The Equilibrium Impacts of Broker Incentives in the Real Estate Market

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Abstract

Commission rates for housing transactions are twice as high in the United States than in other countries. Policymakers have raised concerns that the practice of sellers offering buyers' brokers commissions can lead to high commissions and harm consumers. This paper empirically examines the equilibrium impacts of a proposed policy called "*decoupling*," which would require buyers and sellers to each pay their respective brokers. I develop a structural model integrating buyers, sellers, and brokers to characterize the equilibrium house prices, commissions, and to assess the welfare impacts of the policy. I estimate the model with rich observed heterogeneity and credible sources of identifying variation using shifters of 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% of the total transaction value from having higher net proceeds than the status quo. I find notable surplus gains for buyers across income groups as sellers pass through part of their commission savings to house prices.

Keywords: intermediaries, real estate, competition policy

JEL Code: R21, R31, L13, L14, L43, L85, G50

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1 Introduction

Understanding how intermediaries affect consumer decisions and shape market outcomes is important (Inderst and Ottaviani, 2012), as they are often found in high-stakes settings such as financial services and healthcare. I study the residential real estate brokerage industry in the United States, where the 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 buyers' brokers a portion of the commissions paid to sellers' brokers, and this practice has raised concerns about steered buyers and inflated commission rates.[2] While empirical research has documented the causal impact of broker incentives on consumer outcomes (Barwick et al., 2017; Barry et al., 2023), little is known about how much of the commissions are driven by this practice and what would happen if it 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 based on commissions. Others argue that regulations dictating who is responsible for statutory commissions seem unnecessary because of the independence of physical and economic incidence. Some have voiced concerns that the policy could disproportionately harm low-income buyers who cannot afford brokerage services and sellers who need to sell faster.[4] The effects of the policy on the commission rates and the housing market 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 housing demand, supply, 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 for 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

[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).

intermediation features brokers steering following their incentives and buyers choosing among differentiated brokers to maximize expected utility (Robles-Garcia, 2019; Grennan et al., 2024).[5] On the supply side, brokers set commission rates to maximize profits, while sellers compete on house prices and choose brokers. In doing so, sellers trade off larger sales proceeds (house prices net of commission fees) 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 that account for the direct commission elasticity, which comes from sellers' preference for commission fees. However, the steering motives of buyers' brokers reduces sellers' elasticity with respect to commissions, as offering a greater commission rate *increases* the likelihood of sale, which sellers value. This steering channel increases the markups of brokers, creating distortion. I provide a novel decomposition that quantifies the relative importance of the two channels in determining commission fees.

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

On the demand side, the main empirical objects of interest are the elasticities with respect to house prices and commissions. A potential threat is that house prices and commissions may be correlated with unobserved property and brokerage quality. I use sellers' pre-determined loan characteristics at the time of their purchases, such as loan-to-value ratios and loan terms, 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 selling 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 sales, I use the differentiation instruments

[5] I refer brokerage offices as "brokers" throughout the paper.

(Gandhi and Houde, 2019) that build on the notion that the probability 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 buyers' brokers are sensitive to commission revenues. The estimates suggest 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 buyers' brokers leads to a -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 threat of steering.

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

While equilibrium *list* prices drop, sellers retain 0.3% greater proceeds from the sale net of the commissions, and buyers pay 2.7% less for a house (inclusive commissions) than before. This amounts to a significant consumer welfare gain of 4.1% of the total transaction value. The lowered 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%, while 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 in which 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 drop in list prices, generating significant surplus gains for low-income, price-sensitive buyers.

For sellers, those with low patience gain the least in surplus (1.3%) because the decoupled structure removes a mechanism for impatient sellers to increase the probability of sale through compensating buyers' 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 with those in the highest quantile (3.3%).

The conclusions are robust across various counterfactual scenarios. First, welfare implications remain unchanged if brokers charge a percentage-based fee instead of a flat fee to buyers. Second, the conclusions are also similar in a counterfactual that accounts for potential credit constraints buyers face, especially low-income ones who lack cash to pay commissions. Under this scenario, buyers still gain 3.6% of the total transaction value, driven by buyers passing more of their commissions onto the house prices and many opting not to use a broker.

The debate over decoupling broker incentives has focused on whether it will effectively lower commissions and whether it could harm certain groups of buyers and sellers in the process. I develop a model that quantitatively assesses the main channels relevant to comparing the status quo with the decoupled counterfactual. I find that decoupling significantly reduces commissions. The principle of incidence does not apply 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.[6] In my setting, buyers capture

[6] Buchak et al. (2024) and Grochulski and Wang (2024) also evaluate the potential impact of

a larger share of the 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 linkages between the housing and intermediation markets offering insights into designing broker incentive structures.

Related Literature This paper contributes to the extensive literature on real estate brokers in the United States.[7] I complement the reduced form evidence on the impacts of broker incentives, including steering by buyers' 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 that connects the interactions between the demand-side brokers (Barwick et al., 2017) and the supply-side brokers (Hendel et al., 2009) through a housing market equilibrium to quantify the impacts 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.[8] 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 expands to this body of work by examining the U.S. real estate market, one of the largest, and heavily intermediated industries. I implement credible identification strategies to address confounders of house prices and commissions due to unobserved property and agent quality.

Finally, the model contributes to the broader literature on house price formation. I augment the 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

decoupling on house prices but with exogenously determined commissions. Buchak et al. (2024) treats houses as durable assets and finds that lowered commission fees can lead to an *increase* in the future value of home ownership, resulting in higher house prices.

[7] 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.

[8] 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.

formation throughout the housing cycle (Buchak et al., 2022; Gilbukh and Goldsmith-Pinkham, 2023; Calder-Wang and Kim, 2024). Additionally, I develop a novel model of price formation by sellers, building on insights from the 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

In this section, I briefly describe the common practices involving real estate brokers in the U.S., motivating some of the assumptions made in later sections. I then describe the datasets and provide descriptive statistics for the empirical setting, covering Riverside, California, from 2009 to 2015.

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, two brokers are involved: one representing the buyer and one representing the seller. Buyers rely on their brokers to help find them suitable homes and guide them through the purchasing process. Sellers rely on their brokers to market properties, attract buyers, and secure higher sale proceeds within their desired timeframes.

It is customary for sellers to pay the statutory commission fees, with buyers' brokers expecting half of the fees from sellers.[9] The commissions for buyers' brokers are posted on the local Multiple Listings Service (MLS), a shared database of listed properties for real estate professionals. These posted commissions act as a "bounty" for other brokers, incentivizing them to show the property to buyers and to claim the commission once the sale closes.

In theory, sellers can negotiate on commissions. In practice, sellers are often pressured to meet the "going" rate for buyers' brokers to ensure timely sales. The rate for buyers' brokers becomes the reference point for the seller's broker rate, as both brokers typically expect equal payment. Consequently, brokers are often reluctant to

[9]This norm dates back to 1913 (National Association of Real Estate Exchanges, 2012). The 1913 Code of Ethics states "...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." This practice can be considered a "fair" split, since brokers engage in repeated interactions and may be on either side in future transactions. See Nadel (2021) for extensive treatment of legal issues surrounding the compensation practice.

negotiate their rates .[10]

Buyers are not expected to pay their brokers directly, which effectively eliminates buyers' price sensitivity when choosing a broker. The system also removes buyers' incentives not to use a broker at all to lower purchase prices of properties because the pre-determined contracts between sellers and their brokers often bind the sellers to pay the full commissions *regardless* of the involvement of a buyer's broker.

The Department of Justice (DOJ) and the Federal Trade Commission (FTC) have advocated for "*decoupling*" of commissions that would require buyers and sellers to pay their own broker as early as 2007 (Federal Trade Commission, U.S. Department of Justice, 2007). Despite the recent settlement involving the National Association of Realtors (NAR), the DOJ reopened its investigation to decouple the commissions completely.[11] A shortcoming of the recent settlement is that it primarily prohibits brokers from posting commission offers on the MLS only, leaving several loopholes for buyers' brokers to discriminate against house listings based on offered commission rates. Additionally, buyers' brokers can still suggest to buyers that they are not responsible for the fee by only showing properties of sellers willing to cover the buyer broker's commission.

Proponents argue that decoupling would lower overall commissions because sellers would not have to offer high commissions to buyers' brokers, and it encourages brokers to compete with buyers on price and service quality. However, critics argue that such regulation is unnecessary, as the economic incidence of commissions is independent of whether sellers or buyers pay the commissions. Lastly, some caution that requiring buyers to pay commissions out of pocket could disproportionately impact first-time and lower-income buyers, as these groups may struggle with the upfront costs, potentially limiting their access to homeownership (Schnare et al., 2022). Thus the consequences of the policy are an empirical question.

2.2 Data

The primary dataset, CoreLogic MLS, contains detailed transaction-level outcomes for properties listed through local MLS systems across the U.S. I supplement it with CoreLogic Deeds, Loan-Level Market Analytics (LLMA), and the public Home Mortgage Disclosure Act (HMDA) data to obtain financial and demographic information

[10]According to a survey by Brobeck (2019), only 27% of real estate agents were willing to negotiate.

[11]US DOJ v. The National Association of Realtors (2020).

for the sellers and buyers involved in the observed transactions.

CoreLogic Multiple Listings Service (MLS) CoreLogic MLS data contain house-level transactions with detailed information on properties, including list prices, addresses, characteristics, and notably, seller and buyer brokerage offices and agents, and commissions offered to buyers' brokers. This dataset allows me to estimate the demand and the supply of the real estate market through the observed choices in relation to the observed prices and the commissions offered. The MLS data come from local MLS' maintained by real estate professionals in those areas, cleaned and aggregated by CoreLogic.

I do not observe the total commissions paid by sellers to their brokers, which is a limitation of the data. I only observe the portion of the commission offered to buyers' agents. However, as discussed previously, sellers' brokers are typically paid the same amount as buyers' brokers, so I assume that sellers paid twice the observed commission rate offered to buyers' brokers throughout the analysis.

I infer buyers without broker representation based on the transactions involving an agent representing both the seller and the buyer. In these cases, the seller's broker often becomes a "dual agent" representing both parties. In California, dual agency is permitted with mandatory disclosure, suggesting that unrepresented buyers consciously chose not to use a broker.

Supplementary data To further link the transaction instances with buyer and seller demographics, I incorporate additional supplementary data: CoreLogic Deeds, the public HMDA data, and CoreLogic LLMA. They all contain financing and demographic information on sellers and buyers, including income, origination date, loan-to-value (LTV) ratio, loan amount, initial interest rate, interest rate type (fixed vs. adjustable), loan term, and loan type (e.g., conventional vs. FHA). This allows me to estimate demand and supply with rich heterogeneity in preferences to assess the distributional implications of counterfactual scenarios.

All datasets have information on property locations and purchased prices, enabling me to merge them with the transaction-level data. CoreLogic Deeds, collected at the property level, include property addresses and closing prices. CoreLogic LLMA data are anonymized at the ZIP-month level and contain closing prices. Finally, the HMDA data are anonymized at the tract-year level but contain closing prices. For the LLMA data and the HMDA data, I conduct fuzzy-matching with the transaction data.

Lastly, the HMDA data provide useful metrics for the number of potential buyers in a given area, as they include the universe of approved and denied mortgage applications. Given that approximately 65 to 70% of home purchases are financed through a mortgage, the number of applications serves as an approximate measure of potential homebuyer activity.[12]

2.3 Empirical Setting and Descriptives

The empirical setting for the remainder of the analysis is the real estate market in Riverside, California, from 2009 to 2015. I focus on California because it exhibits cross-sectional variability in commission rates offered to buyers' brokers, unlike uniform markets such as Texas.[13] Figure 1 shows the cross-sectional distributions of commission rates offered to buyers' brokers in Riverside, CA, across 2009 and 2014, revealing a tri-modal pattern rather than the degenerate distribution commonly assumed. I further narrow my focus to Riverside, CA, due to its moderate size, which reduces the computational burden of treating individual sellers and brokerage offices as heterogeneous firms.

Summary statistics of the key variables across transactions, buyers, sellers, and brokerage offices are presented in Table 1. The observed variance in sales outcomes of houses in Panel A informs how to define empirical "markets." While the average time on market of houses sold is 50 days, only about 50% of houses sell within a quarter. Coupled with the fact that it takes buyers on average 10 weeks to find a house (Kasper et al., 2023), I define the empirical "market" as a city-quarter pair.

The list prices show price dispersion, measured by a coefficient of variation of 0.44, covering low-end to high-end properties. As shown in Panels B and C, sellers and buyers are similar in their financial characteristics. Most sellers and buyers bunch at the 80% LTV and take out a 30-year mortgages, conditional on financing. The joint distribution of the property characteristics and the financial observables of the buyers and sellers will help me estimate a choice model with rich observable heterogeneity of the consumers. For the brokers, I treat local brokerage offices as a unit of "firm" throughout the paper rather than individual agents or overarching brands and refer to them as "brokers," as most offices have norms or policies in setting commission rates (Barwick et al., 2017).

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

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

2.4 Descriptive Evidence of Steering

I examine whether sellers offering a lower commission than the "going rate" to buyers' brokers face the threat of steering in the form of lower sales probability within a quarter. This is the key channel through which brokers charge high markups to sellers, as sellers fear delayed sales if they do not offer a "competitive" commission to buyers' brokers. I follow the regression specification used by Barwick et al. (2017):

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

where h denotes house/seller, t denotes the quarter. X_{ht} includes observable characteristics of the house or the seller, as well as fixed effects. ϵ_{ht} represents unobserved factors affecting the sales probability of houses. The coefficient on the low-commission indicator, β^{comm}, 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) covering the Boston metro market from 1998 to 2011, and transparently demonstrate that the key findings from the literature hold within my empirical setting.

Table 2 shows the results. In the main specification, I control for unobserved tract-level neighborhood quality (tract-quarter fixed effects), unobserved broker quality (brokerage office-quarter fixed effects), and unobserved seller characteristics that may be correlated with the macro-housing cycle (seller's year of purchase - (listed) quarter fixed effects), as well as observed property characteristics and seller financials. These controls address concerns that higher commissions may have been offered due to unobservably low-quality properties or brokers, or impatient sellers.

I find that sellers offering less than 2.5% commissions to buyers' brokers experience 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, equivalent to an 11% decrease. These findings are consistent with 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 the specifications.

3 Theoretical Framework

Building on the qualitative and empirical findings from Section 2, I present a stylized model of a broker's profit-maximization problem. The stylized model aims to illustrate how the steering motives of buyers' brokers can lead to higher commissions. I focus only on the interaction between sellers and their brokers, with the remainder of the model introduced in Section 5.

3.1 Seller Chooses a Broker

A seller with house h wants to sell the house and decides whether to list it with broker l. The seller's indirect utility from the broker mainly depends on the price net of the commission rate and the likelihood of selling within a timeframe. Let c_l denote the commission charged by broker l, with half, $\frac{1}{2}c_l$, offered to buyers' brokers. While I carry this "equal split" assumption throughout the paper, I show in Appendix C that this assumption does not affect the key economic mechanisms of interest. I assume the house price, p_h, is exogenously set; this assumption will be relaxed in the full model.

Let the probability that seller h chooses broker l be:

$$s^L_{hl} := s^L_{hl}(p_h(1-c_l), \phi_{hl}(p_h, \frac{1}{2}c_l)),$$

where $p_{hl}(1-c_l)$ is the price net of the commission, or the "direct proceeds" from sale for the seller, and $\phi_{hl}(p_h, \frac{1}{2}c_l)$ represents the probability of sale within a quarter, which depends on the house price, p_h, and the commission offered to buyers' brokers, $\frac{1}{2}c_l$.

