \left[\sum_{h \in \mathcal{H}} \phi_{hl}^{CF} \overbrace{\frac{\partial s_{hl}^{L,CF}}{\partial c_l}}^{(i)<0} \right]^{-1} \sum_{h \in \mathcal{H}} s_{hl}^{L,CF} \phi_{hl}^{CF}, \tag{4}$$

where ^{CF} denotes objects in the decoupled counterfactual. Decoupling necessarily lowers sell-side commissions. However, this model considers only one sell-side broker with exogenous house prices and passive buyers and buy-side brokers. To fully examine the equilibrium effects of decoupling on house prices and welfare through broker competition, I develop an empirical model that incorporates these additional market features.

4 Empirical Model of Intermediated Housing Market

In this section, I present the remaining components of the empirical model and discuss the identification and estimation of key parameters. I begin with buyer demand for housing, which gives rise to the sales probability for sellers, then link the buy-side back to the sell-side discussed in the previous section.

Notation I index buyers with b, seller/house with h, buy-side brokers with k, sell-side brokers with l and markets with t. As conventional, the subscripts denote the level of variation depending on the index. I use superscripts to indicate the relevant choice situations with uppercase letters: H for choosing across houses, K for choosing across buy-side brokers, S for choosing a seller price, L for choosing across sell-side brokers.

4.1 Stage 4. Buyer and Buy-side Broker Demand for Housing

At this stage, each buyer b among B_t buyers has already chosen a buy-side broker k, including those who chose to shop without a broker ($k = 0$), and they together as a pair choose a house h sold through sell-side broker l among the houses for sale in market t, $hl \in \mathcal{H}_t$, that maximizes their joint utility. I omit the market subscript, t, for now.

Buyer's indirect utility from housing The indirect utility for buyer b from house h listed with sell-side broker l is

$$u_{b,hl}^{H} = \overbrace{-\alpha_b^H p_{hl} + X_{hl}^H \beta_b^H + \xi_{hl}^H}^{=:V_{b0,hl}^H} + \epsilon_{b,hl}^H, \tag{5}$$

where p_{hl} is the listed price of the house, X_{hl}^H is the observable characteristics of the house and that of the sell-side broker, ξ_{hl}^H is an index that captures the unobservable (to the econometrician) quality of the house (h) or sell-side broker (l), and ϵ^H captures buyer-specific idiosyncratic taste. Buyer's preference depends on buyer's demographics, d_b. Buyers can choose not to purchase any house on the market, $h = 0$, which yields them the normalized utility of

$$u_{b,0}^H = \epsilon_{b,0}^H. \tag{6}$$

Buy-side broker's utility from housing Buy-side broker k's indirect utility from house-broker pair hl is:

$$\pi_{k,hl}^H = p_{hl}\tilde{c}_{hl} + W_{khl}^H \gamma^H + \omega_{k,hl}^H, \tag{7}$$

where $\tilde{c}_{hl} := \frac{1}{2}c_{hl}$,k with c_{hl} being the total commission rate seller h pays to her sell-side broker, making $p_{hlt}\tilde{c}_{hlt}$ to be the commission revenue the buy-side broker makes upon transaction, W_{khlt} is the observable characteristics capturing buy-side brokers' expertise on a certain group of houses (h) or relationship with the sell-side broker (l), and $\omega_{k,hl}$ captures buy-side broker specific idiosyncratic taste. If buyer chooses the outside good $h = 0$, then the broker gets zero utility:

$$\pi_{k0}^H = 0. \tag{8}$$

Joint decision utility between buyer and buy-side broker With their respective objectives, the buyer and buy-side broker pair bk, choose a house h listed by sell-side broker l that maximizes their joint utility subject to the surplus division weight κ_k, or the "agency weight" of buy-side broker (Robles-Garcia, 2019; Grennan et al., 2024):

$$(1-\kappa_k)(u_{b,hl}^H + W_{khl}^H\gamma^H) + \kappa_k \pi_{khl}^H.$$

Buyers with broker representation, $k > 0$, benefit from their broker's expertise or network, capturing $(1-\kappa_k)$ fraction of the surplus from the broker network, $W^H_{khlt}\gamma^H$.[13] Rescaled by $1 - \kappa_k$, the joint decision problem can be expressed as:

$$\max_{hl \in \mathcal{H}^*} u^H_{bk,hl} = \underbrace{V^H_{b0,hl} + \tilde{\kappa}_k p_{hl} \tilde{c}_{hl} + W^H_{khl} \tilde{\gamma}^H}_{=:V^H_{bk,hl}} + \tilde{\kappa}_k \omega^H_{khl} + \epsilon^H_{bhl}, \tag{9}$$

where $V^H_{b0,hl}$ is defined as in Equation (5), $\tilde{\kappa}_k = \frac{\kappa_k}{1-\kappa_k}$ and $\tilde{\gamma}^H = \frac{1}{1-\kappa_k}\gamma^H$. Assuming $(\tilde{\kappa}_k \omega^H_{k,hl} + \epsilon^H_{b,hl})$ follows an iid Gumbel distribution, $\tilde{\kappa}_k$ measures the degree of correlation between the unobservable preferences of buyer and her broker. If $\kappa_k = 1$, the buy-side broker chooses to maximize her utility with no correlation between the brokers' unobserved portion of the utility and the buyer's.[14] For buyers without a broker, i.e. $k = 0$, the decision problem is:

$$\max_{hl \in \mathcal{H}^*} V^H_{b0,hl} + \epsilon^H_{bhl}. \tag{10}$$

The choice probability of buyer-broker pair bk choosing house h listed by sell-side broker l is:

$$s^H_{bk,hl} = \frac{\exp(V^H_{bk,hl})}{1 + \sum_{(hl)' \in \mathcal{H}^*} \exp(V^H_{bk,(hl)'})}. \tag{11}$$

Empirical specification and identification The key parameters of interests are the price coefficient of buyers, $\{\alpha^H\}_b$, and the preference for commission revenue for buy-side brokers, $\{\tilde{\kappa}\}_k$. The key challenge in obtaining the consistent estimates is that $\{p\}_{hl}$ and the commission rates $\{c\}_l$ are formed in equilibrium and correlated with the unobserved quality of the house or sell-side brokers, ξ^H_{hl} in Equation (5). For example, houses with unobservably (to econometricians) desirable attributes will be listed at a higher price, p_{hlt}, and attenuate the estimates.

I use the sellers' initial loan-to-value (LTV) ratio, interest rate, and number of years since move-in as the set of instruments for both list prices and commissions. The literature on home sellers' pricing behavior has robustly documented that their financial positions influence how they set list prices (Genesove and Mayer, 1997;

[13]This is to stay agnostic whether buy-side brokers' network should be considered as a source of conflict-of-interest or part of the service the broker provides to her buyers, as it could benefit buyers as well (Han and Hong, 2016).

[14]The analogy can be drawn from the framework of nested logit and its implication of relaxing the independence of irrelevant alternative (IIA) assumption. In this case, for a *specific* buyer, the substitution pattern depends on the paired broker's κ_k, relaxing the IIA restriction.

Anenberg, 2011; Guren, 2018; Andersen et al., 2022). For example, sellers with lower equity in the house set higher prices to extract more proceeds from the sale.

Consistent with the prior literature, Figure 2 shows a strong first-stage relationship between sellers' initial LTV and the endogenous variables of interest. It shows that highly leveraged sellers desire to extract as much equity as possible, setting high list prices and paying less commissions.

One concern may be that highly leveraged sellers (i.e., with high LTV) sort into lower-quality houses due to financial constraints. Figure A1 shows that seller LTV is still positively correlated with *close prices* conditional on list price. If seller high LTV sellers sort into lower quality houses, the close prices will reflect such adjustment conditional on list prices. The evidence from the figure supports the idea that seller preference for proceeds drives pricing and the choice of brokers rather than the quality of the houses.

I include tract-quarter fixed effects to control for unobserved neighborhood quality and tract-specific demand shocks. I implement the IVs using the control function approach (Petrin and Train, 2010), which imposes the structure of ξ^H_{hlt} to be:

$$\xi^H_{hlt} = \xi^{H,p}_{hlt} + \xi^{H,c}_{hlt} + \xi^H_{tract(hl)t} + \tilde{\xi}^H_{hlt}, \tag{12}$$

where ξ^p_{hlt}, ξ^c_{hlt} are the components of house/broker quality correlated with house price and commission rate, respectively. $\xi_{tract(hl)t}$ is the tract-market fixed effects, and $\tilde{\xi}_{hlt}$ is the exogenous unobserved quality.[15] I parameterize $\xi^{H,p}_{hlt} + \xi^{H,c}_{hlt}$ to be $\zeta^p \hat{\nu}^p_{hlt} + \zeta^c \hat{\nu}^c_{hlt}$, where $\hat{\nu}^c$ and $\hat{\nu}^p$ are the residuals from regressing $(p_{hlt}, \tilde{c}_{hlt})$, respectively, on the set of instruments and other included variables.

For the covariates included in X^H_{hlt} and W^H_{hlt}, I let the demand for houses to capture the rich variation from interaction of many players involved. From observables varying across houses (e.g. number of bedrooms), sell-side brokers (e.g. average days on market for the listings in the previous year), broker pairs (e.g. whether k and l are from the same brokerage office), sell-side broker and house pairs (e.g. whether h and l are from the same zip code), to buy-side broker and house pairs (e.g. number of transactions k made in the zip code of h). This flexibility in covariates is important, because the variation in demand captured by parameterization will drive the key endogenous variables determining how buyers choose buy-side brokers and sellers

[15] I omit $\tilde{\xi}_{hlt}$ as the estimation requires simulation over an integral with a dimension equal to the number of "products", which is more than 40,000 in this setting. As Petrin and Train (2010) showed, the omission of $\tilde{\xi}_{hlt}$ does not affect the estimates of the rest of the parameters substantively.

choose sell-side brokers in later part of the model.

Lastly, I discuss the parameterization of α_b^H, β_b^H, and $\tilde{\kappa}_k$ that captures the heterogeneity in preference. I let $\beta_b^H = d_b \beta^{H,d}$ and $\tilde{\kappa}_k = x_k \tilde{\kappa}^x$, where d_b and x_k are the vectors of the buyer and buy-side broker observables, respectively, and $\beta^{H,d}$ and $\tilde{\kappa}^x$ are the vectors of preference parameters capturing the correlation between specific buyer/broker observables with house/broker observables. I parameterize $\alpha_b^H = \frac{1}{inc_b^{1-\rho}}(d_b \alpha^{H,d})$, where inc_b is buyer b's annual income and ρ is the Box-cox parameter to be estimated that flexibly captures the degree of income effect, which determines the curvature of housing demand function relaxing ex-ante restriction on the range of pass-through the model can accommodate (Miravete et al., 2022).

Estimation The empirical specification of the indirect utility equation without the idiosyncratic taste term is:

$$V_{bk,hlt}^H = -\alpha_b^H(d_b;\rho)p_{hlt} + X_{hlt}^H \beta_b^H(d_b) + \tilde{\kappa}_k(x_k)\tilde{c}_{hlt} + W_{khlt}^H \tilde{\gamma}^H + \zeta^p \hat{\nu}_{hlt}^p + \zeta^c \hat{\nu}_{hlt}^c + \xi_{tract(hl)t}^H.$$

Let $\Theta^H = \left(\alpha_b^H, \rho, \beta_b^H, \tilde{\kappa}_k, \tilde{\gamma}^H, \zeta^p, \zeta^c\right)$ be the set of parameters to be estimated. I estimate Θ^H via the maximum likelihood estimation (MLE) procedure. It finds a set of parameters Θ^H that matches the model-implied choice probability to the observed choices of buyer and broker pairs' choices across houses.

Let $C_{bk,hlt}^H = 1$ if buyer-broker pair bk chose houses-broker pair hl in market t and 0 otherwise, as observed from data. Then the likelihood for a candidate parameter Θ^H given observed choices $\boldsymbol{C}^H$ is:

$$\mathcal{R}(\Theta^H; \boldsymbol{C}^H) := \sum_{bk} \sum_{(hl)\in\mathcal{H}_t^*} (s_{bk,hlt}^H(\Theta^H))^{C_{bk,hlt}^H}(1 - s_{bk,hlt}^H(\Theta^H))^{1-C_{bk,hlt}^H},$$

where $s_{bk,hlt}^H$ is as defined in Equation (11), and the estimated parameter is the one that maximizes the above likelihood.