The seller's choice probability of broker l decreases with the commission rate ($\frac{\partial s^L_{hl}}{\partial c_l} < 0$) but increases with the sales probability ($\frac{\partial s^L_{hl}}{\partial \phi_{hl}} > 0$). The probability of sale increases with the commission offered to buyers' brokers ($\frac{\partial \phi_{hl}}{\partial c_l} > 0$), as buyers' brokers seek a higher commission payout.

3.2 Broker sets a Commission Rate

Broker l sets a commission c_l to maximize profit. For now, I suppress the notation for the price, p_h, which is assumed to be exogenous. The broker's expected profit from seller h is:

$$\Pi_l(c_l) = s^L_{hl}(c_l, \phi_{hl}(\frac{1}{2}c_l))\phi_{hl}(\frac{1}{2}c_l)(\frac{1}{2}p_h c_l - m_l), \tag{2}$$

where $s^L_{hl}\phi_{hl}$ represents the joint probability that seller h chooses the broker and successfully sells the house. The broker expects revenue of $\frac{1}{2}p_h c_l$ and incurs a marginal cost of m_l per transaction.

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

$$c_l^* = 2\frac{m_l}{p_h} - \left[\phi_{hl}\left(\overbrace{\frac{\partial s_{hl}^L}{\partial c_l}}^{(i)<0} + \overbrace{\frac{\partial s_{hl}^L}{\partial \phi_{hl}}\frac{\partial \phi_{hl}}{\partial c_l}}^{(ii)>0}\right) + \overbrace{s_{hl}^L\frac{\partial \phi_{hl}}{\partial c_l}}^{(iii)>0}\right]^{-1} s_{hl}^L\phi_{hl}. \tag{3}$$

Equation (3) highlights the channels through which the current incentive structure enables brokers to charge higher markups to sellers. First, as is standard, the term (i) captures the broker's natural market power from differentiation, holding all else constant. I refer to this as the *direct* channel.

The last two terms, (ii) and (iii), capture an additional markup arising from buyer brokers' steering motives. Intuitively, offering a higher commission to buyers' brokers raises the sales probability, and the broker sets a commission capturing sellers' valuation of such gain in sales probability. This channel is what (ii) captures. In addition, the seller's broker is incentivized to close the sale quickly, as they generate revenue only upon sale. This incentive is captured by the term (iii). These two channels make seller demand less elastic. Together, these constitute the *steering* channel, as the commission affects the markup indirectly through buyer brokers' steering motives.

Broker profit under decoupling Under decoupling, two aspects will change from the broker's perspective. First, the broker cannot offer a commission to buyers' brokers. This effectively sets the steering channel, (ii) and (iii) in Equation (3), to zero ($\frac{\partial \phi_{hl}}{\partial c_l} = 0$). Second, the broker no longer needs to pay buyers' broker half of the commission. Therefore, the profit function becomes:

$$\Pi_l^{CF}(c_l^{sell}) = s_{hl}^{L,CF}\left(c_l^{sell}, \phi_{hl}^{CF}\right)\phi_{hl}^{CF}\left(p_h c_l^{sell} - m_l^{sell}\right), \tag{4}$$

where ^{CF} denotes objects in the decoupled counterfactual, and ^{sell} denotes quantities pertaining to the sell-side brokers', distinguishing it from what buyers' brokers optimize over in the counterfactual. Again, I treat p_h as an exogenous variable for now.

The new optimal commission function of the broker is then:

$$c_l^{sell,*} = \frac{m_l^{sell}}{p_h} - \left(\phi_{hl}^{CF} \overbrace{\frac{\partial s_{hl}^{L,CF}}{\partial c_l^{sell}}}^{(i)<0} \right)^{-1} s_{hl}^{L,CF} \phi_{hl}^{CF}. \tag{5}$$

In the presence of buyer brokers' steering motives, decoupling necessarily lowers sellers' payments by more than half. However, the magnitude of the decrease depends on the strength of buyer brokers' steering motives. While the stylized model generates valuable insights on how decoupling may be able to lower commissions, it only paints a small part of the picture. How buyer brokers' will set their commissions and how house prices will be affected in equilibrium are all empirical questions that require a full model of the housing market. Hence, I develop an empirical model incorporating these additional market features to examine thoroughly the equilibrium effects of decoupling on the housing market and broker competition in the following section.

4 Empirical Model of Housing Market with Brokers

In this section, I present the full empirical model of the housing market. The model aims to conduct the counterfactual analysis of decoupling and to evaluate its impact on equilibrium house prices, commissions, and the surplus of consumers and brokers. The model involves interactions among four players: buyers, sellers, and their respective brokers, and defines an equilibrium solution concept involving house prices and commissions. I conclude the section by specifying the changes that decoupling would introduce.

The model is partitioned into the demand and supply sides of the real estate market, where the supply side pertains to sellers' and their brokers' decisions, and the demand side concerns buyers' and their brokers' decisions. The game proceeds as follows:

1. (Supply) Each broker sets a commission rate for sellers, half of which is offered to buyers' brokers.

2. (Supply) Sellers choose a broker based on direct proceeds from sale and the probability of sale. After choosing a broker, each seller sets a price.

3. (Demand) Buyers choose a broker based on the broker's value-added, measured by the expected surplus from the housing market

4. (Demand) Each buyer and their broker jointly decide on a house to purchase.

As discussed in Section 2, an empirical market is a city-quarter pair. I begin by describing the demand side, involving buyers and their brokers.

4.1 Demand Side

On the demand side, I model how buyers choose their brokers and, together as a pair, choose a house to purchase.

4.1.1 Buyer and Buyer Broker Demand for Housing

Overview I describe the choice problem of buyers and their brokers *after* each buyer has chosen a broker. When choosing between houses, buyers consider the consumption utility of each house, which depends on its price and physical attributes. At the same time, brokers primarily focus on the commission revenue from each house. This is the main source of buyer steering and conflicts of interest. I capture buyer steering through buyer and her broker's joint decision process of choosing a house, with an agency parameter that gives weight to the broker's indirect utility, following Robles-Garcia (2019). The goal is to capture the demand elasticities with respect to prices and commissions offered.

I index buyers with b and buyers' brokers with k, and the pairs denoted as bk. In cases where a buyer chooses not to have a broker, I denote the pair as $b0$ ($k = 0$). Each pair chooses a house listed by a seller, indexed by h, sold through the seller's broker l, among the set houses listed in market t, $\mathcal{H}_t^*$, to maximize their joint utility. I denote house-broker pair as hl.

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

$$u_{b,hlt}^H = \overbrace{-\alpha_b^H p_{hlt} + X_{hlt}^H \beta_b^H + \xi_{hlt}^H}^{=:V_{b0,hlt}^H} + \epsilon_{b,hlt}^H, \tag{6}$$

where p_{hlt} is the listed price of the house, X_{hlt}^H is a vector of observable characteristics of the house and those of the broker (l), ξ_{hlt}^H is an index that captures the unobservable (to the econometrician) quality of the house (h), the seller's broker (l), or the market (t), and ϵ^H captures buyer-specific idiosyncratic tastes. The superscript H indicates the quantities relevant to a choice situation across houses.

For buyers' preference parameters, α_b^H is the (dis)preference parameter for house prices, and β_b^H is a vector of preferences across the observable characteristics of the house and the seller's broker.[14]

Buyers can choose not to purchase any house on the market, denoted as $h = 0$, which yields them the utility of

$$u_{b,0t}^H = \varphi_t^H + \epsilon_{b,0t}^H, \tag{7}$$

where φ_t^H denotes the value of the outside good in market t.

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

$$\pi_{k,hlt}^H = p_{hlt}\tilde{c}_{hlt} + W_{khlt}^H \gamma^H + \omega_{k,hlt}^H, \tag{8}$$

where $\tilde{c}_{hlt} := \frac{1}{2}c_{hlt}$, with c_{hlt} being the total commission rate the seller h pays to her broker, so $p_{hlt}\tilde{c}_{hlt}$ represents the commission revenue the buyer's broker receives upon transaction. W_{khlt} is the observable characteristic capturing the buyer broker's expertise in a particular group of houses (h) or their relationship with the seller's broker (l), and $\omega_{k,hlt}$ captures the buyer broker's idiosyncratic tastes. If the buyer chooses the outside good $h = 0$, then the broker receives zero utility:

$$\pi_{k,0t}^H = 0. \tag{9}$$

Joint decision utility between buyer and the buyer's broker With their respective objectives, the buyer and her broker pair bk chooses a house h listed by the seller's broker l to maximize their joint utility, subject to the surplus division weight κ_k, or the broker's "agency weight" (Robles-Garcia, 2019; Grennan et al., 2024):

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

[14] This admits a possibility that buyers' decisions can be influenced by sellers' brokers as well, through marketing, persuasion, etc.

Buyers with broker representation, $k > 0$, benefit from their broker's expertise or network, capturing a $(1 - \kappa_k)$ fraction of the surplus generated from the broker's network, $W^H_{khlt}\gamma^H$.[15] Rescaled by $(1-\kappa_k)$, the joint decision problem can be expressed as:

$$\max_{hl \in \mathcal{H}^*_t} u^H_{bk,hlt} = \underbrace{V^H_{b0,hlt} + \tilde{\kappa}_k p_{hlt}\tilde{c}_{hlt} + W^H_{khlt}\tilde{\gamma}^H}_{=:V^H_{bk,hlt}} + \tilde{\kappa}_k \omega^H_{khlt} + \epsilon^H_{bhlt}, \tag{10}$$

where $V^H_{b0,hlt}$ is defined as in Equation (6), $\tilde{\kappa}_k = \frac{\kappa_k}{1-\kappa_k}$ and $\tilde{\gamma}^H = \frac{1}{1-\kappa_k}\gamma^H$. Assuming $(\tilde{\kappa}_k \omega^H_{k,hlt} + \epsilon^H_{b,hlt})$ 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 buyer's broker chooses to maximize her utility with no correlation between the brokers' unobserved portion of the utility and the buyer's.[16] For buyers without a broker, i.e. $k = 0$, the decision problem is:

$$\max_{hl \in \mathcal{H}^*_t} V^H_{b0,hlt} + \epsilon^H_{bhlt}. \tag{11}$$

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

$$s^H_{bk,hlt} = \frac{\exp(V^H_{bk,hlt})}{\exp(\varphi^H_t) + \sum_{(hl)' \in \mathcal{H}^*_t} \exp(V^H_{bk,(hl)'t})}. \tag{12}$$

4.1.2 Buyers' Demand for Brokerage Service

Overview I describe buyer's choice of a broker *prior to* choosing a house to purchase. When choosing across brokers, I allow buyers to consider expected surplus from the housing market based on the ensuing joint decision process described in Section 4.1.1. If buyers are aware of potential steering, buyers will consider the difference in the utilities of their desired outcome and the outcome influenced by brokers. Each buyer solves a discrete choice problem, including the option of proceeding to purchase a house without hiring a broker. Modeling buyer's choice of a broker aims to predict how buyers' demand for brokerage services will change once brokers charge commission fees to buyers.

[15] This formulation captures both potential benefits and conflict of interest from buyer broker's network or expertise (Han and Hong, 2016).

[16] 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.

As before, buyers are indexed by b, and buyers' 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 buyer brokers in market t, $k > 0$, from which buyers can choose. At this stage, I assume buyers are only aware of the distribution of match values across houses, ϵ^H.

Buyer broker value-added The difference in the joint utility (Equation 10) with a broker and the buyer's own utility (Equation 6) is what the buyer actually prefers and what will end up being chosen due to her broker's influence (Grennan et al., 2024). Formally, the expected maximum utility, or "inclusive value," of buyer b from the housing market by choosing to shop with broker k is:

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

In words, Equation (13) captures the buyer's surplus from the housing market when her purchase decision is influenced by her broker k's incentive. It differs from the traditional inclusive value, where the decision and the consumption utilities are the same.

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

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

The first term denotes the expected maximum joint surplus. The second term corrects for the potential surplus loss from steering. Intuitively, the first term captures the correlation between the buyer's preference and the brokers' incentives from the decision utility, $V_{bk,hlt}^H$. The second term captures how much the incentives of the broker, $(p_{hlt}\tilde{c}_{hlt} + W_{khlt}\gamma)$, are correlated with the choice probabilities across houses, $s_{bk,hlt}^H$. This term effectively penalizes the broker's value-added according to the magnitude of the agency problem, κ_k.

If a buyer chooses not to seek broker representation, $k = 0$, then her expected surplus is:

$$I_{b,0t} = \frac{1}{\alpha_b^H} \log\left(1 + \sum_{hl} \exp\left(V_{b0,hlt}^H\right)\right), \tag{15}$$

where $V^H_{b0,hlt}$ is defined in Equation (6).

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

$$u^K_{b,kt} = \overbrace{\lambda I_{b,kt} + X^K_{kt}\beta^K_b + \xi^K_{kt}}^{=:V^K_{b,kt}} + \epsilon^K_{b,kt}, \tag{16}$$

where X^K_{kt} are observable buyer broker characteristics, ξ^K_{kt} is market-specific buyer brokers' vertical quality index, and ϵ^K is the i.i.d. idiosyncratic error term that follows a Gumbel distribution. λ denotes buyers' preference parameter for the expected surplus from hiring broker k, and β^K_b are the preference parameters on the observable broker characteristics. The superscript ^{K} denotes the variables related to buyers' choice of a broker.

I close the model by specifying the outside option, which is to proceed without broker representation, normalized to:

$$u^K_{b,0t} = \overbrace{\lambda I_{b,0t} + \gamma^K_b}^{=:V^K_{b,0t}} + \epsilon^K_{b,0t}, \tag{17}$$

where γ^K_b is a buyer-specific preference for not choosing to be represented by a broker. The distributional assumption of ϵ^K yields the following probability of buyer b choosing broker k:

$$s^K_{b,kt} = \frac{\exp\left(V^K_{b,kt}\right)}{\sum_{k' \in \mathcal{K}_t \cup \{0\}} \exp\left(V^K_{b,k't}\right)}. \tag{18}$$

4.2 Supply Side

With the demand side of the model, I explain how sellers and their brokers interact with the demand side. I first characterize a measure of demand against which sellers and their brokers optimize. I then describe how each seller chooses a broker and sets a price against the demand measure. I conclude the section by explaining how brokers set commissions for the sellers.

4.2.1 Measure of Demand for Houses

Overview On the supply side, each seller with house h makes decisions of 1) choosing a broker and 2) choosing the optimal price to set given demand from buyers. I first introduce the measure of demand, which is the sales probability within a quarter (t), before I introduce the specifics of the sellers in the model.

A seller sees the demand for her house as a probability measure of whether her house will be sold within a quarter, t. I construct the probability by aggregating the choice probabilities of buyers and buyers' brokers for a house. The constructed demand system captures how the sales probabilities change with prices and commissions. Moreover, it also captures how sellers' choice of brokers affects their probability of sales. This rich demand system allows me to impute each seller's price and probability of sale for each possible broker the seller could have chosen.

Sales probability within a quarter I obtain the expected number of buyers for each house by integrating over the joint probability of buyers choosing a broker k, $s^K_{b,kt}$, and the pair choosing a house h listed by listing broker l, $s^H_{bk,hlt}$, from Equations (18) and (12), respectively,

$$q_{hlt} := M_t \int_b \sum_{k \in \mathcal{K}_t} s^K_{b,kt} s^H_{bk,hlt} dD_t, \tag{19}$$

where M_t denotes the market size of buyers and D_t denotes the observed distribution of buyer demographics in market t.

I assume sellers view the buyer arrival process as following a Poisson distribution 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 the probability of more than one buyer showing up to purchase within t (quarter), i.e., $\Pr(q_{hlt} \geq 1)$:

$$\phi_{hlt} := \Pr(q_{hlt} \geq 1) = 1 - \exp(-q_{hlt}). \tag{20}$$

This is a micro-founded measure of liquidity in the model, built up from the indirect utilities of buyers and buyers' brokers. ϕ_{hlt} captures the key channels through which a seller may face different probabilities of sales. Mainly,

$$\phi_{hlt} = \phi_{hlt}(p_{hlt}, c_{lt}; \boldsymbol{p}_{-hlt}, \boldsymbol{c}_{-lt}),$$

which depends on the house itself h, the broker that the seller chooses, l, the prices of own and *other* houses, $(p_{hlt}, \boldsymbol{p}_{-hlt})$, and commissions offered to buyers' brokers by own and other sellers, $(c_{lt}, \boldsymbol{c}_{-hlt})$.

4.2.2 Pricing of Houses by Heterogeneous Sellers

Overview I describe how sellers set house prices given the demand measure. A key feature of the model is that sellers are heterogeneous in setting prices based on their patience. Impatient sellers value sales probabilities over direct proceeds from a sale, while patient sellers prioritize direct proceeds more. Hence, a seller's "patience" captures her willingness to trade direct proceeds for a greater sales probability within a quarter.

Accounting for seller patience is crucial because it links to the key insight from the theoretical model in Section 3; sellers must value timely sales for brokers to charge higher markups. In other words, even if sellers face a lower probability of sale from offering lower commissions, the extent to which brokers can charge higher markups depends on sellers' valuation of the probability of sales. Hence, the patience parameter will not only captures how sellers price, but also their sorting across brokers, similar to what Hendel et al. (2009) documented.

At this point, all sellers have committed to their choice of brokers, and each only chooses a price (Lee and Musolff, 2023). There is no uncertainty for sellers, other than specific realizations of demand-side preference shocks, ϵ^K and ϵ^H. Sellers know the distribution of these shocks and have the correct anticipation of the probability of sale with the broker they have chosen in market (quarter) t, ϕ_{hlt}.

Seller expected proceeds Seller h lists with broker l in quarter t and expects some *direct proceeds* from the sale, $p_{hlt}(1-c_{lt}) - r^S_{ht}$, which is the price net of the commission payment, $p_{hlt}(1-c_{lt})$, and net of the seller's reservation value of selling, r^S_{ht}. The seller also faces a probability of sale within quarter t, ϕ_{hlt}. Assuming sellers are forward-looking, sellers' *expected* proceeds are

$$\begin{aligned} V^S_{hlt} &:= \sum_{t=0}^{\infty}[\beta^S_{ht}(1-\phi_{hlt})]^t \phi_{hlt}(p_{hlt}(1-c_{lt}) - r^S_{ht}) \\ &= \frac{\phi_{hlt}}{1-\beta^S_{ht}(1-\phi_{hlt})}(p_{hlt}(1-c_{lt}) - r^S_{ht}), \end{aligned} \tag{21}$$

where $\beta^S_{ht} \in (0,1)$ is the seller's discount factor, which I refer to as the "*patience*" parameter. I use superscript S to denote quantities related to sellers' pricing problem. Equation (21) follows from the closed-form expression of the infinite-horizon discounting model.[17]

The seller's broker, l, influences the seller's expected proceeds, V^S_{hlt}, through three channels. First, the commission that the broker charges, c_{lt} affects direct proceeds through $p_{hlt}(1-c_{lt})$. Second, sellers face varying sales probability, $\phi_{hlt}(p_{hlt}, \frac{1}{2}c_{lt})$, depending on the broker's characteristics (denoted by the l subscript) and the commission offered to buyers' brokers, $\frac{1}{2}c_{lt}$. Lastly, sellers set price p_{hlt} given the demand function $\phi_{hlt}(\cdot)$ following Equation (22). Hence, the expected proceeds measure, V^S_{hlt}, is a micro-founded quality measure of a seller's broker, reflecting individual sellers' preferences for house price over sales probability through β^S_{ht}.

Intuitively, sellers gain from higher net proceeds and a higher probability of sale, i.e., $\frac{\partial V^S_{hlt}}{\partial p_{hlt}} > 0$ and $\frac{\partial V^S_{hlt}}{\partial \phi_{hlt}} > 0$, but the magnitude of each gain differs across sellers based on their patience, β^S_{ht}. In fact, the gain from the probability of sale, $\frac{\phi_{hlt}}{1-\beta^S_{ht}(1-\phi_{hlt})}$ *decreases* with seller patience, i.e., $\partial\left(\frac{\phi_{hlt}}{1-\beta^S_{ht}(1-\phi_{hlt})}\right)/\partial\beta^S_{ht} < 0$, capturing that patient sellers value direct proceeds over sales probability.

Seller optimal pricing Sellers' trade-off becomes clearer in the first-order condition of the expected proceeds, V^S_{hlt}, with respect to price, p_{hlt}:

$$p^*_{hlt} = \overbrace{\frac{r^S_{ht}}{1-c_{lt}}}^{\substack{\text{(i) Reservation value,}\\ \text{inflated by commission}}} + \underbrace{\left(\frac{1-\beta^S_{ht}(1-\phi_{hlt})}{1-\beta^S_{ht}}\right)}_{\substack{\text{(ii) Additional markup}\\ \text{due to patience, } \beta^S_{ht}>0}} \overbrace{\left(\left|\frac{\partial\phi_{hlt}}{\partial p_{hlt}}\right|\right)^{-1}\phi_{hlt}}^{\text{(iii) baseline markup when fully impatient, } \beta^S_{ht}=0} . \tag{22}$$

Equation (22) highlights the economics of home sellers. Expression (i) shows that the commission inflates the seller's reservation price, and some of this will be passed onto house prices. Expressions (ii) and (iii) together constitute the seller's markup. 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 with just the term (iii). Conversely, sellers with a high β^S_{ht} will list their houses at a higher price than the optimal static price.

[17] The model is valid with the assumption that sellers do not change their expectations once formed, and only update their expectations at the start of each quarter. Incorporating the full dynamics would result in a model where sellers play a dynamic discrete game.

4.2.3 Sellers' Demand for Brokerage Services

Overview I describe how sellers choose a broker based on their expected proceeds from each broker, V^S_{hlt}. Sellers want higher net proceeds, a greater probability of sale, and other "amenity" factors from their brokers. The first two components are captured in the expected net proceeds, $V^S_{hlt}(p_{hlt}(1-c_{lt}), \phi_{hlt})$.

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

$$u^L_{h,lt} = \alpha^L \overbrace{V^{S,*}_{hlt} + X^L_{hlt}\beta^L + \xi^L_{lt}}^{=:V^L_{h,lt}} + \epsilon^L_{h,lt}, \tag{23}$$

where $V^{S,*}_{hlt}$ denotes the expected net proceeds from the broker evaluated at the optimal price point from Equation (22), X^L_{hlt} denotes seller-broker specific observables, ξ^L denotes the unobservable quality or "amenity" of the broker, and ϵ^L_{hlt} is the seller's private, idiosyncratic taste shocks iid from the standard Gumbel distribution, $G^L(\cdot)$. I use superscript L to denote quantities related to the seller's problem of choosing among brokers. If a seller decides not to list, she gets the following indirect utility:[18]

$$u^L_{h,0t} = \varphi^L_t + \epsilon^L_{h,0t}, \tag{24}$$

where φ^L_t denotes the value of the outside option of not listing in market t. Then the choice probability of seller h choosing broker l is:

$$s^L_{h,lt} = \frac{\exp(V^L_{h,lt})}{\exp(\varphi^L_t) + \sum_{l' \in \mathcal{L}_t} \exp(V^L_{h,l't})}. \tag{25}$$

While simple, Equation (23) highlights the model's key complication. Each seller's choice depends on what *other* sellers choose, affecting V^S_{hlt} through which brokers others choose and the prices that others set, i.e.

$$V^{S,*}_{hlt} := V^S(p^*_{hlt}, \phi_{hlt}(p^*_{hlt}; \boldsymbol{p}^*_{-h}), c_{lt}; \beta^S_{ht}, r^S_{ht}), \tag{26}$$

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

[18] I infer the market sizes of sellers from the number of discontinued listings from quarter to quarter. I do not explicitly capture the entry decisions of sellers but adjust the inclusive values of buyers by a factor of the outside good share when solving for an equilibrium to approximately scale both the competitive environment a seller faces and "variety" that buyers get.

Seller subgame equilibrium Because each seller's indirect utility from a broker in Equation (23) depends on other sellers' choice of brokers, an equilibrium solution is warranted where 1) each seller makes her choice of a broker with an expectation of what others will do and 2) such expectation is consistent up to a realization of sellers' mean-zero taste shocks in choosing brokers.

Once those taste shocks are realized, sellers then play a complete information Nash-Bertrand game to price their houses according to Equation (22) (Lee and Musolff, 2023). In other words, all sellers have the same, correct expectation of the housing market and each chooses a broker accordingly. Once the choices of brokers are realized, sellers set prices optimally to their residual demands.

Formally, let $\mathcal{X}_h^L$ be seller h's information set when choosing across brokers, and C_h maps the information set to broker choice for each seller, i.e. $C_h : \mathcal{X}_h^L \to \{0, 1, \ldots, L_t\}$. Sellers have complete information up to a realization of ϵ^L of other sellers (e.g., patience, reservation values, etc. are known), and the distribution from which they are drawn, $\epsilon^L \sim G^L(\cdot)$, is common knowledge. Unlike in other discrete games where players' payoffs directly depend on the actions of others, here, the actions of other sellers affect 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* of all seller-broker pairs, $\mathcal{V}^{S,*} := \{\overline{V}_{hlt}^{S,*}\}_{hlt \in \mathcal{H}_t \times \{\mathcal{L}_t \cup \{0\}\}}$, where $\overline{V}_{hlt}^{S,*}$ is averaged over the distribution of sellers' private information, $G^L(\cdot)$:

$$\overline{V}_{hlt}^{S,*} = \int V_{hlt}^S(p_{hlt}, \phi_{hlt}(p_{hlt}^* | \boldsymbol{p}_{-hlt}^*(\epsilon^L)))dG^L. \tag{27}$$

The vector of anticipated house prices of others, $\boldsymbol{p}_{-hlt}^*(\epsilon^L)$, depends on the belief of other sellers' taste shocks, ϵ^L drawn from $G^L(\cdot)$.

In equilibrium, all sellers "agree" on the set of potential proceeds that everyone will get from their possible choice of brokers, $\mathcal{V}^{S,*}$, and anticipate correctly which brokers other sellers will choose up to a realization of ϵ^L. Then the choice problem of a seller h choosing among brokers becomes:

$$\underset{l \in \mathcal{L}_t}{\operatorname{argmax}} \; \overbrace{\alpha^L \overline{V}_{hlt}^S(c_{lt}, p_{hlt}^*, \phi_{hlt}^* | \mathcal{V}^{S,*}) + X_{hlt}^L \beta^L + \xi_{lt}^L}^{=:V_{h,lt}^L} + \epsilon_{h,lt}^L. \tag{28}$$

I provide a formal treatment of the equilibrium solution concept at the end of the current section.

4.2.4 Broker Pricing of Commission Rates

Overview With an equilibrium play of sellers in mind for a given set of commissions, I describe how brokers set optimal commission rates. In Section 3, I explained how the steering channel allows brokers to charge high markups in a partial equilibrium context. In the context of the full model, the pricing power of brokers stems from the fact that 1) sellers' sales probability increases with commission rates due to buyer broker steering, i.e., $\frac{\partial \phi_{hlt}}{\partial c_l} > 0$, and 2) sellers' expected proceeds (and thus their probability of choosing broker l) increases with the sales probability, i.e., $\frac{\partial V^S_{hlt}}{\partial \phi_{hlt}} > 0$. In other words, sellers are willing to pay a higher commission because a higher commission increases their sales probability, which they value. Brokers set commissions by internalizing this channel.

Broker profit and commission pricing Formally, each broker sets a commission rate c_{lt} to maximize its expected profit:

$$\Pi_{lt}(c_{lt}; \boldsymbol{c}_{-lt}, \overline{p}_t) = \sum_{h \in \mathcal{H}_t} \underbrace{s^L_{hlt}(c_{lt}; \boldsymbol{c}_{-lt})}_{\text{Prob of seller } h \text{ listing with } l} \overbrace{\phi_{hlt}(c_{lt}; \boldsymbol{c}_{-lt})}^{\text{Prob of } h \text{ being sold when listed with } l} (\frac{1}{2}\overline{p}_t c_{lt} - m_{lt}), \tag{29}$$

where s^L_{hlt} is the probability of seller h choosing l from Equation (45) and ϕ_{hlt} is the sales probability of h from Equation (20). Both s^L_{hlt} and ϕ_{hlt} depend on other brokers' commission rates, $(c_{lt}, \boldsymbol{c}_{-lt})$. $\overline{p}_t$ is the average house price of the market and m_{lt} is the marginal cost of transaction. This assumes that brokers price according to the *average* house price and that individual brokers do not internalize how their choice of commission influences market-level house prices. c_{lt} is divided by $\frac{1}{2}$ because sell-side brokers offer half of the seller's commission to buyers' brokers. I assume that the brokers are not forward-looking in setting a commission.

Taking the first-order condition of Equation (29), I obtain a similar expression to Equation (3) in Section 3, with the same three channels present:

$$c^*_{lt} = \frac{m_{lt}}{\overline{p}_t} - \left[\sum_{h \in \mathcal{H}_t} \phi_{hlt} \left(\overbrace{\frac{\partial s^L_{hlt}}{\partial c_{lt}}}^{(i)} + \overbrace{\frac{1}{2} \frac{\partial s^L_{hlt}}{\partial \phi_{hlt}} \frac{\partial \phi_{hlt}}{\partial c_{lt}}}^{(ii)} \right) + \overbrace{s^L_{hlt} \frac{1}{2} \frac{\partial \phi_{hlt}}{\partial c_{lt}}}^{(iii)} \right] \sum_{h \in \mathcal{H}_t} s^L_{hlt} \phi_{hlt}, \tag{30}$$

where the $\frac{1}{2}$ in front of the partials indicates that half of the commission is offered to buyers' brokers. The channels, $(i), (ii)$, and (iii), are the equivalent channels described in Section 3, Equation (3), with (*ii*) and (*iii*) counteracting sellers' direct elasticity to commissions and granting brokers higher market power.

4.3 Equilibrium Concept

I characterize the equilibrium concept of the housing market. An equilibrium involves three objects, each corresponding to a specific game that sellers and brokers play on the supply side. First, once sellers choose their brokers (Section 4.2.2), they play a complete information Nash-Bertrand pricing game. This subgame equilibrium is defined by a vector of house prices, with the realized choices by brokers of the sellers. Second, sellers play an incomplete information discrete choice game of choosing a broker prior to pricing (Section 4.2.3). This subgame equilibrium is defined by a vector of seller-broker pairs' expected proceeds that is common across all sellers, i.e., all sellers have the same, correct belief of what other sellers will choose. Lastly, when each broker sets a commission (Section 4.2.4), brokers play a complete information Nash-Bertrand pricing game and also account for the equilibrium play of the sellers. Hence, an equilibrium is characterized by a tuple containing a vector of commission rates, a vector of expected proceeds, and a vector of ex-post house prices. I provide a formal definition below.

Definition 4.1. An equilibrium solution concept is a tuple $\mathcal{E}_t^* := (\boldsymbol{c}_t^*, \mathcal{V}_t^{S,*}, \boldsymbol{p}_t^*)$ such that it satisfies all of the following systems of equations:

- Brokers set commissions optimally:

$$\frac{\partial \Pi_{lt}}{\partial c_{lt}}(\boldsymbol{c}_t^*) = 0, \quad \forall l \in \mathcal{L}_t,$$

  where Π_{lt} is defined in Equation (29) and $\boldsymbol{c}_t^* = \{c_{lt}\}_{l \in \mathcal{L}_t}$.