4.2 Stage 3. Buyers' Demand for Buy-side Brokerage Service

Before choosing a house to purchase, each buyer chooses a buy-side broker. As before, buyers are indexed by b, and buy-side brokers are indexed by k. $k = 0$ denotes an option to proceed without a broker's help. Let $\mathcal{K}_t$ denote the set of all buy-side brokers in market t, $k > 0$, from which buyers can choose. Again, I omit t until the identification and estimation are discussed.

Buyers may consider the benefit from a buy-side broker for each house on the market $hl \in \mathcal{H}_t^*$, which is captured through the broker's expertise and network, W_{khl}^H, as well as the harm from the agency problem, κ_k, both captured in Equation (9). I assume buyers are only aware of the distribution of match values across houses, ϵ^H. The difference in the joint utility and the buyer's utility creates a wedge between the decision rule, through which the buyer ends up choosing a house, and the maximum utility the buyer could get without the agency problem (Grennan et al., 2024). Formally, the expected maximum utility, or the "inclusive value", of buyer b from the housing market by choosing to shop with broker k is:

$$I_{bk} := \frac{1}{\alpha_b^H} E[u_{b0,h^*l}^H | h^* = \arg\max_{h \in \mathcal{H}} u_{bk,hl}^H]. \tag{13}$$

In words, Equation (13) captures the buyer's own expected maximum utility in Equation (5) when her decision is influenced by her broker k and follows the decision rule in Equation (9).

Following the Gumbel distribution assumption of the idiosyncratic taste shocks, Equation (13) has the following closed-form expression (McFadden and Train, 2000; Dubois et al., 2018; Grennan et al., 2024):

$$I_{bk} = \overbrace{\frac{1}{\alpha_b^H} \log \left(1 + \sum_{hl} \exp \left(V_{bk,hl}^H(\kappa_k) \right) \right)}^{\text{Surplus from the decision utility}} - \overbrace{\frac{1}{\alpha_b^H} \sum_{hl \in \mathcal{H}} s_{bk,hl}^H \kappa_k (p_{hl} \tilde{c}_{hl} + W_{khl}\gamma)}^{\text{Expected loss of surplus due to agency}}. \tag{14}$$

The first term denotes the expected maximum joint surplus. The second term corrects for the potential surplus loss from steering. If the buyer either chooses a buy-side broker k with $\kappa_k = 0$ or chooses to proceed on her own, $k = 0$, then the buyer's surplus coincides with the joint surplus, in which case:

$$I_{b0} = \frac{1}{\alpha_b^H} \log \left(1 + \sum_{hl} \exp \left(V_{b0,hl}^H \right) \right). \tag{15}$$

Then buyers choose a broker $k \in \mathcal{K}_t$ that maximizes the following indirect utility:

$$u_{bk}^K = \overbrace{\lambda(I_{bk} - I_{b0}) + X_k^K \beta_b^K + \xi_k^K}^{=:V_{bk}^K} + \epsilon_{bk}^K, \tag{16}$$

where X_k^K is observable buy-side broker characteristics, ξ_k^K is market-specific buy-side brokers' vertical quality index, and ϵ^K is the i.i.d. idiosyncratic error term that follows Gumbel distribution. Again, the superscript ^{K} denotes the variables related to buyers' choice across buy-side brokers.

I close the model by specifying the outside option, which is to purchase without buy-side broker representation normalized to:

$$u_{b0}^K = \epsilon_{b0}^K. \tag{17}$$

The distributional assumption of ϵ^K yields the following choice probability of buyer b choosing a buy-side broker k:

$$s_{bk}^K = \frac{\exp\left(V_{bk}^K\right)}{1 + \sum_{k' \in \mathcal{K}} \exp\left(V_{bk'}^K\right)}. \tag{18}$$

Identification and estimation The key parameter is λ, buyer's sensitivity to surplus from the housing market when choosing across brokers. Under the counterfactual, where buy-side brokers start charging commissions directly to buyers, λ will capture how sensitive buyers will be to the fees. While λ may change due to how "hidden" the true cost of using a broker under the status quo is, the estimated λ will still be a useful benchmark.

Variation in I_{bkt} comes from the correlation between the buyer's preference and the probability of the buyer choosing a house closer to her own preference under broker k's influence. Concretely, one of the variables included in W_{khlt}^H (hence influencing $V_{bk,hlt}^H$ and $s_{bk,hlt}^H$ in Equation (14)) is the number of past transactions that broker k made in the zip of h. If buyer b values the characteristics of properties in that zip code, the value of I_{bkt} will be greater for such broker than others with no experience of making a transaction in the zip.

Because I_{bkt} is constructed from the estimates from the housing demand model, the key challenge in estimating in λ is not the usual simultaneity but measurement error. I explicit capture the aforementioned variation in $\hat{I}_{bkt}(\widehat{\Theta}^H)$ through the following procedure: For each buyer b, I construct a set of top N_b houses (hl) ranked buyer's own utility, $\hat{V}_{b0,hlt}^H$. Let $\mathcal{H}_b^*$ be such a choice set. Then for every broker k, I construct a choice set ranked by the *decision utility* with the broker k, $\hat{V}_{bk,hlt}^H$. Let $\mathcal{H}_{bkt}^*$ be such choice set. I then compute the difference in inclusive values to construct an instrument for $\hat{I}_{bkt}$:

$$I_{bkt}^{IV} = \frac{1}{\hat{\alpha}_b^H}\left(\log(\sum_{hl\in\mathcal{H}_b^*}\exp(\hat{V}_{b0,hlt}^H)) - \log(\sum_{hl\in\mathcal{H}_{bk}^*}\exp(\hat{V}_{bk,hlt}^H))\right). \tag{19}$$

This explicitly measures the value of the *composition* of the choice set for a buyer b when the ex-ante ranking of the houses is determined with her broker's influence.

The IV satisfies the relevance condition and the exclusion restriction by construction because both $\hat{I}_{bk}$ and $\hat{I}_{bk}^{IV}$ are functions of $\hat{V}_{b0,hl}^H$ and by the timing assumption that ϵ^H is revealed after the choice of broker k. I again implement the IV via the control function method.

Hence the empirical specification of the indirect utility function of buyer b choosing a buy-side broker k is:

$$V_{b,kt}^K = \lambda(\hat{I}_{bkt}(\widehat{\Theta}^{B,H}) - \hat{I}_{b0t}(\widehat{\Theta}^{B,H})) + X_{kt}^K\beta^K + \tilde{\xi}_{kt}^K + \hat{\nu}_{bkt}^K\zeta^K, \tag{20}$$

where $\hat{\nu}_{bkt}^K$ is the residual from regressing $\hat{I}_{bkt}$ on $\hat{I}_{bkt}^{IV}$ and the set of included covariates, X_{kt}^K and broker-market dummies, and $\tilde{\xi}_{kt}^K$ is broker-market specific parameter capturing buy-side brokers' unobserved vertical quality.

The estimation procedure involves finding $\Theta^K := (\lambda, \beta^K, \zeta^K, \xi_{kt})$ that best fits the model-implied choice probability in Equation (18) with the observed instances of buyers choosing buy-side brokers via MLE.

Connection to the sell-side I conclude the buy-side by describing how the primitives of the buy-side connect to the probability of sale for a seller with a house h. First, integrating over the joint probability of buyers choosing a buy-side broker k, and the pair choosing a house h listed by listing broker l, yields the expected number of buyers for each house listed:

$$q_{hlt} := M_t \int_b \sum_{k\in\mathcal{K}_t} s_{b,kt}^K s_{bk,hlt}^H dD_t, \tag{21}$$

where D_t denotes the observed distribution of buyers demographics in market t.

I assume sellers view buyers' arrival process to their houses to be Poisson with an average rate of q_{hlt}. Hence the probability of a house listed (with a broker), hl, being sold in market t is equivalent to having more than one buyer showing up to purchase within t (quarter), i.e., $\Pr(q_{hlt} \geq 1)$:

$$\phi_{hlt} := \Pr(q_{hlt} \geq 1) = 1 - \exp(-q_{hlt}). \tag{22}$$

This is a micro-founded measure of liquidity in the model, built up from the indirect utility of buyers and buy-side brokers. ϕ_{hl} captures the key channels of the *buy-side* through which a seller may face different probability of sales. Writing it explicitly:

$$\phi_{hl} = \phi_{hl}\left(\boldsymbol{p}, \tilde{\boldsymbol{c}}, \boldsymbol{X}^K, \boldsymbol{\xi}^K, \boldsymbol{X}^H, \boldsymbol{W}^H, \boldsymbol{\xi}^H; D_t, \mathcal{K}_t, \Theta^K, \Theta^H\right) \tag{23}$$

shows that the seller's sales probability depends on prices and commissions, $(\boldsymbol{p}, \tilde{\boldsymbol{c}})$, preferences of buyers and buy-side brokers, $(D_t, \Theta^K, \Theta^H)$, as well as the *sell-side* channels, captured by sell-side broker attributes included in $\boldsymbol{X}^H$ and sell-side broker network with buy-side brokers captured in $\boldsymbol{W}^H$.

This framework allows me to infer the *counterfactual* residual demand that a seller would have faced had the seller chosen a different broker from the one observed in the data, making the sell-side estimation possible. In the following sections, I describe the problem of sellers given the primitives of the buy-side.

4.3 Stage 2. Seller Demand for Sell-side Brokerage Service

Sellers have two problems to solve. First, each seller chooses which broker to list with, a discrete choice problem, and at which price, a pricing problem. I assume they solve each problem in such order (Lee and Musolff, 2023).

4.3.1 Stage 2-2. Seller Pricing

I focus on the second part of the seller's problem: pricing. At this point, all sellers have committed to their choice of sell-side brokers, and each only chooses a listing price. There is no uncertainty for the sellers, other than specific realizations of the buy-side preference shocks, $\epsilon^K, \epsilon^B, \omega^H$. Sellers know the distribution of these shocks and have correct anticipation of the probability of sale with the sell-side broker they have chosen in market t, ϕ_{hlt}.

Sellers' *expected* net proceeds from the market is

$$V^S_{hlt} := \frac{\phi_{hlt}}{1 - \beta^S_{ht}(1 - \phi_{hlt})}(p_{hlt}(1 - c_{lt}) - r^S_{ht}), \tag{24}$$

where p_{hlt} is the listing price, c_{lt} is the commission rate to the chosen broker l upon transaction, $\beta^S_{ht} \in (0,1)$ is seller's discount factor or "*patience*" parameter, and r^S_{ht} is the seller's reservation value or other cost of transaction. Equation (24) follows from the closed-form expression of the infinite-horizon discounting model.[16] Intuitively, sellers gain from higher net proceeds, which is captured in $p_{hlt}(1-c_{lt}) - r^S_{ht}$, but the valuation of such gain differs by their patience, β^S_{ht}. Hence, $\frac{\phi_{hlt}}{1-\beta^S_{ht}(1-\phi_{hlt})}$ adjusts the weight between the net proceeds and the sales probability. The trade-off between net proceeds and sales probability becomes clearer once I take the first-order condition of V^S_{hlt} with respect to p_{hlt}:

$$p^*_{hlt} = \overbrace{\frac{r^S_{ht}}{1-c_{lt}}}^{\substack{\text{(i) Reservation value,}\\ \text{inflated by commissions}}} + \underbrace{\left(\frac{1-\beta^S_{ht}(1-\phi_{hlt})}{1-\beta^S_{ht}}\right)}_{\substack{\text{(ii) Additional markup}\\ \text{from seller patience}}} \overbrace{\left(\left|\frac{\partial \phi_{hlt}}{\partial p_{hlt}}\right|\right)^{-1} \phi_{hlt}}^{\text{(iii) "due" markup}} . \tag{25}$$

Equation (25) highlights the economics of home sellers. The expression (i) shows that commission inflates the seller's reservation price, and some will be passed onto house prices. The expressions (ii) and (iii) show that patient sellers set prices above the "market price". As for impatient sellers, i.e., $\beta^S_{ht} \to 0$, the expression (ii) approaches 1, and the price reduces to the optimal price under a static Nash-Bertrand pricing game. Conversely, sellers with high β^S_{ht} will list their houses higher than the optimal static price.

To the extent that the seller's choice of a sell-side broker (l) influences both the commissions c_{lt} and the probability of sale, ϕ_{hlt}, the expected net proceeds measure, V^S_{hlt}, is a micro-founded quality measure of a sell-side broker, reflecting seller preference for net proceeds and sales probability.

Identification and estimation I estimate the parameters that govern how sellers set price, $\Theta^S = (\{\beta^S_h\}_h, \{r^S_{ht}\}_{ht})$. The intuition behind identification is simple; given that econometrician already "knows" the demand function, ϕ_{hlt}, the wedge between the model-implied price, i.e., when (ii) in Equation (25) is equal to one, and the

[16]This is, of course, a reduced-form representation. Incorporating the full dynamics would result in a model where sellers play a dynamic discrete game, making the model intractable and estimation infeasible without much gain. The intuition and the estimation strategy are robust to functional form assumptions. For example, they still hold assuming V^S follows a Cobb-Douglas substitution between net proceeds and sales probability.

observed list prices from the data identifies the parameters.

To gain more insight into the identification and estimation procedure, I denote explicitly what is observed from the data with superscript *obs* and what is already estimated and considered to be "known", with a $\widehat{\ }$. Rearranging (25) yields:

$$\overbrace{\left(p_{hlt}^{obs} - \left(\left|\widehat{\frac{\partial \phi_{hlt}}{\partial p_{hlt}}}\right|\right)^{-1} \hat{\phi}_{hlt}\right)(1 - c_{hlt}^{obs})}^{=:y_{hlt}^{S}} = \left(\frac{\beta_{ht}^{S}}{1-\beta_{ht}^{S}}\right) \overbrace{\left(\left|\widehat{\frac{\partial \phi_{hlt}}{\partial p_{hlt}}}\right|\right)^{-1} \hat{\phi}_{hlt}^{2}(1 - c_{hlt}^{obs})}^{=:x_{hlt}^{S}} + r_{ht}^{S}, \tag{26}$$

which resembles a standard regression model of regressing y_{hlt}^{S} on x_{hlt}^{S} with r_{ht}^{S} as the residual and non-linear parameters β_{ht}^{S}. I further parameterize β_{ht}^{S} to be indirectly inferred from a linear interaction with seller characteristics:

$$\frac{\beta_{ht}^{S}}{1-\beta_{ht}^{S}} =: \tau_{ht}^{S} = \tau_{t}^{S} + d_h \tau^{S,d}, \tag{27}$$

where τ_{t}^{S} are the market-specific intercepts, d_h is a vector of seller characteristics and $\tau^{S,d}$ is a vector of corresponding coefficients. Then the estimation equation becomes:

$$y_{hlt}^{S} = \tau_{ht}^{S} x_{hlt}^{S} + r_{ht}^{S}, \tag{28}$$

where $\boldsymbol{\tau}^{S} = (\tau_{t}^{S}, \tau^{S,d})$ are the key parameters of interest.

Estimating $\boldsymbol{\tau}^{S}$ directly from (28) presents an identification challenge as $y_{hlt}^{S}(p_{hlt}^{obs})$ and $x_{hlt}^{S}(\boldsymbol{p}^{obs})$ are simultaneously determined in equilibrium. Specifically, the seller's unobserved reservation value, r_{ht}^{S}, is correlated with how the markup, captured in x_{hlt}^{S}, is determined in equilibrium through its own price p_{ht}^{obs}.

I use the "demand shifters" as instruments for x_{hlt}^{S}, following the standard identification strategy in the empirical industrial organization literature (Berry and Haile, 2016; Miller and Weinberg, 2017; Backus et al., 2021). The intuition is that other sellers' entry decisions or pre-determined characteristics of houses of competing sellers only affect the equilibrium markup (x_{hlt}^{S}) but not the focal seller's *own* reservation value, r_{ht}^{S}. I employ demand shifters by constructing the differentiation IVs (Gandhi and Houde, 2019) with the number of bedrooms, bathrooms, and square footage within a zip code. Specifically, let $\mathcal{H}_{z(h)t}$ be the set of listed houses in zip z. Then the set of instruments denoted by $x_{hlt}^{S,IV}$ is constructed by:

$$x_{hlt}^{S,IV,bed} = \sum_{h' \in \mathcal{H}_{z(h)t}: h' \neq h} (bed_{h'} - bed_h)^2, \tag{29}$$

and similarly with the other house characteristics. The variables measure the intensity of competition within the characteristics space among the spatially close competitors.

I proceed to estimate τ_h^S via the generalized method of moments (GMM). I residualize $x_{hlt}^S, x_{hlt}^{S,IV}, y_{hlt}^S$ by seller cohort and market fixed effects. Seller cohort, defined by the year in which a particular seller had bought the house, interacted with the current market dummies control for any selection of sellers who list in t due to unobservable macroeconomic conditions. An example would be sellers who decide to sell/move driven by a large interest rate difference between t and $y(h)$. Let $\tilde{}$ denote the residualized vectors.

I first estimate market-specific mean parameters, τ_t^S market by market by minimizing the following criterion function, which is the sample analog of the exclusion restriction $E[\tilde{r}_{ht}^S \tilde{x}^{S,IV}] = 0$:

$$\tau_t^{S,*} = \arg\min_{\tau_t^S} \frac{1}{H_t} \sum_{h=0}^{H_t} \left[(\tilde{y}_{hlt}^S - \tau_t^S \tilde{x}_{hlt}^S) \tilde{x}_{ht}^{S,IV} \right]' W \left[(\tilde{y}_{hlt}^S - \tau_t^S \tilde{x}_{hlt}^S) \tilde{x}_{ht}^{S,IV} \right],$$

where H_t is the number of sellers in market t and W is the weighting matrix.

Once the market average patience, $\hat{\tau}_t^S$, are estimated, I estimate seller heterogeneity parameters, $\tau^{S,d}$ by regressing the interaction of $\tilde{x}_{hlt}^S$ and seller observables d_h, on the residual, $\tilde{y}_{hlt} - \tau_t^S \tilde{x}_{hlt}^S$. I then invert $\hat{\tau}_{ht}^S$ based on (27) and recover seller patience parameters, $\hat{\beta}_{ht}^S$.

4.3.2 Stage 2-1. Seller Choice of Sell-side Broker

I describe how sellers choose a sell-side broker. Sellers want higher net proceeds, greater probability of sale, and other "amenity" factors from their brokers. The first two components are captured in the expected net proceeds in Equation (24), V_{hlt}^S.

Seller chooses a sell-side broker l among the set of brokers on the market $\mathcal{L}_t$ that maximizes the following indirect utility:

$$u_{hlt}^L = \alpha^L V_{hlt}^{S,*} + X_{hlt}^L \beta^L + \xi_{lt}^L + \epsilon_{hlt}^L, \tag{30}$$

where $V_{hlt}^{S,*}$ denotes the expected net proceeds from the sell-side broker evaluated the at optimal price point from the Equation (25), X^L_{hlt} denotes seller-broker specific observables, ξ^L denotes unobservable quality or "amenity" of the broker, and ϵ^L_{hlt} is seller's private, idiosyncratic taste shocks iid from the standard Gumbel distribution, $G^L(\cdot)$.

While simple, Equation (30) highlights the model's key complication. Each seller faces a *distinct* demand for every broker and sets the optimal price accordingly, which in turn depends on what *other* sellers choose, i.e.

$$V^{S,*}_{hlt} := V^S(p^*_{hlt}, \phi_{hlt}(p^*_{hlt}; \boldsymbol{p}_{-h}), c_{lt}; \beta^S_{ht}, r^S_{ht}), \tag{31}$$

where $\boldsymbol{p}_{-h}$ denotes other sellers' pricing decisions.

Lastly, if a seller decides not to list, she gets the following indirect utility:[17]

$$u^L_{h0t} = \epsilon^L_{h0t}. \tag{32}$$

Subgame equilibrium concept Let $\mathcal{X}^L_h$ be seller h's information set when choosing across brokers. Seller choice is denoted by $C_h = 1, \dots, L_t$, where L_t is the number of sell-side brokers in market t. Then, the information set is an input to the choice function, $C_h : \mathcal{X}^L_h \to \{0, 1, \dots, L_t\}$.

I assume sellers have complete information up to the realization of ϵ^L of other sellers (e.g., patience, reservation values, etc.), but the distribution from which they are drawn, $G^L(\cdot)$, is known. Unlike other discrete games where the payoffs of players directly depend on the actions of other players, here, actions of other sellers affect the payoffs *only through* the probability of sale, $\phi_{hlt}(\boldsymbol{p}^*)$.

Hence, the subgame equilibrium is characterized by a vector of *ex-ante, expected proceeds*, $\mathcal{V}^{S,*} := \{\overline{V}^{S,*}_{hl}\}_{hl \in \mathcal{H}_t \times \{\mathcal{L}_t \cup \{0\}\}}$, where $\overline{V}^{S,*}_{hl}$ is averaged over the distribution of private information of sellers, G^L:

$$\overline{V}^{S,*}_{hl} = \int V^S_{hl}(p_{hl}, \phi_{hl}(p^*_{hl} | \boldsymbol{p}^*_{-hl}(\epsilon^L))) dG^L. \tag{33}$$

The vector of anticipated house prices $\boldsymbol{p}^*_{-hl}(\epsilon^L)$ depends on what other sellers choose for their brokers, which depends on the ϵ^L draws.

[17] I infer the market size of sellers from the number of discontinued listings from quarter to quarter. I do not explicitly capture the entry decision of sellers but adjust the inclusive value of buyers by a factor of sellers' outside good share when solving for equilibrium to approximately scale both the competitive environment a seller faces and the "variety" that buyers get. Given that over 1,000 individual sellers are in a quarter, such an approximation may be appropriate.

In equilibrium, all sellers "agree" on the proceeds that everyone gets, $\mathcal{V}^{S,*}$, anticipate correctly what broker other sellers will choose up to the realizations of ϵ^L, then choose a broker l that maximizes the following indirect utility:

$$\underset{l \in \mathcal{L}_t}{\operatorname{argmax}} \; \overbrace{\alpha^L \overline{V}^S_{hlt}(p^*_{hlt}, \phi^*_{hlt} | \mathcal{V}^{S,*}) + X^L_{hlt}\beta^L + \xi^L_{lt}}^{=: V^L_{hlt}} + \epsilon^L_{hlt}. \tag{34}$$

Estimation and identification I estimate seller parameters governing broker choice via the two-step estimation method of (Ellickson and Misra, 2012), assuming that the observed equilibrium, i.e., the observed seller choices of brokers and list prices, is the unique equilibrium.

I first compute one-off deviation proceeds for each seller. That is, I ask what p^*_{hl} and $\phi^*_{hl}(p^*_{hl})$ would have been for all unrealized seller and broker hl matches, *holding fixed* other sellers' choices of brokers or prices. This is possible because the parameters governing seller pricing, Θ^S, are estimated, and optimal prices can be computed as in Equation (25). Once $\widehat{V}^{S,*}_{hl}$ are computed for all pairs, I estimate the parameters in Equation (30).

The main threat in estimating α^L is that $\widehat{V}^{S,*}$ is prone to measurement error stemming from potential model misspecification, attenuating the estimate of α^S. Intuitively, α^L should be identified from commissions that sell-side brokers charge across sellers. I isolate such "signal" from $\hat{V}^{S,*}$, by multiplying the *observed* listing price of h, p^{obs}_h, and the *observed* average commission rate of broker l, c^{obs}_{lt} to construct $p^{obs}_h(1 - c^{obs}_{lt})$. This measures sellers' direct net proceeds across brokers.