- Sellers anticipate the optimal expected proceeds consistent with the common belief $\epsilon^L \sim G(\cdot)$:

$$\overline{V}_{hlt}^{S,*} = \overline{V}_{hlt}^{S,*}\left(p_{hlt}^*, \phi_{hlt}^*, c_l^*; \mathcal{V}_t^{S,*}(\boldsymbol{\epsilon}_t^L)\right) \quad \forall hl \in \mathcal{H}_t \times \{\mathcal{L}_t \cup \{0\}\},$$

  where $\mathcal{V}^{S,*} := \{\overline{V}_{hlt}^{S,*}\}_{hl \in \mathcal{H}_t \times \{\mathcal{L}_t \cup \{0\}\}}$, and $\boldsymbol{\epsilon}_t^L := \{\epsilon_{hlt}^L\}_{hl \in \mathcal{H}_t \times \{\mathcal{L}_t \cup \{0\}\}}$.

- Sellers set prices optimally given their choices of broker:

$$\frac{\partial V_{hlt}^S(\boldsymbol{\epsilon}^{L,*})}{\partial p_{hlt}}(\boldsymbol{p}_t^*) = 0 \quad \forall hl \in \mathcal{H}_t^*,$$

where $\boldsymbol{\epsilon}_t^{L,*} := \{\epsilon_{hlt}^L\}_{h \in \mathcal{H}_t}$ denoting a vector of *realized* taste shocks from $G(\cdot)$.

Lastly, given the equilibrium commissions and prices in $\mathcal{E}_t^*$, each buyer chooses a broker and chooses a house to purchase with respect to their indirect utility specified in Equation (16) and (10).

4.4 Key Changes under Decoupling

I conclude the section by specifying two main changes and two main responses to those changes under decoupling. For the changes, first, sellers cannot offer a commission to buyers' brokers, and second, each buyer broker sets a flat-fee commission for buyers through price competition. In response to the changes, buyers choose their broker based on the commission charged, and seller brokers respond by each setting a commission only to sellers' direct elasticity with respect to commission. I describe each one of these explicitly. I omit the market subscript t.

Change 1: Buyers pay their broker a commission upon purchasing a house

Buyer and her broker choose a house according to the following joint utility, changed from Equation (10):

$$\max_{hl \in \mathcal{H}^*} u_{bk,hl}^{H,CF} = \underbrace{V_{b_0,hl}^H - \alpha_b^H \overbrace{c_k^{buy}}^{\text{buyer commission payment}} + \overbrace{\tilde{\kappa}_k c_k^{buy}}^{\text{changed broker incentive}} + W_{khl}^H \tilde{\gamma}^H + \tilde{\kappa}_k \omega_{khl}^H}_{=:V_{bk,hl}^{H,CF}} + \epsilon_{bhl}^H, \tag{31}$$

where c_k^{buy} is a flat-fee commission that the broker charges to the buyer to be paid upon purchasing.

Now the commission incentives are *invariant* to houses, denoted by their subscript k. However, the source of conflict of interest still exists through $\tilde{\kappa}_k c_k^{buy}$ as the brokers still want their buyers to purchase a house.

The choice probability of buyer-broker pair bk choosing house-broker pair hl in the counterfactual is then:

$$s_{bk,hl}^{H,CF} = \frac{\exp(V_{bk,hl}^{H,CF})}{\exp(\varphi_t^H) + \sum_{h \in \mathcal{H}^*} \exp\left(V_{bk,hl}^{H,CF}\right)}. \tag{32}$$

Response 1: Buyers choose brokers based on commissions

Buyers, knowing they need to pay their broker a commission upon transaction, choose their broker accordingly. Instead of their indirect utility from choosing a broker in Equation (16), the counterfactual indirect utility of buyers is:

$$V_{bk}^{K,CF} = \lambda^{CF} I_{bk}(c_k^{buy}) + X_k^K \beta_b^K + \xi_k^K, \tag{33}$$

where $I_{bk}(c_k^{buy})$ is computed as before in Equation (14), but with $V^{H,CF}$ in Equation (31). In a later section, I discuss the assumption regarding how buyers may become more sensitive to the explicit "price" their broker charges through λ^{CF}. Let $s_{bk}^{K,CF}$ be the choice probability of buyer b choosing broker k with the changed indirect utility function above.

Change 2: Brokers compete on commissions for buyers

Buyer brokers now actively set commissions given the changed buyer demand. Let $s_{bk,1}^{H,CF} := \sum_{h \in \mathcal{H}^*} s_{bk,hl}^{H,CF}$ to be the probability that a buyer purchases *any* property on the market conditional on choosing broker k. Then, the expected profit of broker k in the counterfactual is:

$$\Pi_k^{buy,CF}(c_k^{buy}; c_{-k}^{buy}) = \sum_b s_{bk}^{K,CF} s_{bk,1}^{H,CF} (c_k^{buy} - m_k^{buy}), \tag{34}$$

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 $c_k^{buy} - m_k^{buy}$. I assume buyers' brokers engage in price competition, each setting $c_k^{buy,*}$ that maximizes its profit in Equation (34). I discuss my assumption regarding m_k^{buy} in a later section.

Response 2: The supply side's response to the changes in the demand side

Given the changes on the demand side, sellers and their brokers re-optimize. Let ϕ_{hl}^{CF} denote the sales probability in the counterfactual, integrating over the probabilities of buyers choosing a broker and choosing a house in the counterfactual, $s^{K,CF}$ and $s^{H,CF}$. Sellers re-optimize by each setting a new price $p_{hl}^{*,CF}(\phi_{hl}^{CF})$, yielding the new expected proceeds from sale, $V_{hl}^{*,CF}(p_{hl}^{*,CF}, \phi_{hl}^{CF})$. Lastly, sellers' brokers maximize following the new expected profit function:

$$\Pi_l^{sell,CF}(c_l^{sell}; c_{-l}^{sell}) = \sum_{h \in \mathcal{H}_t} s_{hl}^{L,CF} \phi_{hl}^{CF} (\bar{p}^{CF} c_l^{sell} - m_l^{sell}). \tag{35}$$

where the superscript ^{sell} makes a distinction from the buyer brokers' quantities explicitly, and $s_{hl}^{L,CF}$ denotes the changed choice probabilities of sellers in response to the new commissions charged by their brokers, c_l^{sell}. The optimal broker commission implied by the first-order condition of (35) follows (5), removing the steering channel. Sellers' brokers now cannot offer half of their commissions, so their revenues do not get halved as before.

Counterfactual equilibrium Given the specific changes above, I define a new "*decoupled*" counterfactual equilibrium solution concept. The solution concept is similar to that of the status quo's, defined in Definition 4.1, with an addition of buyer brokers' Nash-Bertrand pricing game after sellers choose their prices.

Specifically, an equilibrium is characterized by a tuple of four objects; seller 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 buyer broker commissions that depend on the realized house prices, $\boldsymbol{c}^{buy,*}(p_{hl}^{CF,*}, \epsilon^{L,*}) = \{c_k^{buy,*}\}_{k\in\mathcal{K}}$:

$$\mathcal{E}^{CF,*}(\epsilon^{L,*}) := (\boldsymbol{c}^{sell,*}, \mathcal{V}^{S,CF,*}, \boldsymbol{p}^{CF,*}(\epsilon^{L,*}), \boldsymbol{c}^{buy,*}(\epsilon^{L,*})). \tag{36}$$

4.5 Model Implications on Commissions and Market Efficiency

I conclude the section by discussing whether the model, a priori, predicts that decoupling will lower commissions and produce a more efficient outcome. Whether commissions will decrease depends on how sensitive buyers become once their brokers directly charge them. In the model, this is governed by the parameter λ in Equation (16) and λ^{CF} in Equation (33).

The model also admits the possibility of potential efficiency loss from the policy. This mainly depends on the extent to which brokers influence buyers' demand. The model allows for two channels through which buyers' brokers alter the *market*-level demand for housing.

First, brokers make market demand less elastic because they earn higher revenues from buyers purchasing more expensive houses. In the model, this is captured by brokers' agency parameter, $\tilde{\kappa}$, which counteracts buyers' price sensitivity, α^H, in Equation (10). Less elastic market demand then inflates house prices.

Second, brokers shift the market demand curve outward, because brokers only collect revenue upon transaction. In the model, this occurs through the functional form of the joint decision process in Equation (10). Holding fixed the value of the outside good, φ^H, buyers who choose to shop with a broker are more likely to choose an inside good (i.e. close a sale) than those who do not. Given that 80% to 90% of buyers choose to hire a broker, this feature shifts the market demand outward, inflating house prices and generating more sales than otherwise occur.

Therefore, the model does not a priori restrict whether decoupling will result in efficiency gains or losses. This outcome depends on the empirical estimates of the discussed economic forces. For instance, efficiency loss could occur if all buyers decide not to hire a broker, resulting in an inward shift of market demand and fewer transactions than the status quo. Thus, whether commissions will decrease and whether decoupling will improve market efficiency are ultimately empirical questions.

5 Identification and Estimation Results

In this section, I discuss parameterization, identification and estimation of the parameters introduced in Section 3. At a high level, the parameters are estimated from the choice instances recorded in the CoreLogic MLS data mentioned in Section 2. I address the endogeneity concerns when estimating the parameters from the observed choices, as the observed commissions and prices are formed in equilibrium. In estimating the model, I further restrict the sample discussed in Section 2 to brokers with more than 20 listings and five transactions per year.

5.1 Demand Side Estimates

On the demand side, I estimate the parameters of the buyer-broker housing choice model and the buyer's choice model of a broker. With the transaction-level data coupled with observed buyer demographics, I estimate a discrete choice model with random coefficients via maximum likelihood estimation. I provide a detailed treatment of concerns about endogeneity and measurement errors in each choice model.

5.1.1 Estimating Buyer and Broker Preference for Houses

Overview I estimate the preference parameters governing how buyers and their brokers choose across houses. I present the estimation and identification of the parameters in the indirect utility function in Equation (10), restated here:

$$V_{bk,hlt}^{H} = \overbrace{-\alpha_b^H p_{hlt} + X_{hlt}^H \beta_b^H + \xi_{hlt}^H}^{=:V_{b0,hlt}^H} + \tilde{\kappa}_k p_{hlt} \tilde{c}_{hlt} + W_{khlt}^H \tilde{\gamma}^H + \tilde{\kappa}_k \omega_{khlt}^H. \quad (10)$$

The two key estimates are the buyers' (dis)preference for prices, α^H, and the broker's preference for commission revenue, $\tilde{\kappa}$. I estimate the parameters via the maximum likelihood estimation (MLE) procedure, by finding a set of parameters that best matches the model-predicted choice probabilities in Equation (12) to the observed choices in the data. I address the key endogeneity concern of prices and commissions being correlated with the unobserved (to the econometrician) quality of the houses, leveraging sellers' tendency to set high or low prices depending on their financial positions, a fact well documented in the real estate literature.

Identification The key challenge in obtaining consistent estimates of buyer (dis)preference for house prices and broker preference for commission revenue is that house prices $\{p\}_{hlt}$ and commission rates $\{\tilde{c}\}_{lt}$ are formed in equilibrium and are correlated with the unobserved qualities of houses or seller brokers, ξ_{hl}^H in Equation (10). For example, houses with unobserved desirable attributes will be listed at a higher price, and when not properly accounted for, such correlation will attenuate the estimates of α^H and $\tilde{\kappa}$. Hence, candidate instruments should be a good predictor of both house prices and commission rates and must be independent of the unobserved qualities of the houses or the sellers' brokers.

I use a set of sellers' financial characteristics as instruments for prices and commissions. These characteristics act as "supply shifters" and determine how sellers choose prices above or below the "market price" of their properties as well as how much commission to offer to buyers' brokers. Specifically, I employ 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.

Sellers' financial positions, especially how much equity a seller has in a property, are determinants of seller pricing strategy involving the trade-off between proceeds from sale and sales probability. A seller who prefers to extract more proceeds from sale will set a higher price and will wait longer. Seller LTV, for example, is one measure that has been consistently found to be correlated with a seller's tendency to set high vs. low prices in the literature (Genesove and Mayer, 1997; Anenberg, 2011; Guren, 2018; Andersen et al., 2022). This prediction extends to sellers' choice of commissions; high-LTV sellers will choose to offer a *lower* commission to maximize their proceeds from the sale.

Crucially, the theory generates *opposite* predictions for chosen prices and commissions, which can be tested. Figure 2 shows strong first-stage relationships between sellers' initial LTV and prices and commissions within tract-quarters. As discussed, the data supports the theory that high-LTV sellers setting higher house prices and offer lower commissions to buyers' brokers to extract more proceeds from sales.

To satisfy the exclusion restriction, the candidate variables should be independent of the unobserved quality of houses and sellers' brokers. The general concern is sorting between sellers and properties, or between sellers and brokers, based on sellers' characteristics. Examples of violation of the exclusion restriction would be highly leveraged sellers sorting into unobservably low-quality houses, or highly-leveraged sellers listing with unobservably low-quality brokers.

I address these concerns in two ways. First, I control for observable house characteristics and measures of broker quality. I also include tract-quarter fixed effects to control for unobserved neighborhood quality and tract-specific demand shocks. Hence, the identifying variation comes from sellers with varying levels of initial LTV, for example, setting prices above or below the *average price* in their tract-quarter. The similar identifying variation is leveraged for the commissions as well.

Second, *if* sellers sort across properties based on their financial characteristics, it is likely that sellers' purchase prices *when* the sellers had bought their houses are correlated with their initial LTVs. The direction could be either positive (sellers leverage to buy a high-quality housing) or negative (sellers who are financially constrained can only afford low-quality housing). The presence of such selection can be partially checked by examining the correlation between the sellers' purchase prices and their financial positions *at the time of purchase*. Figure A1 shows that seller LTV shows no correlation with their purchase prices. The evidence from the figure supports the idea that seller preference for proceeds drives their pricing and commissions rather than the quality of houses or brokers, conditional on granular neighborhood-time fixed effects.

I implement the IVs using the control function approach (Petrin and Train, 2010), which imposes the structure of ξ^H_{hlt} in Equation (10) to be:

$$\xi^H_{hlt} = \xi^{H,p}_{hlt} + \xi^{H,c}_{hlt} + \xi^H_{tract(hl)t} + \tilde{\xi}^H_{hlt}, \tag{37}$$

where $\xi^{H,p}_{hlt}, \xi^{H,c}_{hlt}$ are the components of house/broker quality correlated with house price and commission rate, respectively. $\xi^H_{tract(hl)t}$ is the tract-market fixed effects, and $\tilde{\xi}^H_{hlt}$ is the exogenous unobserved quality.[19] 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 the interactions of many players involved. These covariates vary across houses (e.g. number of bedrooms), sellers' brokers (e.g. average days on market the listings in the previous year), broker pairs (e.g. whether k and l are from the same brokerage office), seller's broker and house pairs (e.g. whether h and l are from the same ZIP code), to buyer's 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 estimated variation in housing demand will give rise to the key variables determining how buyers and sellers choose their brokers in the later part of the model.