The empirical specification of Equation (34) is:

$$V^L_{hlt} = \alpha^L \widehat{V}^{S,*}_{hl} + X^L_{hlt}\beta^L + \hat{\nu}^L_{hlt}\zeta^L + \tilde{\xi}^L_{lt}, \tag{35}$$

where $\hat{\nu}^L_{hlt}$ is the residual from regressing $\widehat{V}^{S,*}_{hl}$ on $p^{obs}_{ht}(1 - c^{obs}_{lt})$, X^L_{hlt}, and sell-side broker-market fixed effects, and $\tilde{\xi}^L_{lt}$ is broker-market intercepts that absorbs any unobserved quality of a broker that may be correlated with commissions, c_{lt}, it charges. Under this specification, α^L is identified from within-broker variation in sellers' proceeds, $p^{obs}_{ht}(1 - c^{obs}_{lt})$, driven by the distribution of house prices.

I estimate $\Theta^L := \left(\alpha^L, \beta^L, \zeta^L, \tilde{\boldsymbol{\xi}}^L\right)$ via MLE. The choice probability of a seller h

choosing to list with sell-side broker l is then:

$$s^L_{hl} = \frac{\exp(V^L_{hlt})}{1 + \sum_{l' \in \mathcal{L}_t} \exp(V^L_{hl't})}. \tag{36}$$

4.4 Stage 1. Broker pricing of commission rates

The sell-side brokers each sets a commission rate c_{lt} to maximize the expected profit. For each seller with property h, the probability of a transaction occurring through sell-side broker l is:

$$q_{hlt}(c_{lt}; c_{-lt}) = \underbrace{s^L_{hlt}(c_{lt}; c_{-lt})}_{\text{Prob of seller } h \text{ listing with } l} \overbrace{\phi_{hlt}(c_{lt}; c_{-lt})}^{\text{Prob of } h \text{ being sold when listed with } l}, \tag{37}$$

where s^L_{hlt} comes from Equation (36) and ϕ_{hlt} comes from the buy-side (Equation 22). Both s^L_{hlt} and ϕ_{hlt} depend on commission rates, (c_{lt}, c_{-lt}).

The expected profit for sell-side broker l is:

$$\Pi_{lt}(c_{lt}; c_{-lt}, \overline{p}_t) = \sum_{h \in \mathcal{H}_t} q_{hlt}(c_{lt}; c_{-lt})(\frac{1}{2}\overline{p}_t c_{lt} - mc_{lt}), \tag{38}$$

where $\overline{p}_t$ is the average price of the market and mc_{lt} is the marginal cost of transaction. This assumes that brokers price according to the *average* price of the housing market and that individual brokers do not internalize how their choices of commissions influence the market-level housing prices. c_{lt} gets divided by $\frac{1}{2}$ because sell-side brokers offer half of the commission they charge to buy-side brokers. The rest of the broker's problem is the same as explained in Section 3.

4.5 Equilibrium Concept

I conclude the section by characterizing the equilibrium. First, sell-side brokers set the optimal commission rates $\boldsymbol{c}^*_t = \{c_{lt}\}_{l \in \mathcal{L}_t}$. They have complete information on other brokers' marginal costs, seller preference, and buyer and buy-side broker preference. Second, sellers choose a broker l that maximizes the indirect utility (30) against the equilibrium expected proceeds, $\mathcal{V}^{S,*} = \{\overline{V}^{S,*}_{hl}\}_{hl \in \mathcal{H}_t \times \{\mathcal{L}_t \cup \{0\}\}}$, taking an expectation over the distribution of other sellers' taste draws, G^L. Once the choices of sell-side brokers are revealed, sellers engage in a complete-information pricing game and set the optimal listing price $\boldsymbol{p}^*_t(\epsilon^{L,*}) = \{p^*_{h(l)t}\}_{h \in \mathcal{H}_t}$, where $\epsilon^{L,*} \sim G^L$ denote a realized vector of seller preference shocks. Lastly, given sellers' choices of brokers and prices listed, each buyer chooses a buy-side broker and chooses a house to purchase with respect to their indirect utility specified in Equation (16) and (9). Hence, the equilibrium is characterized by a tuple $\mathcal{E}^*(\epsilon^{L,*}) := (\boldsymbol{c}_t^*, \mathcal{V}^{S,*}, \boldsymbol{p}_t^*(\epsilon^{L,*}))$, with commission rates of brokers, the expected proceeds of sellers, and house prices with the realized seller choices of sell-side brokers.

Model fit To assess the performance of the equilibrium model of the housing market presented thus far, I simulate the status quo with the estimated parameters, find $\widehat{\mathcal{E}}^*(\epsilon^{L,*})$, and plot the simulated list prices, $\hat{\boldsymbol{p}}_t^*(\epsilon^{L,*})$, against the observed list prices against in Figure A3. The model fits the distribution well.

5 Estimation Results

In this section, I discuss the estimated parameters from the model and the implied relevant economic quantities. Because of its richness, I focus only on the key aspects of the model. The complete list of covariates, parameters, and standard errors are reported in the Appendix Table A2, A3, A4, and A5.

5.1 Buy-side Estimates

Panel A in Table 2 reports the key estimates from the buy-side. First, I find buyers are sensitive to house prices with heterogeneity across the income distribution. Sellers face elastic residual demands with an average own-price elasticity of -7.7. This magnitude is close to what Guren (2018) and Carrillo (2012) find, which is -5.6 and -7.8, respectively.[18]

Second, I find that brokers are sensitive to commission revenues. The estimated parameter, $\overline{\kappa}$, implies that an average seller lowering her commission rate offer by 0.5*pp* faces 3.6% drop in sales probabilities. Barwick et al. (2017) finds 7.5% drop in sales probability if the commissions go below 2.5pp.

Lastly, the estimated $\hat{\lambda}$ suggests that buyers are not sensitive to the value of buy-side brokers. An average buy-side broker faces inelastic demand with 0.23 elasticity with respect to the value they provide to buyers, measured by I_{bk}. This echoes the concern that buyers regard broker services as close to being "free," unaware of the value they are getting. The low elasticity helps to rationalize that the U.S. has the

[18] Authors' conversion from days on the market to the probability of sale within 13 weeks.

highest utilization rate of buy-side brokers, with over 90% of buyers using them, compared to the average of 33% in other countries.[19]

5.2 Seller Estimates

Panel B in Table 2 summarizes the estimates of the seller parameters. I validate the estimates of $\widehat{\beta}^S$ by plotting them against the observed list prices and commissions in Figure 3. It replicates what is observed in the data in Figure 2. Furthermore, the relationship between the estimated patience and the chosen commissions holds, despite the fact that the tendency of patient sellers to choose lower commissions was not explicitly modeled or jointly estimated.

To put the estimates into perspective, I compute sellers' valuation over liquidity. That is the ratio between the marginal increase in V^S_{ht} from an increase in price and from an increase in the probability of sale, $\frac{\partial V^S_h}{\partial p_h}$ and $\frac{\partial V^S_h}{\partial \phi_h}$ respectively. On average, sellers are "patient", with the ratio being more than 1. In terms of days-on-market, the estimates imply that the median seller values 1% of proceeds to 16 shorter days on the market.[20] For a similar quantity, Genesove and Mayer (1997) finds 18 days for the most patient group of sellers, Hendel et al. (2009) finds 13 days, and Barwick et al. (2017) finds 8 days to be equivalent to 1% of prices for sellers. I also find sellers with high LTV ratios tend to be more patient and set high prices, consistent with the prior literature.

With the estimate of α^L, I assess seller elasticity to commission rates across brokers. The current incentive structure makes seller sensitivity to proceeds, α^L, and patience parameter, β^S to, interact with buy-side brokers' preference for commissions, κ, influencing sellers' probability of sale. I find that this interaction makes sellers less elastic to commissions. Under the status quo, sell-side brokers face, on average, -2.9 own-elasticity of seller demand. However, if sellers' commissions do not affect the sales probabilities, holding all else equal, the brokers face much more elastic demand with -5.0.

5.3 Broker Estimates

The preference estimates of the buy-side and the sell-side allow me to decompose the markup of the brokers under the status quo. Table 3 shows the decomposition of the current commission rates. On average, the sell-side brokers charge 5.7pp to sellers.

[19] KBW Research Smith (2024).

[20] I map the model-implied probability of sale within a quarter to the observed days on the market.

2.7pp goes to buy-side brokers, which can be treated as "cost". Of the remaining 2.7pp, I find 63% is the markup. Of the markup, 44% is coming from the "indirect" channel from how brokers are compensated. Figure A2 visualizes the results. To my knowledge, such quantification of the real estate brokers' additional markup due to the current incentive structure has not been studied.

6 Counterfactual Results

6.1 Setup

In the counterfactual under "decoupling," there are two main changes: sellers cannot offer commissions to buy-side brokers, and each buy-side broker sets a fee for buyers and engages in price competition. I present modified objective functions of buyers and the buy-side brokers and characterize the new equilibrium for a given market t, omitting the subscript hereafter.

Buyer and buy-side broker demand for houses When choosing across listed houses, the buyer and buy-side broker decide to purchase with the following joint utility, changed from Equation (9):

$$\max_{hl \in \mathcal{H}^*} u_{bk,hl}^{H,CF} = \underbrace{V_{b_0,hl}^{H} - \alpha_b^H \overbrace{c_k^{buy}}^{\text{buyer commission payment}} + \tilde{\kappa}_k c_k^{buy} + W_{khl}^{H} \tilde{\gamma}^H + \tilde{\kappa}_k \omega_{khl}^{H}}_{=:V_{bk,hl}^{H,CF}} + \epsilon_{bhl}^{H}, \tag{39}$$

where c_k^{buy} is a flat-fee commission that the buy-side broker charges to the buyer, to be paid upon transaction. The choice probability of the pair bk choosing hl in the counterfactual is then:

$$s_{bk,hl}^{H,CF} = \frac{\exp(V_{bk,hl}^{H,CF})}{1 + \sum_{h \in \mathcal{H}^*} \exp\left(V_{bk,hl}^{H,CF}\right)}. \tag{40}$$

Buyer demand for buy-side brokers Buyers choose a buy-side broker based on the changed decision utility in Equation (40). The new indirect utility of buyers in the counterfactual is:

$$u_{bk}^{K,CF} = \lambda^{CF} I_{bk}(c_k^{buy}) + X_k^K \beta_b^K + \xi_k^K + \epsilon_{bkt}^{B,K}, \tag{41}$$

where $I_{bk}(c_k^{buy})$ is computed as before, but with $u^{k,CF}$. λ^{CF} is the changed sensitivity of buyers in the counterfactual, which I discuss with other assumptions below. Let ϕ_{hl}^{CF} denote the counterfactual sales probability that a seller faces, integrating over the counterfactual choice probabilities, $s^{K,CF}$ and $s^{H,CF}$.

Buy-side broker profit maximization Buy-side brokers now actively set commissions given the changed buyer demand. Let $s_{bk}^{K,CF}$ be the choice probability of buyer b choosing broker k from maximizing the indirect utility in Equation (41). Define $s_{bk,1}^{H,CF} := \sum_{h\in\mathcal{H}^*} s_{bk,hl}^{H,CF}$ to be the probability that the buyer purchases *any* property on the market conditional on choosing broker k. Then, the expected profit of broker k in the counterfactual is:

$$\Pi_k^{buy,CF}(c_k^{buy};c_{-k}^{buy}) = \sum_b s_{bk}^{K,CF} s_{bk,1}^{H,CF}(c_k^{buy} - mc_k^{buy}), \tag{42}$$

where $s_{bk}^{K,CF} s_{bk,1}^{H,CF}$ denote the joint probability of buyer b choosing the broker and ending up purchasing a house, at which point the broker earns the profit of $c_k^{buy} - mc_k^{buy}$. I assume buy-side brokers engage in price competition, setting $c_k^{buy,*}$ maximizing Equation (42).

Sell-side response to the buy-side Given the changes from the buy-side, sellers re-optimize by setting a new price $p_{hl}^{*,CF}(\phi_{hl}^{CF})$, yielding new expected proceeds from sale, $V_{hl}^{*,CF}(p_{hl}^{*,CF}, \phi_{hl}^{CF})$. Lastly, the sell-side brokers maximize following the new expected profit function:

$$\Pi_l^{sell,CF}(c_l^{sell};c_{-l}^{sell}) = \sum_{h\in\mathcal{H}_t} s_{hl}^{L,CF} \phi_{hl}^{CF}(\bar{p}^{CF} c_l^{sell} - mc_l^{sell}). \tag{43}$$

where the superscript ^{sell} makes a distinction to the buy-side brokers' quantities explicitly, and $s_{hl}^{L,CF}$ denotes the changed choice probability of sellers in response to the buy-side and new commissions charged by their brokers, c_l^{sell}. The optimal sell-side broker commission implied by the first-order condition of (43) follows (4), removing the indirect channel of the commission they set affecting the sales probabilities of sellers.

Counterfactual equilibrium I define the new counterfactual equilibrium to be a tuple of four equilibrium objects; sell-side broker commissions, $\boldsymbol{c}^{sell,*} = \{c_l^{sell,*}\}_{l\in\mathcal{L}}$, seller ex-ante expected proceeds, $\mathcal{V}^{S,CF,*} = \{\overline{V}_{hl}^{S,CF,*}\}_{hl \in \mathcal{H} \times \{\mathcal{L}_t \cup \{0\}\}}$, seller ex-post house prices after revelation of the $\epsilon^{L,*}$ taste draws, $\boldsymbol{p}^{CF,*}(\epsilon^{L,*}) = \{p_{hl}^{CF,*}\}_{h \in \mathcal{H}}$, and buy-side broker commissions that depends on seller choice of brokers and house prices, $\boldsymbol{c}^{buy,*}(p_{hl}^{CF,*}, \epsilon^{L,*}) = \{c_k^{buy,*}\}_{k \in \mathcal{K}}$. Hence, the counterfactual equilibrium is characterized by a tuple:

$$\mathcal{E}^{CF,*}(\epsilon^{L,*}) := (\boldsymbol{c}^{sell,*}, \mathcal{V}^{S,CF,*}, \boldsymbol{p}^{CF,*}(\epsilon^{L,*}), \boldsymbol{c}^{buy,*}(\epsilon^{L,*})). \tag{44}$$

Computation Before solving for $\mathcal{E}^{CF,*}$, I make following assumptions. First, I assume buyers become as elastic as sellers with respect to the counterfactual commissions. Under the status quo, the own-elasticities of buy-side brokers with respect to I_{bk} was found to be low in Section 5, implying that the value of brokers may not be salient to buyers. This assumption amounts to finding λ^{CF} in Equation (41) so that the average elasticity of demand for brokerage service across buyers and sellers are equal to each other, i.e. $E[\varepsilon_{bk}^{K,CF}] = E[\varepsilon_{hl}^{L,CF}]$, where

$$\begin{aligned}
\varepsilon_{bk}^{K,CF} &:= \frac{\partial u_{bk}^{K,CF}}{\partial {c_k^{buy}}_k} s_{bk}^{K,CF}(1 - s_{bk}^{K,CF}) \\
\varepsilon_{hl}^{L,CF} &:= \frac{\partial u_{hl}^{L,CF}}{\partial {c_l^{sell}}_k} s_{hl}^{L,CF}(1 - s_{hl}^{L,CF}).
\end{aligned} \tag{45}$$

Second, I impute buy-side brokers' marginal cost, mc_k^{buy}, from the sell-side brokers' estimated marginal costs because I do not have an estimate of them. I map the quantiles of vertical quality distribution estimated from the model between buy-side brokers and sell-side brokers, i.e., $F(\hat{\xi}^L)$ vs. $F(\hat{\xi}^K)$, and assign sell-side brokers' marginal costs to the buy-side brokers in the corresponding quantile of the quality distribution. For example, a buy-side broker at the 90th percentile of the distribution in $F(\xi^K)$ inherits the marginal cost of the sell-side broker at the 90th percentile of the distribution in $F(\xi^L)$. Since it may be more costly to help sellers sell houses than help buyers, I assume buy-side brokers incur half of sell-side brokers' marginal cost.

With these assumptions, I first simulate the status quo equilibrium, $\hat{\mathcal{E}}^{sq,*}$ with draws of ϵ^L from the standard Gumbel distribution. The superscript sq explicitly denotes the status quo equilibrium objects. Using the same set of draws, I solve for $\hat{\mathcal{E}}^{CF,*}$ until all equilibrium objects converge between iterations.

6.2 Results

I focus on the welfare measures of buyers, sellers, and brokers in the housing market. This focuses on the changes in equilibrium objects after the realization of the seller's choice of sell-side brokers.

Seller surplus I define seller surplus change to be:

$$\Delta CS_h^{seller} = V_{hl}^{S,CF}(c_l^{sell,*}, p_{hl}^{CF,*}, \phi_{hl}^{CF}(\boldsymbol{p}^{CF,*})) - V_{hl}^{S,sq}(c_l^{sq,*}, p_{hl}^{sq,*}, \phi_{hl}^{sq}(\boldsymbol{p}^{sq,*})), \quad (46)$$

Buyer surplus I define buyer surplus change to be:

$$\begin{aligned}\Delta CS_b^{buyer} = &\sum_k s_{bk}^{K,CF} \frac{1}{\alpha_b^H} \log\left(1 + \sum_{hl \in \mathcal{H}^{CF,*}} \exp\left(V_{b0,hl}^H(p_{hl}^{CF,*}) - \alpha_b^H c_k^{buy,*}\right)\right) \\ &- \frac{1}{\alpha_b^H} \log\left(1 + \sum_{hl \in \mathcal{H}^*} \exp\left(V_{b0,hl}^H(p_{hl}^*)\right)\right).\end{aligned} \quad (47)$$

This measures the surplus change from the new house prices and the statutory commissions.

Broker revenue I define the aggregate change in sell-side broker revenue to be:

$$\Delta Rev^{sell} = \frac{s_1^{L,cf}}{s_1^{L,sq}} \sum_h \phi_{hl}^{CF} p_{hl}^{CF,*} c_{l(h)}^{sell,*} - \sum_h \phi_{hl} p_{hl}^* \frac{c_{l(h)}^*}{2}, \quad (48)$$

where $\frac{s_1^{L,cf}}{s_1^{L,sq}}$ adjusts for the extensive margin of sellers.

The buy-side broker aggregate change in revenue is defined as:

$$\Delta Rev_l^{buy} = B_t \int_b s_{b,kt}^{K,CF} s_{bk,1}^{H,CF} c_k^{buy,*} dD - \sum_h \phi_{hl} p_{hl}^* \frac{c_{l(h)}^*}{2}, \quad (49)$$

where the first term is the expected revenue from buyers choosing to purchase any property, and the second term is the same as that of sell-side brokers' because they split the commissions equally in the status quo.

6.2.1 Impact on the Housing Market

Table 4 shows the aggregate changes on the market level, averaged across markets. Panel A presents the aggregate house price, commission, and traded quantity before and after decoupling. First, brokers' posted commissions drop because sell-side brokers no longer charge the higher markup, and buy-side brokers compete for price-sensitive buyers. The lowered commissions then get captured in the house prices. Sellers pass through their savings, and buyers pass through their statutory commissions onto house prices, both of which put downward pressure on the *posted* equilibrium house prices. However, sellers still get more proceeds due to the lowered commissions, and buyers pay less than before, even after accounting for their share of commissions. Figure A4 visualizes the change in the post price and the relevant prices. Lower commissions and house prices invite more sellers and buyers to the market, increasing the total number of transactions.

The surplus changes presented in Panel B explicitly measures consumer benefit from decoupling. I express the magnitude of surplus changes as a percentage of the total transaction values in the status quo, measured by $\sum_h \phi_h p_h$. First, broker revenue drops by 2.6 percentage points (pp). Given that the average commissions in the status quo is 5.4% of the prices, decoupling halves the revenues of the brokers. The lost revenue then gets redistributed among buyers and sellers, through the house prices. Between sellers and buyers, buyers enjoy the benefit of a drop in commissions than sellers. Drop in house prices attract more buyers to participate, and buyers overall gain 2.8pp in surplus. Sellers also gain from the greater net proceeds and the number of transactions, gaining 1.3pp in surplus.

6.2.2 Distributional Impact

Next, I examine the distributional impact of decoupling across demographics of buyers and sellers. Table 5 shows the changes in surplus for buyers across their income distribution and for sellers across their house price and patience distribution. First, contrary to the concern that low-income buyers may get hurt, I find that buyers across the income distribution gain. While it seems that buyers in the highest income gain the most, this is partially driven by the larger base of surplus they have. In terms of the relative gain, measured in the percentage change, low-income buyers experience about 17% increase. I visualize this intuition in Figure 4. As shown, the cheapest set of houses has dropped prices the most, delivering large gains in surplus for low-income buyers.

This findings connect to the changes in seller surplus across their distribution of house prices and patience, which are shown in Panel B. I find that impatient sellers with low-priced houses gain the least, while patient sellers with high-priced houses gain the most. Low-priced houses with impatient sellers are on the less-elastic part of the concave demand curve, and prices must be dropped significantly to regain the desired level of sales probability. In contrast, high-priced houses used to price on the elastic part of the demand curve and hence experience a large probability gain with a relatively small drop in prices, passing through only some of their commission savings.

This intuition is visualized in Figure 5, which plots price changes and sales probability across house price quantiles and above vs. below median patient sellers within each bin. First, sellers in the lowest quantile experience the most significant drop in house prices while gaining the lowest sales probability. On the contrary, sellers in the highest house price quantile experience the least drop in house prices while gaining the most in sales probability. This echoes the intuition coming from the concave residual demand that the sellers face. Second, *within* each quantile, impatient and patient sellers show the opposite pattern; impatient sellers drop their prices for a larger gain in sales probability, while patient sellers forgo less of the proceeds from the sale.

The results from the housing market and the distributional impact on buyers and sellers picture a coherent story. Decoupling makes brokers engage in more intense price competition, lowering the commission paid in the economy significantly. These commission savings are then captured into the new equilibrium house prices, which facilitates the re-distributional impact across sellers and buyers. Low-income buyers still gain because their "target" houses at the lower part of house price distribution drop their prices the most. Low-patient sellers gain the least from decoupling as they lost a method to incentivize buy-side brokers to boost their probability of sale. Lastly, Table A6 shows the results under scenarios with alternative assumptions and the qualitative takeaways of decoupling stays.

7 Conclusion and Further Discussions

In this paper, I examined the equilibrium effect of broker incentive structure on competition, house prices and transactions, and welfare by building an empirical model of the intermediated housing market. The model allows me to compare real estate brokers' status quo incentive structure, where sellers compensate buy-side brokers with the *decoupled* incentives, where buyers and sellers pay for their respective brokers.

I find decoupling can improve market efficiency. Lowered commissions drive this as sell-side brokers no longer price to sellers' willingness to pay for the probability of sale, and buy-side brokers face price-sensitive buyers. This facilitates a large transfer of commissions from brokers to consumers. Among consumers, buyers capture most of the benefit because sellers pass through most of their savings onto house prices. Hence, my paper emphasizes the role of competition among intermediaries in shaping the market outcome and the importance of considering the interaction between how intermediaries compete and how providers compete.

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8 Tables

Table 1. Effect of Low Commissions on Sales Probability

	(1)	(2)	(3)	(4)	(5)
$\hat{\beta}$	-0.088***	-0.088***	-0.047***	-0.045***	-0.041***
	(0.007)	(0.007)	(0.009)	(0.008)	(0.009)
% of $E[1\{\text{Sold}_{ht}\}]$	-24%	-24%	-13%	-12%	-11.3%
Market FE	Y				
Market-Tract FE		Y	Y	Y	Y
Market-Broker FE			Y	Y	Y
Property Controls				Y	Y
Seller Controls					Y
Num. FEs	28	2,518	12,647	12,647	13,462
N_{ht}	68,086	68,086	53,182	53,182	52,813

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The unit of observations is house(h)-quarter(t) pair. A "market" is defined to be city-quarter pair. Property controls include log(list price), number of bedrooms and bathrooms, square footage, built year, and an indicator for single-family building. Seller controls include seller initial LTV, interest rate, loan term, and seller year-of-purchase dummies interacted with list quarters. "Broker" refers to seller's brokerage offices. The standard errors are clustered at zip-level. Changes in N_{ht} across specifications come from dropping singletons and observations with missing data. $E[1\{\text{Sold}_{ht}\}] = 0.36$.