I also parameterize α^H_b, β^H_b, and $\tilde{\kappa}_k$ capturing the heterogeneity in preferences. I let $\beta^H_b = d_b \beta^{H,d}$ and $\tilde{\kappa}_k = x_k \tilde{\kappa}^x$, where d_b and x_k are the vectors of the buyers' and their brokers' observable characteristics, 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 $\alpha^H_b = \frac{1}{inc_b^{1-\rho}}(d_b \alpha^{H,d})$, where inc_b is buyer b's annual income and ρ is the Box-Cox coefficient to be estimated, which flexibly captures the degree of the income effect. This determines the curvature of housing demand function and relaxes ex-ante restrictions on the range of pass-through the model can accommodate (Miravete et al., 2022). For the full list of covariates and the demographic-based random coefficients, see Appendix A1.

Estimation The estimation involves two steps. First, I recover buyers' and their brokers' preference parameters from the observed choices. Then, I estimate the market-specific value of the outside good, φ^H_t, by matching the observed shares of buyers who chose the outside good, which I infer from the public HMDA data as a fraction of loan applications for ownership purposes that did not result in origination.[20]

The empirical specification of the indirect utility equation without the idiosyn-

[19] 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.

[20] This includes approved but no action taken, withdrawn applications, and denied applications.

cratic taste term is:

$$V^H_{bk,hlt} = -\alpha^H_b(d_b;\rho)p_{hlt} + X^H_{hlt}\beta^H_b(d_b) + \tilde{\kappa}_k(x_k)\tilde{c}_{hlt} + W^H_{khlt}\tilde{\gamma}^H + \zeta^p\hat{\nu}^p_{hlt} + \zeta^c\hat{\nu}^c_{hlt} + \xi^H_{tract(hl)t}.$$

Let $\Theta^H = \left(\alpha^{H,d}_b, \rho, \beta^{H,d}_b, \tilde{\kappa}^x, \tilde{\gamma}^H, \zeta^p, \zeta^c\right)$ be the set of parameters to be estimated. I estimate Θ^H via the maximum likelihood estimation (MLE) procedure, which finds a set of parameters Θ^H that best matches the model-implied choice probabilities to the observed choices of buyer and broker pairs across houses.

To explain the estimation procedure in more detail, let $C^H_{bk,hlt} = 1$ 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:

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

where $s^H_{bk,hlt}$ is as defined in Equation (12), and the estimated parameters are those that maximize the above likelihood. I then estimate φ^H_t by matching the model-implied average outside good shares with the shares inferred from the public HMDA data.

5.1.2 Estimating Buyer Preference for Brokerage Services

Overview I present the identification and estimation of the preference parameters in the indirect utility function of buyers when choosing their brokers in Equation (16) restated here:

$$V^K_{bkt} = \lambda I_{bkt} + X^K_{kt}\beta^K_b + \mathbb{1}\{k=0\}\gamma^K_b + \xi^K_{kt}, \tag{16}$$

The key estimate is the preference for surplus from the housing market associated with choosing with a broker k, which is λ. I estimate the parameters via the MLE procedure, matching the observed buyers' choices in the data.

Identification and estimation Given that λ is the key object of interest, I discuss the variation in I_{bkt} that identifies λ. In essence, what I_{bkt} (defined in Equation 14) aims to capture is whether the broker will show the houses that align well with the buyer's true preferences. For example, for a price-sensitive buyer, a broker showing the buyer cheaper houses would have a higher value of I_{bkt} than a broker showing expensive houses. Hence, it is a measure of the correlation between what the buyer wants for a house, $V^H_{b,hlt}$, and what the broker would like to show, $\pi^H_{k,hlt}$, both of which are defined in Equation (6) and (8), respectively. To the extent that these are positively correlated, buyers benefit from such a broker.

The model-implied $\hat{I}_{bkt}$ can be prone to measurement error due to noise in the estimate of $\widehat{\Theta}^H$ or model mis-specification in constructing I_{bkt}. As a result, the estimated λ with be attenuated. I remedy this by constructing a proxy of $\hat{I}_{bkt}$ that captures the correlation between buyers' utilities and their brokers' utilities more explicitly in two different ways.

First, I construct a choice set containing top n houses according to their *decision utility*, defined in Equation (10), for each buyer-broker pair. It aims to remedy the measurement problem coming from the fact that I_{bkt} sums over thousands of potential houses that a buyer can choose from. Second, I evaluate each choice set's inclusive value based only on the buyer's consumption utility, $V^H_{b0,hlt}$, across those houses. This directly measures buyers' preference for the houses instead of the decision utilities as in Equation (14). Hence the proxy explicitly measures the value of the choice set each broker provides for a given buyer.

Specifically, define $\mathcal{H}_{bkt}(n)$ as a choice set containing the top n houses ranked by buyer-broker pair's decision utility $\hat{V}^H_{bk,hlt}$. Then I compute its inclusive value:

$$\hat{I}^{IV}_{bkt} = \frac{1}{\hat{\alpha}^H_b} \log\Big(\sum_{hl \in \mathcal{H}_{bkt}(n)} \exp(\hat{V}^H_{b0,hlt})\Big). \tag{38}$$

The IV satisfies the exclusion restriction because of the timing assumption that house-specific taste shocks, ϵ^H, are revealed after buyers' choice of broker k. I implement the IV via the control function method. The empirical specification of the indirect utility function of buyer b choosing a broker k is:

$$V^K_{b,kt} = \lambda \hat{I}_{bkt}(\widehat{\Theta}^H) + X^K_{kt}\beta^K + \mathbb{1}\{k=0\}\gamma^K_b + \tilde{\xi}^K_{kt} + \hat{\nu}^K_{bkt}\zeta^K, \tag{39}$$

where $\hat{\nu}^K_{bkt}$ is the residual from regressing $\hat{I}_{bkt}$ on $\hat{I}^{IV}_{bkt}$ and the set of included covariates, X^K_{kt} and broker-market dummies, and $\tilde{\xi}^K_{kt}$ is broker-market specific parameter capturing the brokers' unobserved vertical quality. The estimation procedure involves finding $\Theta^K := (\lambda, \beta^K, \zeta^K, \{\xi^K_{kt}\}_{kt})$ that best fits the model-implied choice probability in Equation (18) with the observed instances of buyers choosing brokers via MLE.

5.1.3 Demand-side Estimation Results

I focus on the key estimates and their implications for the relevant economic quantities, which are presented under Panel A in Table 3. The complete table of the estimated parameters are in Appendix Table A1 and Table A2. 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 are -5.6 and -7.8, respectively.[21] Also consistent with the previous findings, I find the housing demand to be concave shown by the estimated Box-Cox coefficient closer to 1.

Second, I find that brokers are sensitive to commission revenues. The estimated parameter, $\overline{\kappa}$, implies a seller lowering her commission rate by 0.5 percentage points (pp) faces a 3.6% drop in sales probabilities on average. Barwick et al. (2017) find 7.5% drop in sales probability if sellers list with commissions below 2.5%. While not directly comparable, the magnitude of their findings correspond to a seller dropping 1pp in commissions with the estimates I find.

Lastly, the estimated $\hat{\lambda}$ suggests that buyers are not sensitive to the value-added of their brokers. An average broker faces an inelastic demand with 0.23 elasticity with respect to the value they provide to buyers, measured by I_{bkt}. This echoes the concern that buyers regard broker services as close to being "free," being unaware of the value they are getting. The low elasticity helps to rationalize that the U.S. has the highest buyers' utilization rate of brokers with over 90% of buyers using them, compared to an average of 33% in other countries.[22]

5.2 Seller Estimates

I move on to estimate parameters governing how sellers price and choose brokers with the estimated demand-side primitives.

5.2.1 Seller Pricing Parameters

Overview I estimate the parameters that govern how sellers set prices, which are their patience and reservation values. The intuition behind identification of the patience parameters are simple; given the estimated demand function, $\hat{\phi}_{hlt}$, I measure how sellers differentially respond to demand shocks. For example, in respond to a

[21] Authors' conversion from days on the market to the probability of sale within 13 weeks.
[22] KBW Research, Smith (2024).

positive demand shock, patient sellers will be respond by increasing their prices more than impatient sellers. Hence the "demand shifter" instruments will measure how responsive a seller is for a change in sales probability, which informs how patient a seller is. Once the patience parameters are recovered, sellers' reservation values are simply the residuals of the observed prices net of the implied markups.

Identification and estimation To gain more insight into the identification and estimation procedure, I explicitly denote what is observed from the data with superscript *obs* and what is already estimated with $\widehat{\ }$.

The model assumes that the observed prices are the optimal prices that sellers had chosen, i.e. $p^{obs}_{hlt} = p^*_{hlt}$, and the commissions are also observed. I restate sellers' optimal pricing equation, Equation (22), denoting explicitly the quantities that are observed and estimated from the demand side:

$$p^{obs}_{hlt} = \frac{r^S_{ht}}{1 - c^{obs}_{lt}} + \left(\frac{1 - \beta^S_{ht}(1 - \widehat{\phi}_{hlt})}{1 - \beta^S_{ht}}\right)\left(\left|\widehat{\frac{\partial \phi_{hlt}}{\partial p_{hlt}}}\right|\right)^{-1} \widehat{\phi}_{hlt}. \tag{22}$$

Rearranging (22) yields:

$$\overbrace{\left(p^{obs}_{hlt} - \left(\left|\widehat{\frac{\partial \phi_{hlt}}{\partial p_{hlt}}}\right|\right)^{-1} \hat{\phi}_{hlt}\right)(1 - c^{obs}_{hlt})}^{=:y^S_{hlt}} = \left(\frac{\beta^S_{ht}}{1 - \beta^S_{ht}}\right) \overbrace{\left(\left|\widehat{\frac{\partial \phi_{hlt}}{\partial p_{hlt}}}\right|\right)^{-1} \hat{\phi}^2_{hlt}(1 - c^{obs}_{hlt})}^{=:x^S_{hlt}} + r^S_{ht}, \tag{40}$$

which resembles a standard regression model of regressing y^S_{hlt} on x^S_{hlt}, with non-linear parameters β^S_{ht} and r^S_{ht} as the residuals. I parameterize β^S_{ht} to be indirectly inferred from linear interactions with sellers' characteristics:

$$\frac{\beta^S_{ht}}{1 - \beta^S_{ht}} =: \tau^S_{ht} = \tau^S_t + d_h \tau^{S,d}, \tag{41}$$

where τ^S_t 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:

$$y^S_{hlt} = \tau^S_{ht} x^S_{hlt} + r^S_{ht}, \tag{42}$$

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

Estimating $\boldsymbol{\tau}^S$ directly from (42) presents an identification challenge as $y^S_{hlt}(p^{obs}_{hlt})$

and $x^S_{hlt}(p^{obs}_{hlt})$ are simultaneously determined in equilibrium. Specifically, the seller's unobserved reservation value, r^S_{ht}, is correlated with how the markup is determined in equilibrium through its own price p^{obs}_{hlt}.

Intuitively, patient sellers will increase their prices through adjustments in their markups more than impatient sellers facing the same demand shocks. To isolate such variation, I use "demand shifters" as instruments for x^S_{hlt}, 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 competing sellers' pre-determined characteristics of houses only affect the equilibrium markup (x^S_{hlt}) but not the focal seller's *own* reservation value, r^S_{ht}. The instruments isolate responsiveness of sellers in adjusting their markups to demand shocks, which identifies sellers' patience.

I construct the demand shifters with the differentiation instruments (Gandhi and Houde, 2019), based on the number of bedrooms, bathrooms, and square footage within a ZIP. Specifically, let $\mathcal{H}^*_{z(h)t}$ be the set of listed houses in ZIP z. Then the set of instruments denoted by $x^{S,IV}_{hlt}$ is constructed as follows:

$$x^{S,IV,bed}_{hlt} = \sum_{h' \in \mathcal{H}_{z(h)t} : h' \neq h} (bed_{h'} - bed_h)^2, \tag{43}$$

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^S_h via the generalized method of moments (GMM). I residualize $x^S_{hlt}, x^{S,IV}_{hlt}, y^S_{hlt}$ 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 quarter 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^S_t market by market by minimizing the following criterion function, which is the sample analog of the exclusion restriction $E[\tilde{r}^S_{ht}\tilde{x}^{S,IV}] = 0$:

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

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 (41) and recover the seller patience parameters, $\hat{\beta}_{ht}^S$.

5.2.2 Seller Preference for Brokers

Overview I estimate the preference parameters of sellers in choosing a broker. Seller's indirect utility function in Equation (23) is restated here:

$$V_{h,lt}^L = \alpha^L V_{hlt}^S(p_{hlt}^*(1 - c_{lt}), \phi_{hlt}) + X_{hlt}^L \beta^L + \xi_{lt}^L, \tag{23}$$

where the key parameter of interest is α^L, which governs sellers' choices among brokers based on how much of the expected proceeds each broker offers.

The key complication in estimation is that I only observe the realized pairs of sellers and brokers, and hence, I do not observe the expected proceeds, $V_{hlt}^{S,*}$, for the unrealized choices. However, the estimated demand primitives, the seller pricing function coupled with the subgame equilibrium concept discussed in Section 4.2.2, allow me to impute $V_{hlt}^{S,*}$ for every seller-broker pair. I describe each step in detail below.

Estimation and identification I estimate sellers' parameters governing their 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. That is, I assume all sellers chose their brokers anticipating that the observed broker choices of other sellers will happen. This means that ex-ante, no seller had an incentive to choose a broker aside from their realized choice of broker. While this may be a strong assumption on the surface, the choice of an individual seller is rather insensitive to how others choose because there are often more than 1,000 sellers in an empirical market.

Implementation is the following. First, I compute one-off deviations in expected proceeds for each seller. That is, for a seller h, I ask what p_{hlt}^* and $\phi_{hlt}^*(p_{hlt}^*)$ would have been for all l in her choice set, *holding fixed* other sellers' choices of brokers and prices. The prices for all seller-broker pairs are computed following Equation (22), and $\phi_{hlt}(p_{hlt}^*)$ can be computed from the estimated demand primitives. Once $\widehat{V}_{hl}^{S,*}(p_{hlt}^*, \phi_{hlt})$ are computed for all of the pairs, I estimate the parameters in Equation

(23) via MLE.

Estimating α^L from the imputed $\widehat{V}^{S,*}$ could be prone to a measurement error from potential model misspecification, which may attenuate the estimate. In essence, what differentiates one broker from another in the *data* is the commissions they charge, even though the model generates predictions of prices and the sales probabilities.

Hence I construct a proxy for $\widehat{V}^{S,*}$ using the observed prices and commissions from the data. I multiply the *observed* listing price of h, p_{ht}^{obs} with the *observed* average commission rate of broker l, c_{lt}^{obs} to construct $p_{ht}^{obs}(1-c_{lt}^{obs})$. This isolates the variation in sellers' direct net proceeds across brokers.

The empirical specification of Equation (28) is:

$$V_{hlt}^L = \alpha^L \widehat{V}_{hl}^{S,*} + X_{hlt}^L \beta^L + \hat{\nu}_{hlt}^L \zeta^L + \tilde{\xi}_{lt}^L, \tag{44}$$

where $\hat{\nu}_{hlt}^L$ is the residual from regressing $\widehat{V}_{hl}^{S,*}$ on $p_{ht}^{obs}(1-c_{lt}^{obs})$, X_{hlt}^L are seller-broker interaction observables (e.g. whether they are in the same ZIP), and $\tilde{\xi}_{lt}^L$ are broker-market intercepts that absorb any unobserved quality of brokers that may be correlated with commissions, c_{lt}, it charges. Under this specification, α^L is identified from within-broker variations of $p_{ht}^{obs}(1-c_{lt}^{obs})$ across sellers. Sellers with high-priced houses choosing low-commission brokers is an example of an identifying variation.