Table 2. Buy-side and Sell-side Estimates of Key Quantities

	Estimates
Panel A: Buy-side Estimates	
$\overline{\alpha}_b^H$: buyer preference for house price	-0.040
with $p_{25}(\text{income}_b)$	-0.042
with $p_{75}(\text{income}_b)$	-0.040
$\overline{\kappa}_k$: broker preference for commission revenue	0.036
λ: buyer preference for broker inclusive value	0.188
Avg. price elasticity	-7.7
Avg. I_{bk} elasticity	-0.23
Panel B: Sell-side Estimates	
$\overline{\beta}_{ht}^S$: seller patience	0.82
with $LTV_h < 0.8$	0.80
with $LTV_h \geq 0.8$	0.84
α^L: seller preference for expected proceeds	0.68
Avg. commission elasticity	-2.9
Direct elasticity, holding ϕ_{hl} fixed	-5.0

Notes: Estimated quantities are using the estimates from Table A2, A3, A4, and A5. See appendix for standard errors.

Table 3. Decomposition of Commission Rates

	Value	% of Commission
Sell-side Commission (%)	2.7	-
Marginal Cost	1.0	37%
Markup	1.7	
Direct channel	0.95	35%
Indirect channel	0.75	28%

Notes: Average across sell-side broker-market pairs, $N_{lt} = 9,644$. Values are net of the commissions to the buy-side. The "direct" channel refers to the portion of markup coming from sellers' inverse commission elasticities, holding seller sales probabilities fixed. The "indirect" channel refers to the markup from the inverse elasticities of sales probabilities from the marginal commission offered to buy-side brokers. The first-stage f-stat

Table 4. Counterfactual Results: Market Outcomes

	Status Quo	Decoupled CF	%Δ
Panel A: Housing Market			
Seller: House Price net of Comm ($1,000s)	233	234	+0.3%
Buyer: House Price with Comm ($1,000s)	246	239	–2.7%
Sell-side Broker: Posted Comm. (%)	5.2	2.0	–61.3%
Buy-side Broker: Posted Comm. (%)	0	1.2	
Num. Trx, $\sum \phi$	367	374	+1.9 %

Panel B: Welfare	Δ Decoupled CF (as % total trx. value)
Total Welfare (%)	1.5
Broker Revenue (%)	-2.6
Consumer Surplus (%)	4.1
Seller Surplus (%)	1.3
Buyer Surplus (%)	2.8

Notes: Variables in Panel A are averaged across 20 markets, from Q3 of 2010 to Q3 of 2015, weighted by the predicted number of transactions in each market. House prices sellers (buyers) are computed after subtracting (adding) expected commissions across brokers. Commissions are *posted* commissions, with buy-side broker commission converted from a flat-fee to % in house prices. Panel B denotes the differences between the status quo and the counterfactual quantities, divided by the total transaction value simulated under the status quo, $\frac{1}{T}\sum_t \sum_h \hat{p}^{sq}_{ht}\hat{\phi}^{sq}_{ht} = \$85.3M$.

Table 5. Countefactual Results: Distributional Impact across Consumers

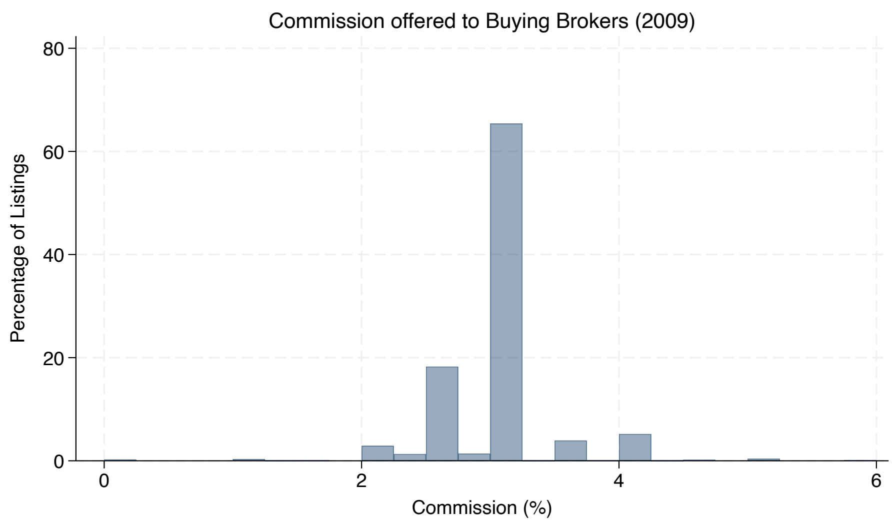
	Δ Decoupled CF (as % of total trx. value)
Panel A: Buyer Surplus	
By Income Quantile	
1st	.34
2nd	.47
3rd	.68
4th	1.29
Panel B: Seller Surplus	
By House Price Quantile	
1st	.03
2nd	.22
3rd	.40
4th	.69
By Patience (β^S) Quantile	
1st	.27
2nd	.34
3rd	.35
4th	.38

Notes: Averaged across 20 quarters, from Q3 of 2010 to Q3 of 2015. "Δ Decoupled CF" denotes the differences between the status quo and the counterfactual quantities, divided by the total transaction value simulated under the status quo, $\frac{1}{T}\sum_t \sum_h \hat{p}_{ht}^{sq}\hat{\phi}_{ht}^{sq} = \$85.3M$. The quantiles are constructed within each market. Seller surplus is $\hat{V}_{hl}^S$ with simulated sell-side broker choice with equilibrium list prices and probability of sale. Seller house price quantiles are based on the observed list prices.

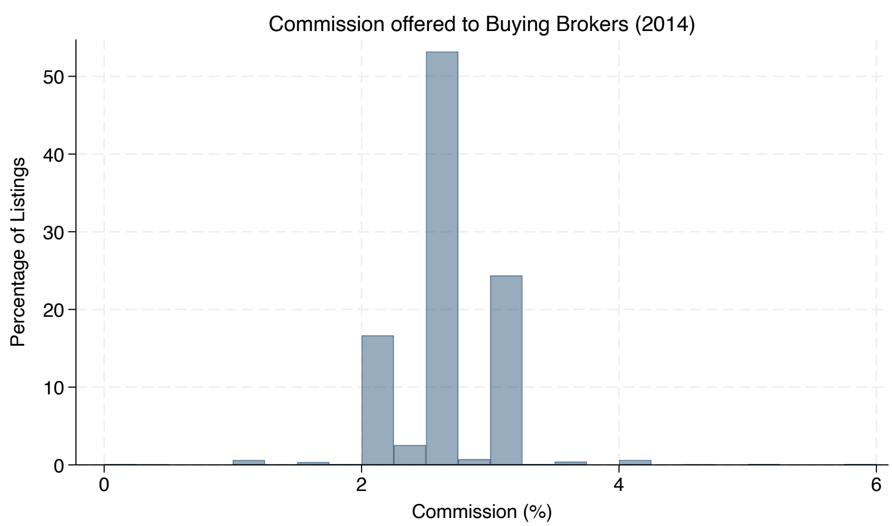
9 Figures

Figure 1. Cross-sectional distribution of commission rates in Riverside, CA

(a) 2009



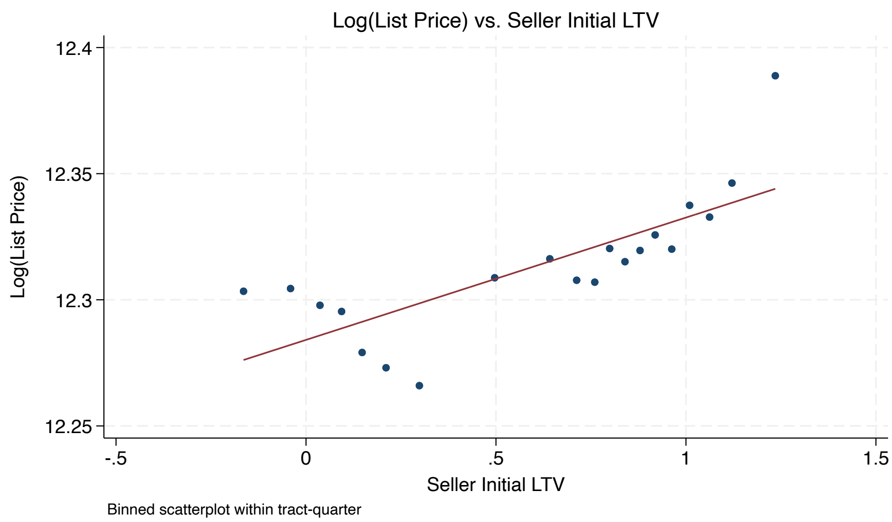
(b) 2014



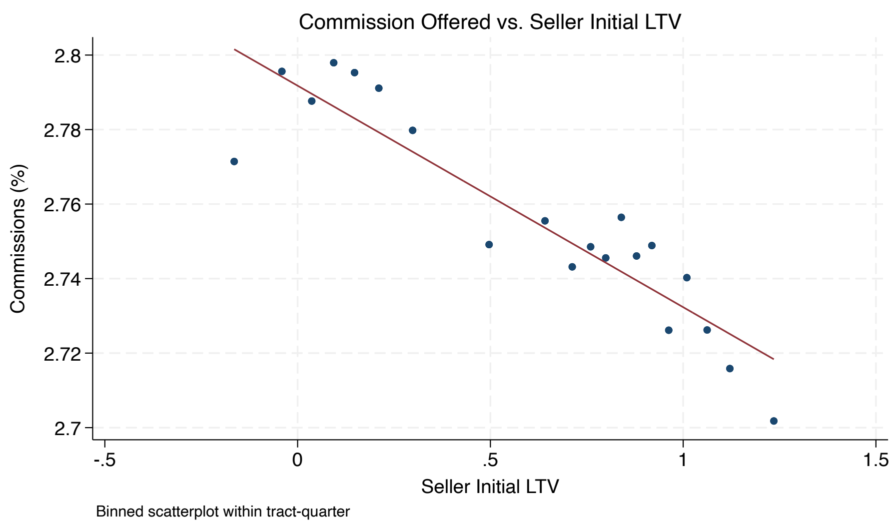
Notes: The sample is from Riverside, CA, across 68,086 pairs of property and calendar quarter.

Figure 2. Seller initial LTV as supply-shifter for list prices and commissions

(a) Log(List Price) vs. Seller LTV



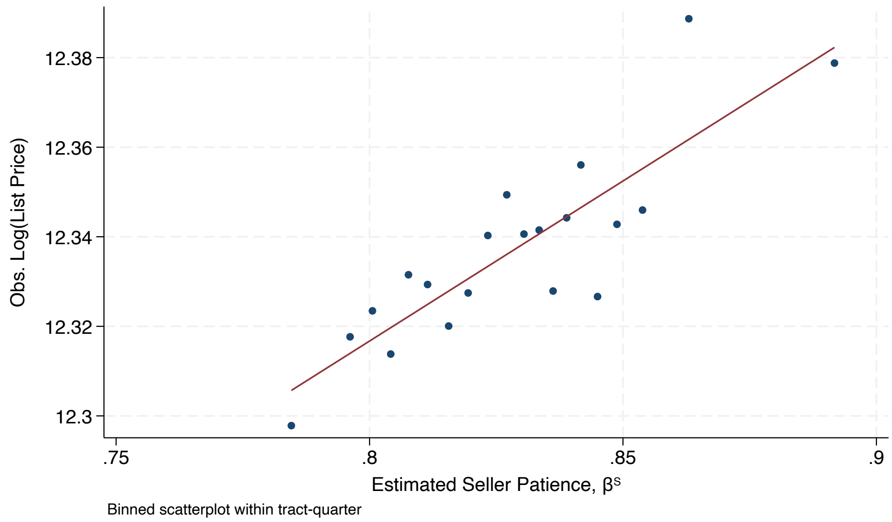
(b) Commissions vs. Seller LTV



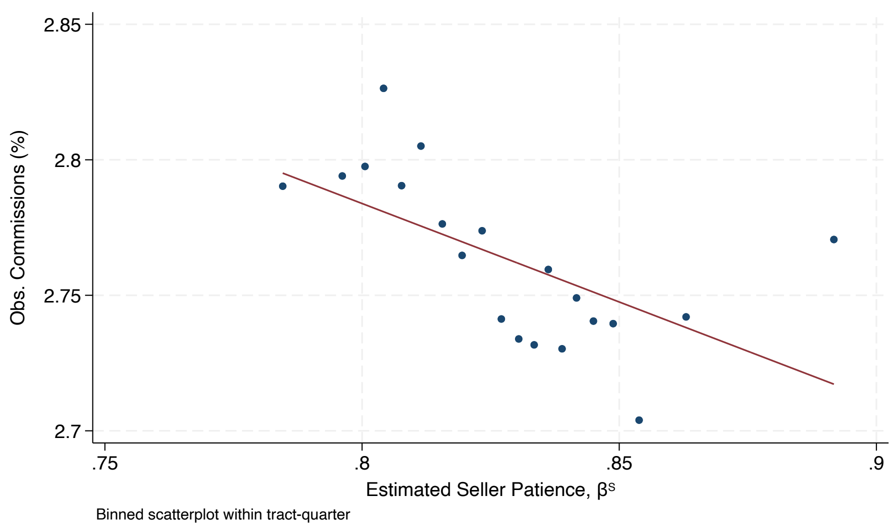
Notes: The sample is from Riverside, CA, across 37,341 listings. They plot binned scatterplots of seller initial LTV against observed log(list price) and commissions offered to buy-side brokers within tract-quarter.