I estimate $\Theta^L := \left(\alpha^L, \beta^L, \zeta^L, \tilde{\boldsymbol{\xi}}^L\right)$ via MLE. I restrict sellers' choice sets to only include brokers that have a record of making a transaction in the sellers' tract. Let $\mathcal{L}_{ht}$ be seller-specific choice set of brokers. The choice probability of a seller h choosing to list with sellers' broker l is then:

$$s_{hl}^L = \frac{\exp(V_{hlt}^L)}{\exp(\varphi_t^L) + \sum_{l' \in \mathcal{L}_{ht}} \exp(V_{hl't}^L)}. \tag{45}$$

I estimate φ_t^L from the share of unsold but discontinued listings from one quarter to another.

5.2.3 Seller Parameter Estimation Results

Similar to the discussion of demand estimation results, I focus on the key estimates and relevant quantities. which are summarized under Panel B in Table 3. For the full results, see Appendix Tables A3 and A4. First, I find that the average of the estimated patience parameters across sellers, $\overline{\beta}_{ht}^S$ is 0.82. Consistent with the prior literature and the empirical findings from this paper, sellers with higher initial LTVs are estimated to be more patient than those with lower initial LTVs.

To put the patience estimates into perspective, I compute sellers' valuation of sales probability as 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.[23] 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 that sellers with high LTV ratios tend to be more patient and set high prices, consistent with the prior literature.

I further validate the estimates of $\widehat{\beta}^S$ by plotting the estimated patience parameters, $\hat{\beta}^S_{ht}$, against the observed list prices and commissions in Figure 3. The figure replicates Figure 2, which plots relationships between a "patience" proxy from the data, in this case sellers' initial LTVs, with the observed prices and commissions. Furthermore, the negative 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.

With the estimate of α^L, I assess seller elasticity to commission rates across brokers. Explicitly written, the elasticity of sellers with respect to commissions can be decomposed as follows:

$$\varepsilon^L_{hlt} := \overbrace{\alpha^L}^{\frac{\partial V^L_{hlt}}{\partial V^S_{hlt}}} (\underbrace{\frac{\partial V^S_{hlt}}{\partial c_{lt}}}_{\text{direct sensitivity to commissions } (\beta^S)} + \overbrace{\frac{1}{2}\frac{\partial V^S_{hlt}}{\partial \phi_{hlt}}\frac{\partial \phi_{hlt}}{\partial c_{hlt}}}^{\text{valuation of sales prob. from steering } (\beta^S, \kappa, \alpha^H)})(1 - s^L_{hlt})c_{lt}, \tag{46}$$

where the parameters in parenthesis are to explicitly marked to show which of the demand- and the supply-side parameters drive each of the effects. The steering channel makes the seller patience parameter, β^S, interact with buyers' broker preference for commissions, κ, influencing sellers' probability of sale, which depends on buyers' price sensitivity, α^H, as well.

I find that this interaction makes sellers less elastic to commissions. As shown at the bottom of Panel B in Table 3, brokers face an average own-elasticity of seller demand of -2.9. However, if the commissions do not affect sellers' sales probabilities

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

holding all else equal, brokers face much more elastic demand of -5.0. The gap between these two elasticities is the source of additional markups brokers can charge.

5.3 Broker Markup and Marginal Cost Estimates

With the estimated seller elasticities, I infer broker marginal costs from the first-order condition derived in Section 4.2.4. Brokers are indexed by l. The expression for the optimal commissions in Equation (30) is restated here:

$$c_{lt}^{*} = \frac{mc_{lt}}{\overline{p}_t} - \left[\sum_{h \in \mathcal{H}_t} \phi_{hlt} \left(\overbrace{\frac{\partial s_{hlt}^{L}}{\partial c_{lt}}}^{(i)} + \overbrace{\frac{1}{2} \frac{\partial s_{hlt}^{L}}{\partial \phi_{hlt}} \frac{\partial \phi_{hlt}}{\partial c_{lt}}}^{(ii)} \right) + \overbrace{s_{hlt}^{L} \frac{1}{2} \frac{\partial \phi_{hlt}}{\partial c_{lt}}}^{(iii)} \right] \sum_{h \in \mathcal{H}_t} s_{hlt}^{L} \phi_{hlt}. \qquad (30)$$

All but broker marginal costs, mc_{lt}, are either observed or estimated. The average house prices and commissions are observed, and the sales probabilities, ϕ_{hlt}, and the seller choice probabilities, s_{hlt}^{L}, are estimated. I recover the broker marginal costs directly. I quantitatively decompose the recovered broker markups into the standard markup, (i), and the additional markup from the steering channel, $(ii) + (iii)$.

5.3.1 Broker Estimation Results

Table 4 shows the decomposition of the current commission rates. On average, brokers charge 5.7% of the house prices to sellers. Half, 2.7%, goes to buyers' brokers, which can be treated as a "cost." Of the remaining 2.7 percentage points (pp), I find that 63% is the markup. Of the markup, 44% is an additional markup due to the steering motive of buyers' brokers. Figure A2 visualizes the results. To my knowledge, such quantification of the real estate brokers' additional markup has not been estimated.

5.4 Equilibrium Model Fit

With all the primitives of the model estimated, I simulate the current equilibrium to assess model fit. First, I draw several vectors of $\boldsymbol{\epsilon}^{L}$, and find $\widehat{\mathcal{E}}^{*}(\boldsymbol{\epsilon}^{L})$ as defined in Definition 4.1. Then I take a draw, $\epsilon^{L,*}$, and plot the simulated equilibrium list prices, $\hat{\boldsymbol{p}}_{t}^{*}(\epsilon^{L,*})$, against the observed list prices against in Figure A4. While the model slightly underestimates the observed prices, it is only mean-shifted by a small amount and fits the observed distribution well in almost every part of the distribution.

6 Evaluating the "Decoupled" Counterfactual

In this section, I discuss the equilibrium impacts of "*decoupling*." At a high level, the goal is to empirically assess the impacts of banning sellers from compensating buyers' brokers on equilibrium commissions, house prices, and the number of transactions made. By comparing the decoupled equilibrium with the status quo, I can quantify the welfare effects of decoupling on heterogeneous buyers, sellers, and brokers.

Assumptions I make two assumptions, both of which can be relaxed. First, I assume buyers' sensitivity to what brokers value-added, captured by λ^{CF} in Equation (33), changes. I justify this assumption based on evidences from qualitative sources discussed in Section 2 and the empirical estimate of $\hat{\lambda}$, which suggests that the implicit "price" of the brokers is not a salient feature to buyers. When brokers start charging buyers explicitly, buyers will become more sensitive to the commissions. In the baseline specification, I set λ^{CF} such that buyers are as sensitive to broker fees as sellers.

Second, since I do not have estimates of buyer brokers' marginal costs, m_k^{buy} in Equation (34), I impute them from the seller brokers' estimated marginal costs, $\widehat{m}_l$ from Equation (30) through mapping their vertical quality distributions recovered from the demand estimation, i.e., $F(\hat{\xi}^L)$ vs. $F(\hat{\xi}^K)$. For example, a buyer broker at the 90th percentile of the distribution in $F(\xi^K)$ inherits the marginal cost of the seller 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 (e.g. more out-of-pocket cost for the broker to hire photographers, set up staging, hold open houses, etc), I assume buyer brokers incur half of the seller brokers' marginal costs.

6.1 Measures of Surplus

I focus on the surplus of buyers and sellers from the *housing market*, excluding their measured surplus gains from the brokerage "amenities." This measure can be interpreted relative to the total transaction value (the sum of house prices times the number of transactions) from the housing market, making the results more interpretable.

Seller surplus I define seller surplus change to be:

$$\Delta CS_h^{seller} = V_{hl}^{S,CF}(c_l^{sell,*}, p_{hl}^{CF,*}, \phi_{hl}^{CF}(\boldsymbol{p}^{CF,*})) - V_{hl}^S(c_l^*, p_{hl}^*, \phi_{hl}(\boldsymbol{p}^*)), \tag{47}$$

where $V_{hl}^{S}(\cdot)$ refers to the sellers' expected net proceeds defined in Equation (21) evaluated at the realized prices and sales probability, i.e. after ϵ^{L} draws are revealed.

Buyer surplus I define buyer surplus change to be:

$$\Delta CS_b^{buyer} = \sum_k s_{bk}^{K,CF} \frac{1}{\alpha_b^H} \log\left(\exp(\varphi_t^H) + \sum_{hl \in \mathcal{H}^{CF,*}} \exp\left(V_{b0,hl}^H(p_{hl}^{CF,*}) - \alpha_b^H c_k^{buy,*}\right)\right) \\ - \frac{1}{\alpha_b^H} \log\left(\exp(\varphi_t^H) + \sum_{hl \in \mathcal{H}^{*}} \exp\left(V_{b0,hl}^H(p_{hl}^{*})\right)\right), \tag{48}$$

which means that I measure buyers' surplus only from the housing market, not accounting for the estimated surplus change from broker steering.

I discuss the empirical results of decoupling on house prices and consumer surplus, then access the heterogeneity in gains across consumer demographics.

6.2 Impact on the Housing Market

Panel A of Table 5 shows the aggregate changes in the housing market, averaged across quarters from 2010 to 2015. First, I find that the sum of the *posted* commissions drops from 5.4% to 3.2% of house prices. Sellers' commissions drop by more than 50%, because in addition to not offering buyers' broker commissions, the channel of the additional markups due to the steering motives disappears. Empirically, this is mainly driven by the estimates of how patient sellers are, how sensitive they are to commissions, and how significant the steering threat from buyers' brokers from offering lower commissions is.

Brokers charge buyers an amount equivalent to 1% of the counterfactual listed house prices. While this is partially driven by the assumptions about buyer brokers' marginal costs and how sensitive to commissions buyers become to commissions, it is also influenced by the estimated buyers' elasticity with respect to house prices. Overall, I find that decoupling decreases equilibrium commissions through by intensifying competition among brokers.

The lowered commission rates affect house prices in two main ways. On the supply side, sellers compete for buyers and pass through their commission savings onto house prices. On the demand side, the market demand is dampened by the statutory commissions buyers pay for their brokers and their brokers' lowered incentives to close a deal. This margin includes buyers choosing to shop without a broker, who are assumed to be less likely to close a transaction. These forces from the demand side further decrease equilibrium house prices. Figure A3 illustrates these two forces through a stylized model of the market.

The estimates of house price changes are presented in Panel A of Table 5. While the *listed* house prices fall by 3%, sellers walk away with more proceeds than before due to the lowered commissions they pay to their brokers. Buyers also benefit despite paying commissions, as their effective prices have decreased by 2.7%. Figure A5 decomposes the effects of these forces on house prices. Lowered commissions and house prices invite more sellers and buyers to the market, slightly increasing the total number of transactions.

The surplus changes presented in Panel B of Table 5 reflect sellers getting higher direct proceeds and buyers purchasing at lower prices due to the lowered commissions. For easier interpretation, I measure the magnitude of surplus changes as a percentage of the total transaction values in the status quo. First, broker revenue drops by 2.6% of the total transaction value, which corresponds to roughly halving the revenues of the brokers. Consumers overall benefit with a surplus increase of 4.1% (of the total transaction value), driven by the transfer of lost revenues from the brokers and the extensive margin of new transactions, resulting in a 1.5% increase in total welfare. Considering the total transaction value of the U.S. residential real estate market was $2.3 trillion in 2022, 4% of consumer surplus gain is not a trivial amount.[24]

I find that decoupling could be favorable to buyers. Of the 4.1% gain in consumer surplus, buyers capture 2.8% and sellers capture 1.3%. Sellers, with varying degrees of markups, can pass through their savings to prices without being less profitable than under the status quo. Hence, this result comes from the empirical estimates of the relative elasticities of sellers and buyers.

Overall, decoupling intensifies brokers' price competition, significantly lowering the commissions paid in the economy. These commission savings are then captured in the new equilibrium house prices and transferred to sellers and buyers. While the adjustments to the equilibrium house prices benefit both sellers and buyers, I find that buyers primarily benefit from the lowered prices they pay.

6.3 Distributional Impact

I further examine decoupling policy's distributional impacts on heterogeneous buyers and sellers. Table 6 shows the changes (as a fraction of the total transaction value in

[24] National Association of Realtors (2022).

the status quo) in surplus for buyers across the income groups and for sellers across their house price and patience groups.

Contrary to the concern that buyers may be hurt by decoupling, I find that buyers benefit across the income groups. Even low-income buyers gain by 0.34% of the total transaction value. While high-income buyers gain the most in terms of the dollar measure, the relative gains, measured as percentage changes, show an opposite pattern. Figure 4 visualizes the surplus changes and provides some intuition behind why low-income buyers can still be better off. Primarily, low-income buyers benefit from a large drop in prices in the least expensive set of houses.

Empirically, this is driven by the curvature of the demand, which is estimated to be concave through the Box-Cox coefficient (Miravete et al., 2022). This result coincides with other studies documenting the demand for housing exhibiting concavity (Guren, 2018; Andersen et al., 2022). Under concave demand, demand becomes *less* elastic to price as the price decreases. Hence, sellers with low-priced houses set prices to less elastic demand and pass through a large part of their commission savings. Conversely, this implies that the current commission structure disproportionately harms low-income buyers as they bear a heavier incidence of the high commissions than the sellers. The same intuition carries to high-income buyers and explains why they experience a relatively low gain in surplus as shown in Figure 4.

Next, I examine the impact across sellers, which are shown in Panel B of Table 6. Sellers with low-priced houses remain about the same, while sellers with high-priced houses gain the most. Again, this is due to the features of concave demand; sellers with high-priced houses face elastic demand and can trade a small decrease in prices with a large increase in sales probabilities. Across the seller patience distribution, decoupling provides the least benefit to the most impatient sellers. This result is intuitive, since decoupling takes away from sellers a method of increasing their sales probabilities through incentivizing buyers' brokers. Hence, impatient sellers may have still benefited from the structure itself if it had not resulted in higher equilibrium commissions.

I summarize the policy's distributional impact on sellers through Figure 5. The figure plots changes in sellers' expected proceeds across house price (top) and patience quantiles (bottom). Sellers, regardless of their house price and patience quantile, gain in expected proceeds despite the drop in list prices. This overall increase in seller proceeds is driven by 1) drop in commission payments and 2) increase in market liquidity.

There still is substantial heterogeneous impacts of *decoupling* on sellers, however. First, sellers in the cheaper segments of the housing market gain the least because of the concavity of the demand. Second, impatient sellers gain the least because they had been benefited from incentivizing buyers' brokers for faster sales.

To summarize the distributional impacts of *decoupling*, I find *decoupling* can benefit even low-income buyers because of the house price adjustments. Concretely, they still gain because their "target" houses in the lower part of the house price distribution drop their prices the most, driven by the concavity of the demand. However, the policy has the potential to harm impatient sellers, as it removes a method for them to incentivize buyers' brokers to expedite their sales.

6.4 Results under Alternative Assumptions

I run additional counterfactual scenarios under a few alternative assumptions. In the baseline, I assume that buyers' brokers charge flat fees instead of percentage fees. The assumption is based on the reasoning that it may not make sense for buyers to pay a commission to their brokers that *increases* with the house prices they pay, as it could motivate their brokers to up-sell. I relax this assumption and the results are largely unchanged as shown in Column (1) of Table A5.

Second, I consider the potential down-payment concern of buyers in paying commissions. In a way, the status quo allows buyers to pay their economic incidence of the commissions captured in the house prices through mortgages rather than in cash. The baseline assumes that buyers are as sensitive to a dollar in commissions as a dollar in house prices. I run another counterfactual where buyers become more sensitive to commissions than house prices, based on their observed loan-to-value ratios to mimic the "cash only" scenario. Specifically, I increase the price coefficients of the buyers by the inverse of one minus their loan-to-value ratios up to a factor of 4. For example, buyers with a loan-to-value ratios greater than 80 will be four times as sensitive to commissions as to house prices, and cash-only buyers will still treat the commissions as the same.

Column (2) in Table A5 shows the results under this scenario. Under this scenario, buyers become even more sensitive to the commissions they pay and end up further decreasing broker revenue. While the total welfare decreases, this is not driven by buyers leaving the market due to high commissions, but because a large portion of buyers choose not to use a broker. If, in fact, brokers' incentives or expertise do not play a significant role in closing a deal, the estimated magnitude of decoupling would be an underestimation. Nevertheless, buyers still come out ahead, again, due to the adjustment in house prices and sellers are harmed from such a situation.

6.5 Further Discussions

I conclude this section by discussing potential limitations and extensions of the findings. Broadly, I address concerns related to the findings on equilibrium commissions, particularly how the long-run equilibrium of the brokerage market might affect the interpretations of the results. Additionally, I discuss my findings on house prices and whether commission savings will be capitalized into house prices, considering that houses are durable assets rather than strictly consumption goods.

Medium- and long-run broker responses Given that the total revenue of the brokerage industry halves in the counterfactual, it is likely that many brokers will exit, resulting in higher concentration than before. These exits will drive commissions back up to some extent. While the model does not endogenize entry or exit decisions of brokers, it can still simulate the couterfactual with a selected set of brokers based on ex-post profits, to gauge the magnitude of this equilibrium response on commissions.

The model also assumes broker qualities stay fixed. While the model cannot endogenize alternative contract structure or business models for brokers under decoupling, it is likely that brokers will further differentiate and offer less service to compensate for the decreased profitability.

Collusion The model conservatively assumes that brokers engage in the most fierce form of competition, which is static Nash-Bertrand price competition. *If* there is collusive force among brokers that is not accounted for, my findings would likely understate the impact of decoupling on equilibrium commission rates. While the model does not predict whether decoupling will affect the incentive compatibility of collusive brokers, Hatfield et al. (2019) shows that the policy can weaken collusive forces. Therefore, my model's supply model would result overestimate brokers' marginal costs and understate the decrease in commission rates under decoupling.

Houses as durable assets In the current model, houses are treated as consumption goods, and the demand and supply models take a static form. The "market size" of buyers and sellers are also taken as exogenous variables. Thus, with lowered commissions, the model predicts list prices to drop in equilibrium as any market involving a consumption good would.

In reality, houses are not strictly consumption goods; some people view them as investments (Poterba, 1984). Additionally, in housing markets, buyers become sellers and sellers become buyers (Anenberg and Bayer, 2020). Given these market features and assuming sufficiently forward-looking consumers, it is possible that lowering commissions could *increase* house prices, as the reduction in future transaction costs gets capitalized into house prices. This result is demonstrated by Buchak et al. (2024).

I now informally discuss how my model can be extended to capture such effects. First, the exogenous market sizes of buyers and sellers can be extend to be endogenous, based on the number of transactions. As more transactions occur, more sellers will exit the market (decrease in market supply or low inventory) and those sellers will then become buyers (increase in market demand), further pushing up prices. Second, the prices that buyers pay may be adjusted to include expected future returns including the future transaction costs. In this case, house prices will reflect the anticipated future savings from reduced commission payments when buyers sell the house at the end of their tenure.

In the context of my findings, this suggests that the results are more reflective of a short-run effect. In the short-run, the competitive effect among sellers dominate as they view lower commissions as a negative marginal cost shock and compete to lower prices. This effect may apply to the first few "generations" of sellers, and the market may gradually converge to an equilibrium with higher house prices as more transactions occur. It is clear that consumers benefit under decoupling, but the distinction between "buyer" and "seller" surplus becomes blurred. In the long-run, this implies that part of the "buyer" surplus gains may be captured into house prices and transferred to "sellers."

7 Conclusion

In this paper, I examined the equilibrium impacts of broker incentives in the real estate market. I do so by building an empirical model of the housing market featuring buyer demand, broker steering, seller pricing, and broker competition. The model allows me to compare the real estate brokers' status quo incentive structure, where sellers compensate buyers' brokers, with the *decoupled* incentives, where buyers and sellers each pay for their respective brokers.

I find decoupling has a large potential to improve market efficiency and significantly improves consumer surplus by lowering the equilibrium commissions. The commissions decrease significantly as brokers no longer set commissions internalizing the steering motives of the buyers' brokers, and buyers' brokers competing on commissions for price-sensitive buyers. As a result, brokers transfer a large amount of surplus to consumers.

Contrary to concerns about causing harm to buyers by making them directly pay their commissions, I find the contrary; buyers capture a large part of the benefit because sellers pass through 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 sellers compete.

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8 Tables

Table 1. Descriptive Statistics of Transactions, Sellers, Buyers, and Brokerage Offices

	Mean	Std
Panel A: Transactions		
List Price ($)	246,373	109,677
Pr(Sold Within 90 Days)	.49	.50
Days Until Sold	50	66
Fraction of Same Agent Transactions	.16	.37
N_{listing}	37,341	
Panel B: Sellers		
Fraction with Mortgage	.86	.35
LTV Ratio	.86	.15
Interest Rate (%)	4.9	.8
Loan Term (months)	346	62
N_{seller}	21,589	
Panel C: Buyers		
Fraction with Mortgage	.86	.35
LTV Ratio	.87	.15
Interest 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
Listings in a Quarter	2.3	3.8
Sell-side Transactions in a Quarter	1.4	2.6
Buy-side Transactions in a Quarter	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 appearance 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 2. Effect of Low Commissions on Sales Probability

	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}\{\text{Comm}_{ht} < 2.5\}$	-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 3. Demand- and Supply-side Estimates of Key Quantities

	Estimates
Panel A: Demand Estimates	
$\overline{\alpha}^H$: Buyer preference for house price	-0.040
with $p_{25}(\text{inc}_b)$	-0.042
with $p_{75}(\text{inc}_b)$	-0.040
ρ: Box-Cox coefficient	0.79
$\overline{\kappa}$: Broker preference for commission revenue	0.036
λ: Buyer preference for broker inclusive value	0.188
Avg. own-price elasticity	-7.7
Avg. I_{bkt} elasticity	-0.23
Panel B: Supply Estimates	
$\overline{\beta}^S$: 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 A1, A2, A3, and A4. See appendix for standard errors.

Table 4. Decomposition of Commission Rates

	Value	% of Commission
Seller Commission (%)	2.7	-
Marginal Cost	1.0	37%
Markup	1.7	
from Seller Direct Elas.	0.95	35%
from Steering	0.75	28%

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

Table 5. Counterfactual Results: Market Outcomes

	Status Quo	Decoupled CF	%Δ
Panel A: Housing Market			
Seller Broker: Posted Comm. (%)	5.2	2.0	–61.3%
Buyer Broker: Posted Comm. (%)	0	1.2	
Listed House Price ($1,000s)	246	238	–3.1%
Seller: House Price net of Comm. ($1,000s)	233	234	+0.3%
Buyer: House Price with Comm. ($1,000s)	246	239	–2.7%
Number of Transactions	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 and transactions, 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 per market, $85.3M.

Table 6. Countefactual Results: Distributional Impact across Consumers

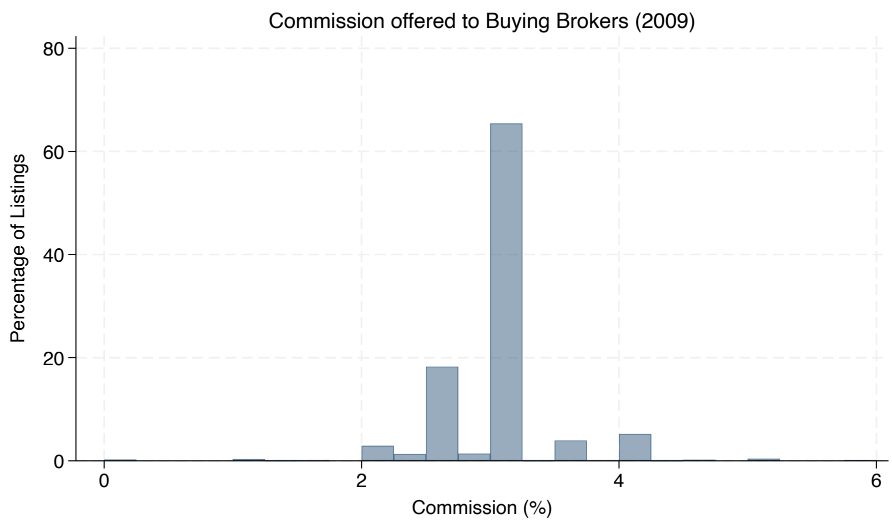
	Δ Decoupled CF (as % of total trx. value)
Panel A: Buyer Surplus	
By Income Quantile	
1st	.34
2nd	.47
3rd	.68
4th	1.29
Panel B: Seller Surplus	
By House Price Quantile	
1st	.03
2nd	.22
3rd	.40
4th	.69
By Patience (β^S) Quantile	
1st	.27
2nd	.34
3rd	.35
4th	.38

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, \$85.3M. The quantiles are constructed within each market. Seller surplus is $\hat{V}^S_{hl}$ with the simulated broker choice with the equilibrium prices and the probabilities of sales. Seller house price quantiles are based on the observed list prices.

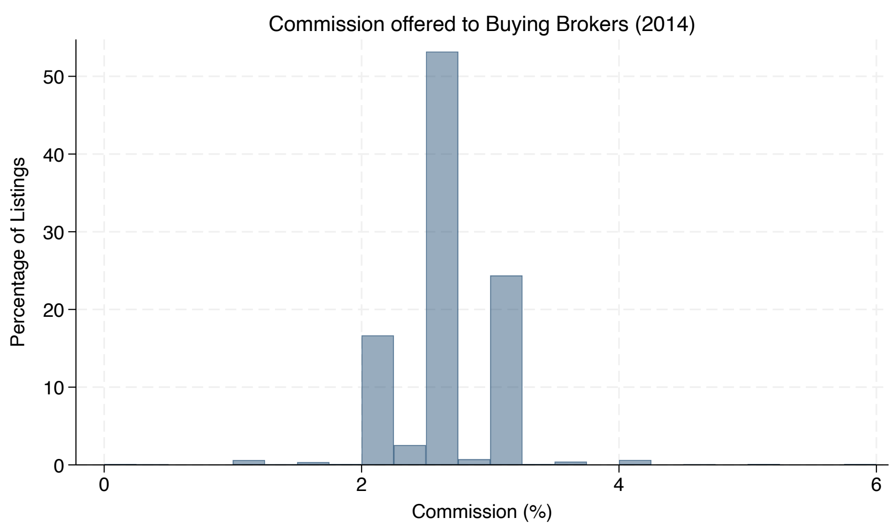
9 Figures

Figure 1. Distribution of commission rates in Riverside, CA

(a) 2009



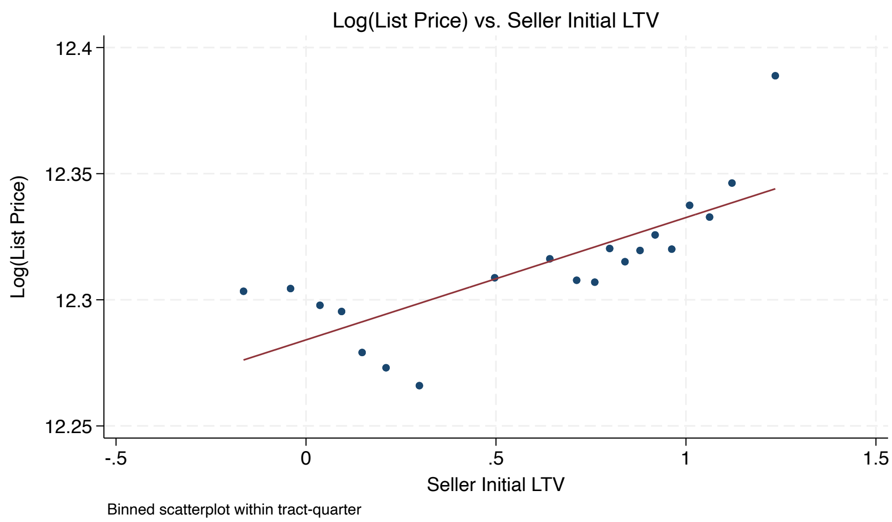
(b) 2014



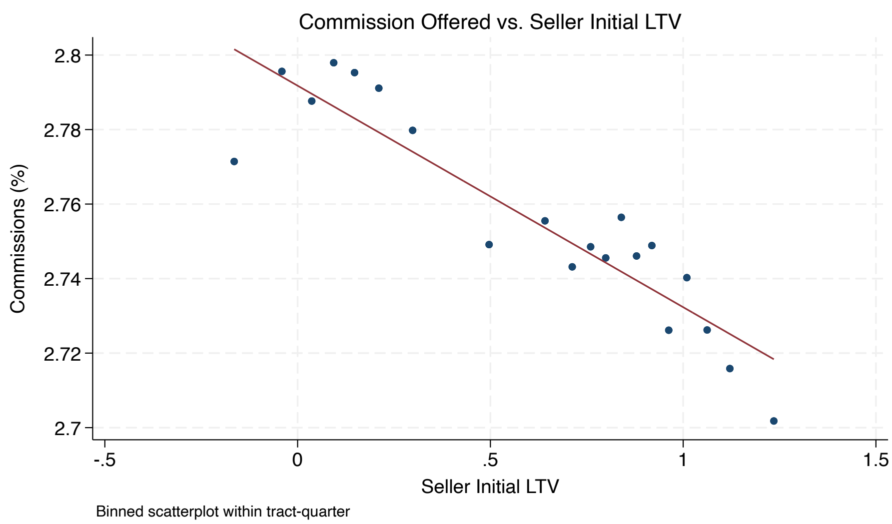
Notes: The sample is from Riverside, CA, across 68,086 pairs of property and calendar quarter.

Figure 2. First Stage: Seller Initial LTV vs. List Prices and Commissions

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



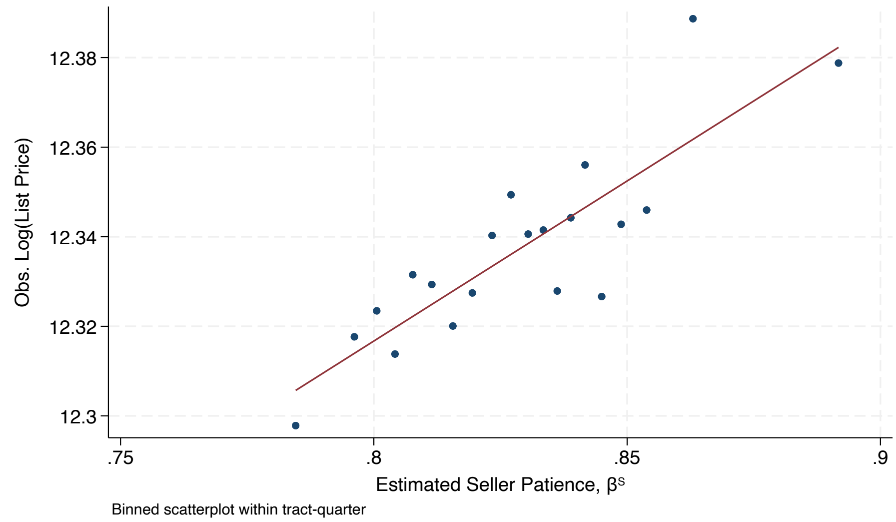
(b) Commissions vs. Seller LTV



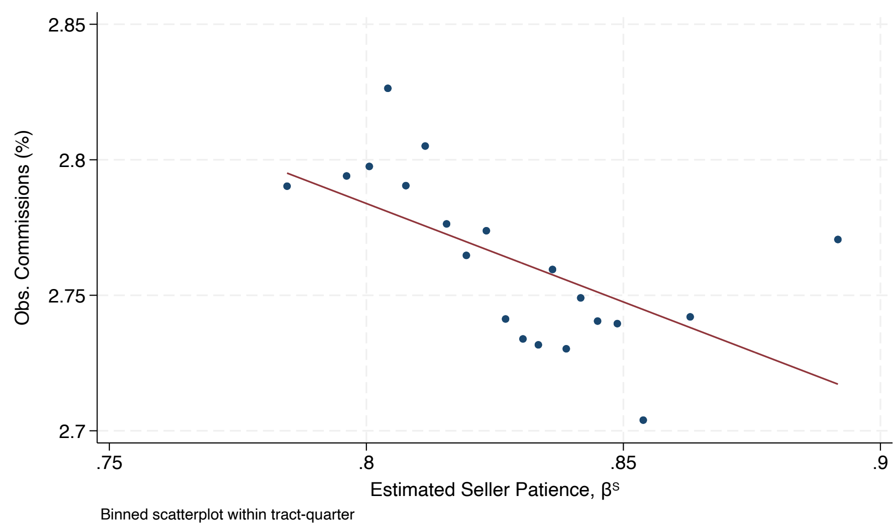
Notes: The sample is from Riverside, CA, across 37,341 listings. The plots are binned scatterplots of seller initial LTV against observed log(list price) and commissions offered to buy-side brokers within tract-quarter.