Figure 3. Validating seller patience estimates, $\widehat{\beta}^S$, against observed prices and commissions

(a) Observed Log(List Price) vs. Estimated Seller Patience, $\widehat{\beta}^S$

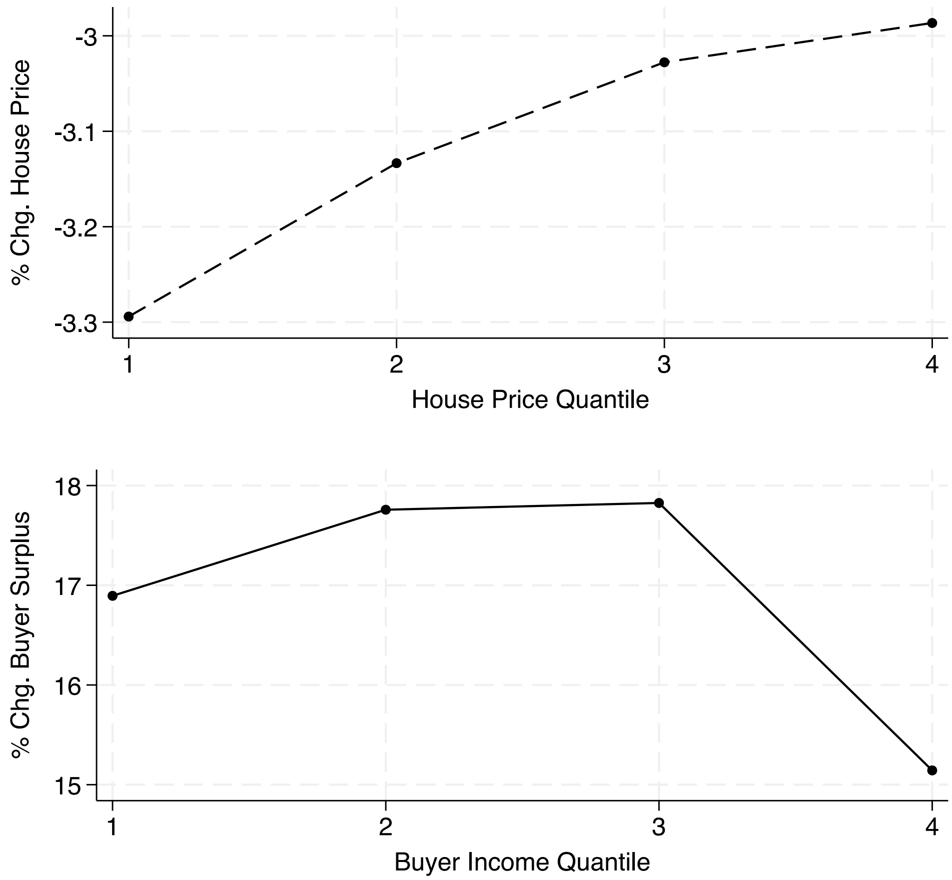


(b) Observed Commissions vs. Estimated Seller Patience, $\widehat{\beta}^S$



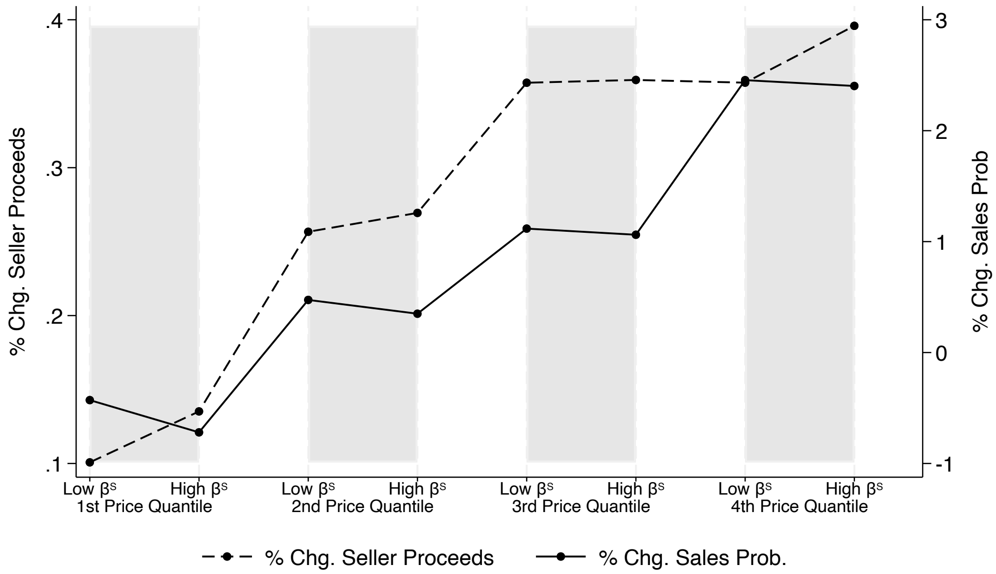
Notes: The sample is from Riverside, CA, across 43,705 pairs of property (h) and calendar quarter (t). They plot binned scatterplots of estimated $\hat{\beta}^S$ against the observed log(list price) and commissions offered to buy-side brokers within tract-quarter.

Figure 4. Impact of decoupling on buyers across income with changes in house prices across price quantile



Notes: Averaged across 20 quarters, from Q3 of 2010 to Q3 of 2015. The quantiles are constructed within each market. Seller house price quantiles are based on the observed list prices.

Figure 5. Impact of decoupling on seller proceeds and sales probability across house price and patience distributions



Notes: Averaged across 20 quarters, from Q3 of 2010 to Q3 of 2015. The quantiles are constructed within each market. House price quantiles are based on the observed list prices. "Low" patience means $\hat{\beta}^S$ below median within a market, and "high" patience indicates above median. Seller proceeds are computed by subtracting seller commission payments from the posted prices.

A Appendix Tables

Table A1. Descriptive Statistics of Transactions, Sellers, and Buyers

	Mean	Std
Panel A: Transactions		
List Price ($)	246,373	109,677
Pr(Sold within 90 days)	.49	.50
Days until sold	50	66
Frac. same agent trx	.16	.37
N_{listing}	37,341	
Panel B: Sellers		
Frac. Mortgage	.86	.35
LTV Ratio	.86	.15
Int. Rate (%)	4.9	.7
Loan Term (Months)	345	62
N_{seller}	21,589	
Panel C: Buyers		
Frac. Mortgage	.86	.35
LTV Ratio	.87	.15
Int. Rate (%)	4.9	.8
Loan Term (Months)	345	63
Annual Income ($1,000s)	79	33
N_{buyer}	11,084	
Panel D: Brokerage Offices		
Commission (%)	2.7	.44
Avg. Listings in Qtr	2.3	3.8
Avg. Sell-side Trxs in Qtr	1.4	2.6
Avg. Buy-side Trxs in Qtr	1.9	4.0
N_{brok}	6,373	

Notes: Summary statistics from the cleaned sample of transactions in Riverside, California from 2009 to 2015. A listing refers to unique instance of a property being on the market, not double counting repeated appearence of the same property across time periods. Both the probability of being sold in a quarter and days until sold conditions on sold properties. For sellers and buyers, the summary statistics of the loan characteristics conditions on financing via mortgage.

Table A2. Buyer and Buy-side Broker for Housing Preference Estimates

Variable	Coefficient (Standard Error)
Property attribute (X_h^H)	
Baths_h	0.82 (0.26)
Beds_h	0.72 (0.01)
Indicator: Single Family_h	4.91 (0.62)
Age of Building_h	-0.02 (0.00)
ν^p	0.04 (0.00)
ν^c	-0.01 (0.02)
Sell-side broker attribute (X_l^H)	
$\log(\overline{DOM}_{l,yr(t)-1})$	-0.16 (0.01)
$\Pr(\text{sold}_{l,yr(t)-1})$	0.88 (0.03)
Indicator: $\text{Zip}_h = \text{Zip}_l$	0.18 (0.05)
Num $\text{Trx}_{l,zip(h),yr(t)-1}$	0.30 (0.01)
Buyer heterogeneous preference for house price ($p_h \times d_b$)	
Indicator: Income Bin 1	-0.092 (0.006)
Indicator: Income Bin 2	-0.097 (0.006)
Indicator: Income Bin 3	-0.096 (0.006)
Indicator: Income Bin 4	-0.103 (0.006)
log(Down payment($))	0.001 (0.001)
Buyer LTV	-0.001 (0.001)
Indicator: Mortgage Insurance	0.000 (0.000)
Indicator: FHA Loan	-0.000 (0.002)
Indicator: Conv. Loan	-0.002 (0.001)
Indicator: Cash Purchase	-0.012 (0.001)
Indicator: No Buy-side Broker	0.001 (0.000)
Box-Cox Coeff. on Income_b	0.79 (0.036)
Buyer heterogeneous preference for property attribute ($X_h^H \times d_b$)	
$\text{Baths}_h \times \text{Family}_b$	0.02 (0.02)
$\text{Baths}_h \times \text{Income}_b$	0.05 (0.02)
$\text{Condo}_h \times \text{Income}_b$	0.02 (0.01)
$\text{Condo}_h \times \text{Family}_b$	0.32 (0.05)
Single $\text{Family}_h \times \text{Income}_b$	-0.13 (0.06)
Single $\text{Family}_h \times \text{Family}_b$	0.25 (0.047)
Buy-side broker Incentive ($p_h c_h$)	
Commission Revenue	0.03 (0.02)
Commission Revenue$\times\log(sold_{k,t-1})$	0.00 (0.00)
Broker network/expertise (W_{hlk}^H)	
Num $\text{Trx}_{k,zip(h),yr(t)-1}$	1.34 (0.01)
$h(l)k$ from same office	2.86 (0.03)
$h(l)k$ from same brand	0.19 (0.06)
$h(l)k$ from same zip	0.34 (0.19)
$\log(\text{Num Trx}_{l,k,t-1})$	0.94 (0.02)

Notes: Estimated on the full sample of buyer-broker and house-broker pairs, $N_{b(k)} = 15,446$, $N_{h(l)t} = 43,705$, $N_{b(k)h(l)t} = 20,065,668$. For each buyer, choice set are constructed by filtering houses that listed after each buyer's observed closing date of a house. Seller initial LTV, loan term in months, and number of years since purchase were used to instrument for p_h and $c_{hl}p_h$. The first-stage Kleibergen-Paap rk wald f-stat is 13.6. The standard errors are clustered at house level and bootstrapped 50 times following Petrin and Train (2010).

Table A3. Demand for Housing Preference Parameter Estimates

Variable	Coefficient (Standard Error)
I_{bkt}	0.19 (0.00)
No broker$_t$ $\times$ Income$_b$	0.62 (0.00)
No broker$_t$ $\times$ LTV$_b$	0.11 (0.05)
ν^K_{bkt}	-0.19 (0.01)

Notes: Estimated on full sample of buyer and buy-side broker pairs, $N_b = 15,446$, $N_{kt} = 5,144$, and $N_{bk} = 2,895,414$. The control function is the residual from regressing $\hat{I}_{bk}$ on I^{IV}_{bk} and the included variables. The reported standard errors are analytical robust standard errors.

Table A4. Seller Patience Estimates

Variable	Coefficient (Standard Error)
LTV$_h$	0.640 (0.200)
Tenure$_{ht}$	0.117 (0.014)
Loan Term$_h$	-0.018 (0.004)
Interest Rate$_h$	0.065 (0.039)
Log(Income$_h$)	0.081 (0.030)

Notes: Estimated on sample of listings, $N_{ht} = 43,705$. The standard errors are computed across 100 bootstraps. All loan characteristics are initial characteristics at the time of purchase.

Table A5. Demand for Sell-side Broker Preference Parameter Estimates

Variable	Coefficient (Standard Error)
V^S_{hlt}	0.68 (0.000)
Indicator: Zip$_h$ = Zip$_l$	-2.74 (0.030)
Num Trx$_{l,zip(h),yr(t)-1}$	-4.70 (0.008)
Pr(sold$_{l,yr(t)-1}$) $\times$ log (income$_h$)	-2.33 (0.016)
$\log(\overline{DOM}_{l,yr(t)-1})$ $\times$ log (income$_h$)	0.44 (0.004)
Pr(sold$_{l,yr(t)-1}$) $\times$ β^S_{ht}	18.3 (0.216)
$\log(\overline{DOM}_{l,yr(t)-1})$ $\times$ β^S_{ht}	10.8 (0.048)
ν^L_{hlt}	-0.61 (0.000)

Notes: Estimated on the full sample of seller and sell-side broker pairs, $N_{ht} = 43,705$, $N_{lt} = 9,644$, $N_{hlt} = 3,220,414$. The estimates are conditional on broker-market intercepts, δ_{lt}. For each seller, choice set for brokers are constructed based on brokers' record of making a transaction in the seller's census tract, with a minimum of three available brokers per seller. The control function is the residual from regressing $\hat{V}^S_{hl}$ on the observed list price and commissions, $p^{obs}_h(1 - c_l)$ and the included variables. The reported standard errors are analytical robust standard errors.

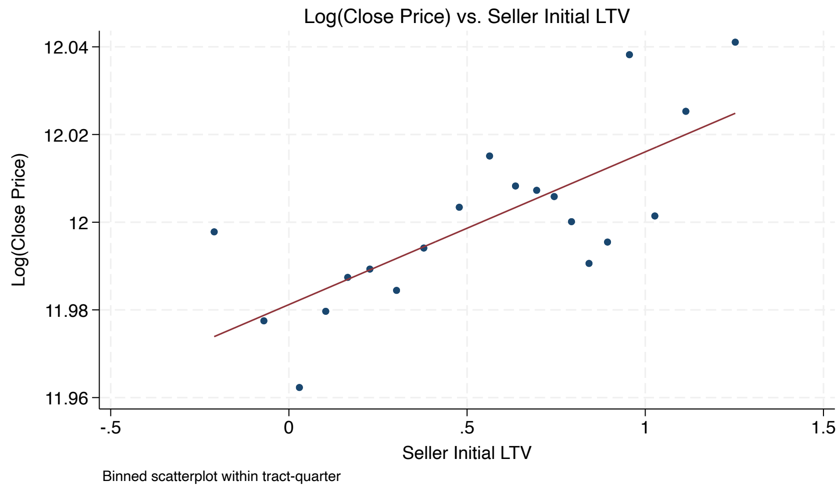
Table A6. Counterfactual Results: Market Outcomes with Varying Assumptions

	Status Quo	Baseline CF	(1)	(2)
Panel A: Housing Market				
Seller: House Price net of Comm ($1,000s)	233	234	234	233
Buyer: House Price with Comm ($1,000s)	246	240	240	238
Sell-side Broker Comm. (%)	5.2	2.0	2.0	2.0
Buy-side Broker Comm. (%)	0	1.2	1.3	2.0
Num. Trx, $\sum \phi$	367	374	375	359
Panel B: Welfare (as % of total trx. volume)				
Total Welfare (%)	.	1.5	1.7	–.65
Broker Revenue (%)	.	–2.6	–2.9	–3.4
Consumer Surplus (%)	.	4.1	4.2	2.3
Seller Surplus (%)	.	1.3	1.4	-1.4
Buyer Surplus (%)	.	2.8	2.8	3.6

Notes: Variables in Panel A are averaged across 20 markets, from Q3 of 2010 to Q3 of 2015, weighted by the predicted number of transactions in each market. House prices sellers (buyers) are computed after subtracting (adding) expected commissions across brokers. Commissions are *posted* commissions, with buy-side broker commission converted from a flat-fee to % in house prices. Panel B denotes the differences between the status quo and the counterfactual quantities, divided by the total transaction value simulated under the status quo, $\frac{1}{T}\sum_t \sum_h \hat{p}^{sq}_{ht}\hat{\phi}^{sq}_{ht} = \$85.3M$. Column (1) simulates a scenario where buy-side brokers charge a percentage-fee. Column (2) simulates a scenario where buyers' price coefficients for commissions are multiplied by $\frac{1}{1-LTV_b^{mult}}$ across four LTV_b bins, making their indirect disutility from houses to be $-(\alpha_b^B p_h + \frac{\alpha_b^B}{1-LTV_b^{mult}} c_k)$ to mimic credit constraint of buyers.

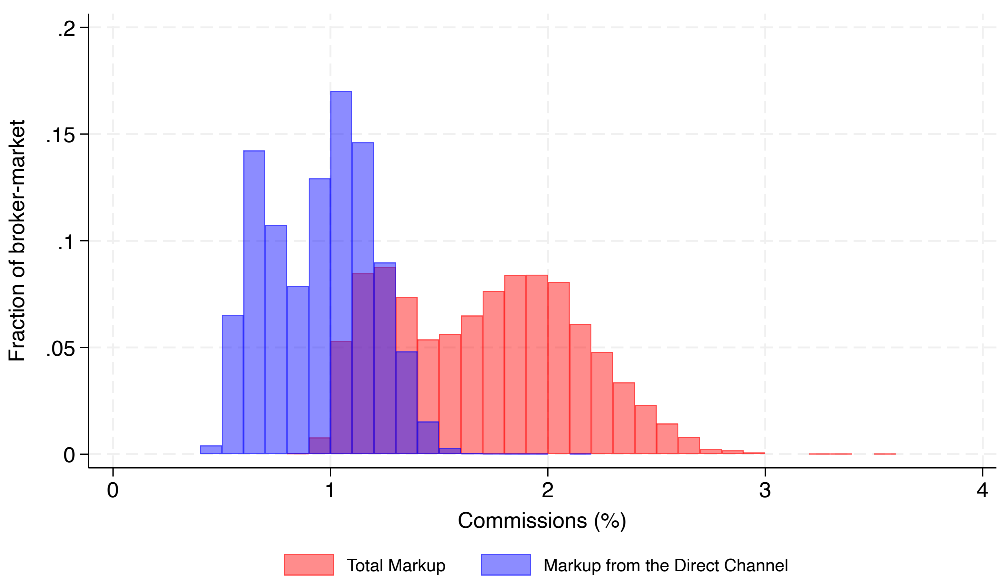
B Appendix Figures

Figure A1. Sellers with greater initial LTV extract equity from high close prices



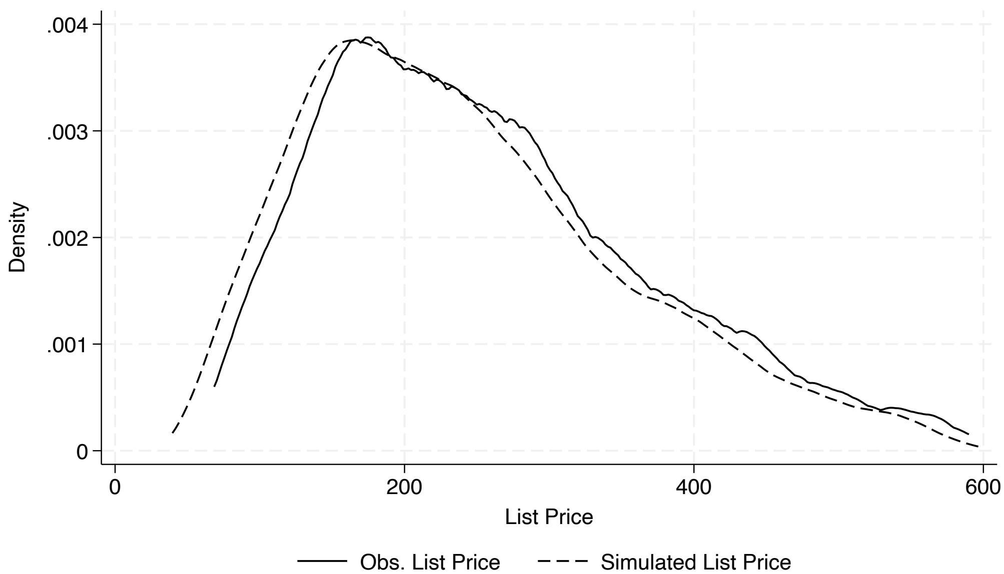
Notes: The sample is from Riverside, CA, across 14,012 sold listings. They plot binned scatterplots of seller initial LTV against observed log(close price) and commissions offered to buy-side brokers within tract-quarter.

Figure A2. Distribution of total vs. direct commission markups



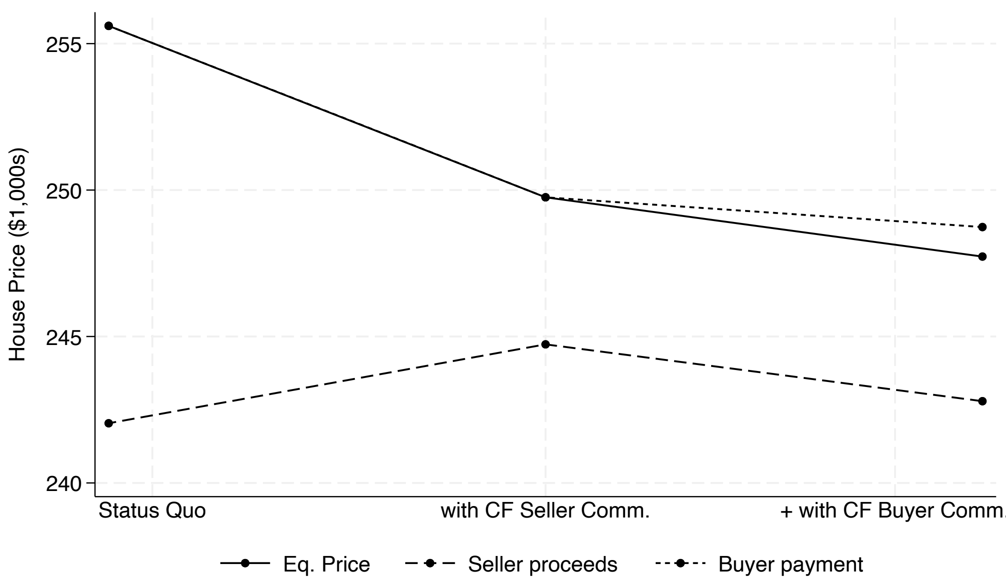
Notes: Average across sell-side broker-market pairs, $N_{lt} = 9,644$. The "direct" channel refers to the portion of markup coming from sellers' inverse commission elasticities, holding seller sales probabilities fixed.

Figure A3. Assessing model fit: simulated vs. observed list price distributions



Notes: Across 20 markets, from Q3 of 2010 to Q3 of 2015, $N_{ht} = 27,629$.

Figure A4. Changes in equilibrium prices from seller and buyer counterfactual statutory commissions



Notes: Averaged across 20 markets, from Q3 of 2010 to Q3 of 2015, weighted by the predicted number of transactions in each market. House prices sellers (buyers) are computed after subtracting (adding) expected commissions across brokers.