Figure 3. Validating Estimated Seller Patience, $\widehat{\beta}^S$

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

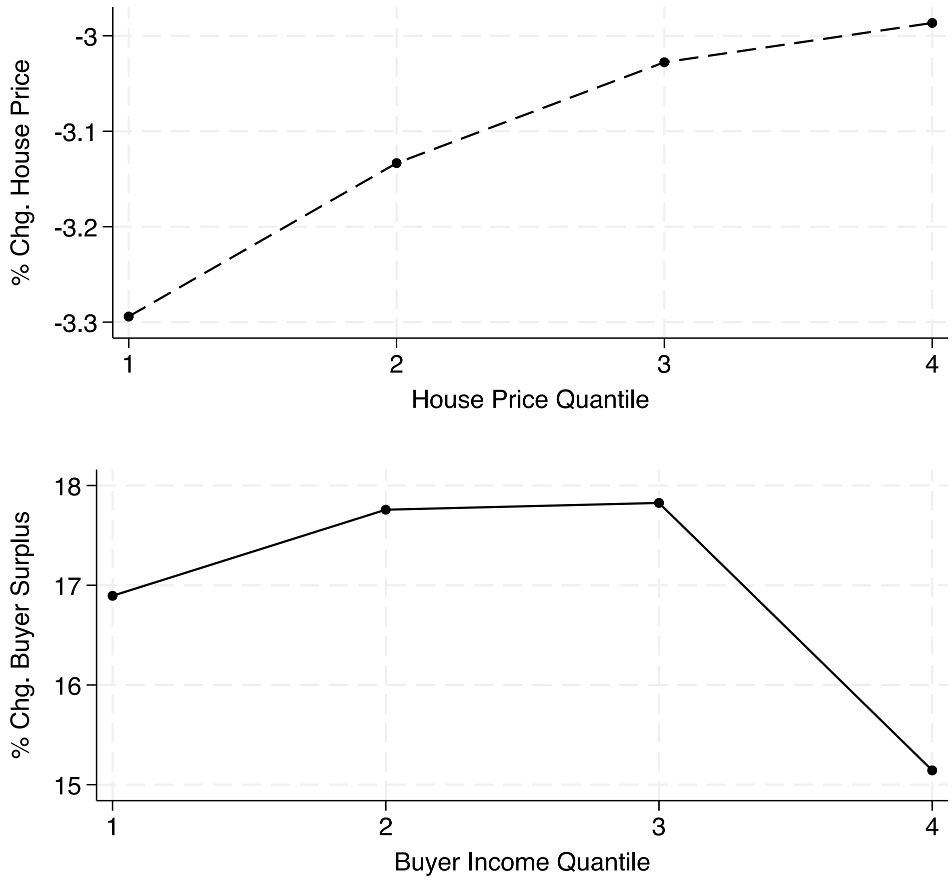


(b) Observed Commissions vs. Estimated Seller Patience, $\widehat{\beta}^S$



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

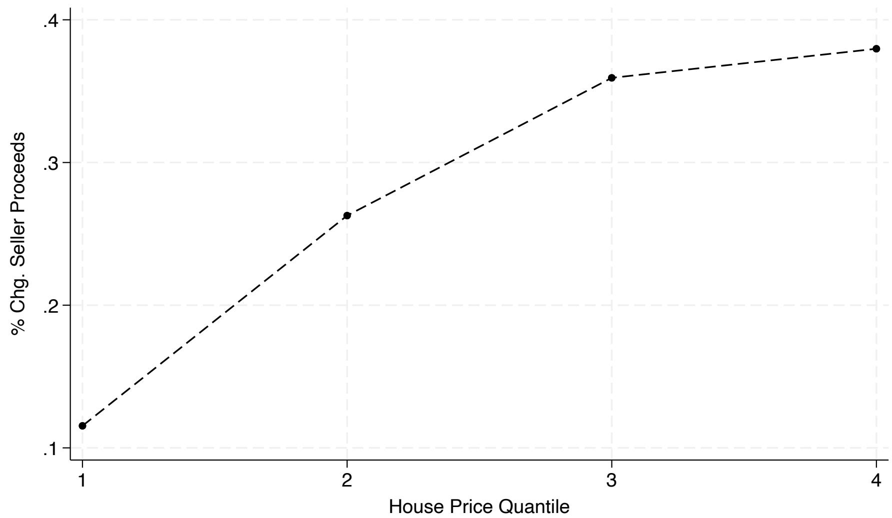
Figure 4. Impact of Decoupling across Buyer Income and House Price Distribution



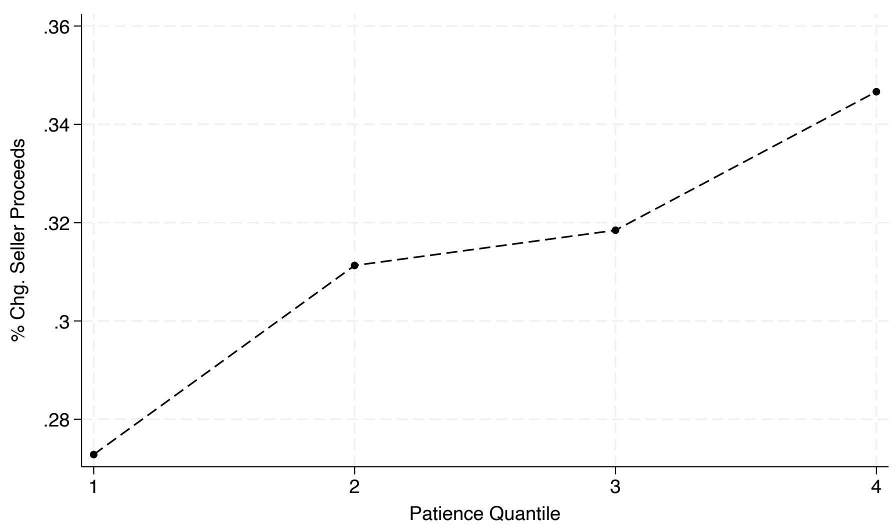
Notes: Averaged across 20 quarters, from Q3 of 2010 to Q3 of 2015. The quantiles are constructed within each market. Seller house price quantiles are based on the observed list prices.

Figure 5. Impact of Decoupling on Sellers across Price and Patience Distribution

(a) Seller Proceeds Change by House Price Quantile



(b) Seller Proceeds Change by Patience Quantile



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. Seller proceeds are computed by subtracting seller commission payments from the posted prices.

A Appendix Tables

Table A1. Estimates for Buyer and Buyer's Broker Preference for Housing

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)
Seller 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: Zip$_h$ = Zip$_l$	0.18 (0.05)
Num 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($))	0.001 (0.001)
Buyer LTV	-0.001 (0.001)
Indicator: Mortgage Insurance	0.000 (0.000)
Indicator: FHA Loan	-0.000 (0.002)
Indicator: Conv. Loan	-0.002 (0.001)
Indicator: Cash Purchase	-0.012 (0.001)
Indicator: No Broker	0.001 (0.000)
Box-Cox Coeff. on Income$_b$	0.79 (0.036)
Buyer heterogeneous preference for property attribute ($X_h^H \times d_b$)	
Baths$_h \times$Family$_b$	0.02 (0.02)
Baths$_h \times$Income$_b$	0.05 (0.02)
Condo$_h \times$Income$_b$	0.02 (0.01)
Condo$_h \times$Family$_b$	0.32 (0.05)
Single Family$_h \times$Income$_b$	-0.13 (0.06)
Single Family$_h \times$Family$_b$	0.25 (0.047)
Broker incentives ($p_h c_h$)	
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 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(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 A2. Estimates of Buyer Preference for Brokers

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 buyer 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 A3. Estimates for Seller Patience

Seller Characteristics	$\widehat{\tau}^{S,d}$ (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 full 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 A4. Estimates for Seller Preference for Brokers

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 seller 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 A5. Counterfactual Results: Market Outcomes with Varying Assumptions

	Status Quo	Baseline CF	(1)	(2)
Panel A: Housing Market				
Seller Broker: Posted Comm. (%)	5.2	2.0	2.0	2.0
Buyer Broker: Posted Comm. (%)	0	1.2	1.3	2.0
Seller: House Price net of Comm ($1,000s)	233	234	234	233
Buyer: House Price with Comm ($1,000s)	246	240	240	238
Number of Transactions $\sum \phi$	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

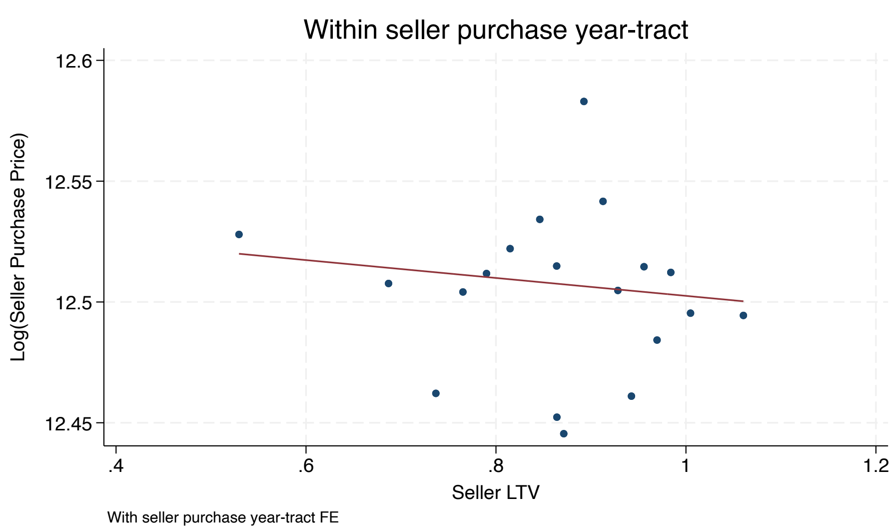
Notes: Variables in Panel A are averaged across 20 markets, from Q3 of 2010 to Q3 of 2015, weighted by the predicted number of transactions in each market. House prices sellers (buyers) are computed after subtracting (adding) expected commissions across brokers. Commissions are *posted* commissions, 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, $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 Initial LTV vs. Seller Purchase Prices

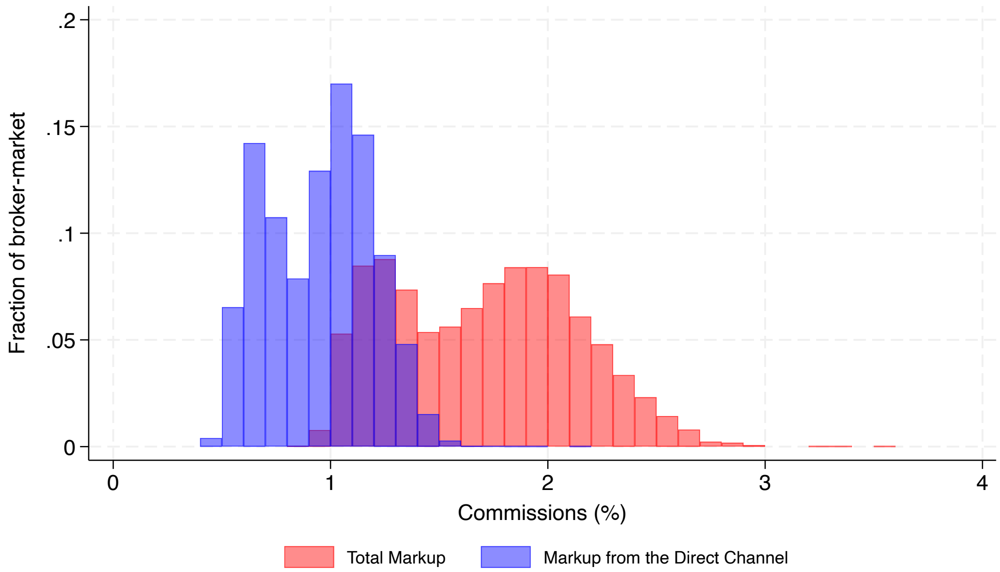
(a) Within Seller Purchase Year

(b) Within Seller Purchase Tract-Year



Notes: The sample is from Riverside, CA, across 4,556 matched sellers. The plots are binned scatterplots of seller initial LTV against observed log(purchase price).

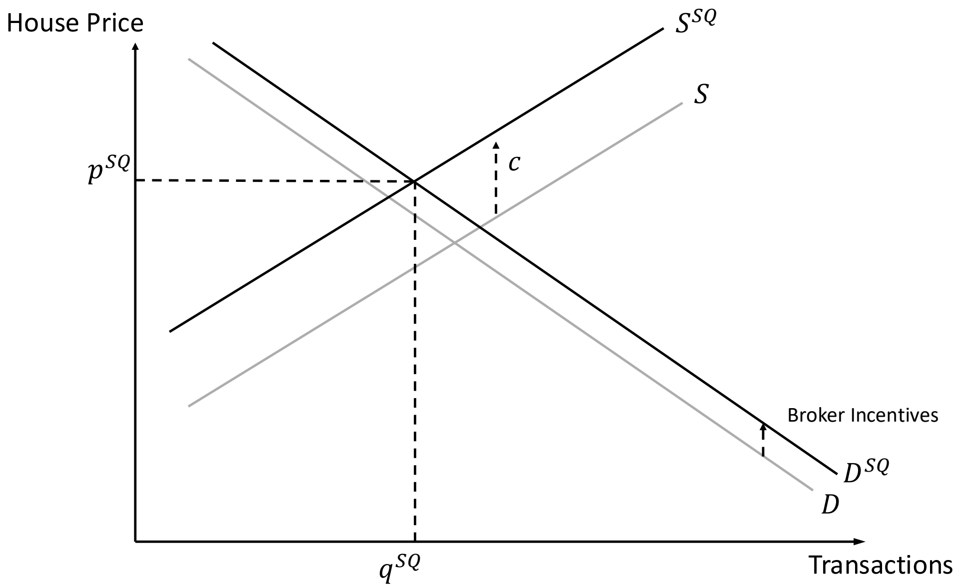
Figure A2. Distribution of Total vs. Direct Commission Markups



Notes: Average across seller 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. Stylized Illustration of the Impact of Decoupling on Housing Market

(a) Status Quo



(b) Decoupled CF

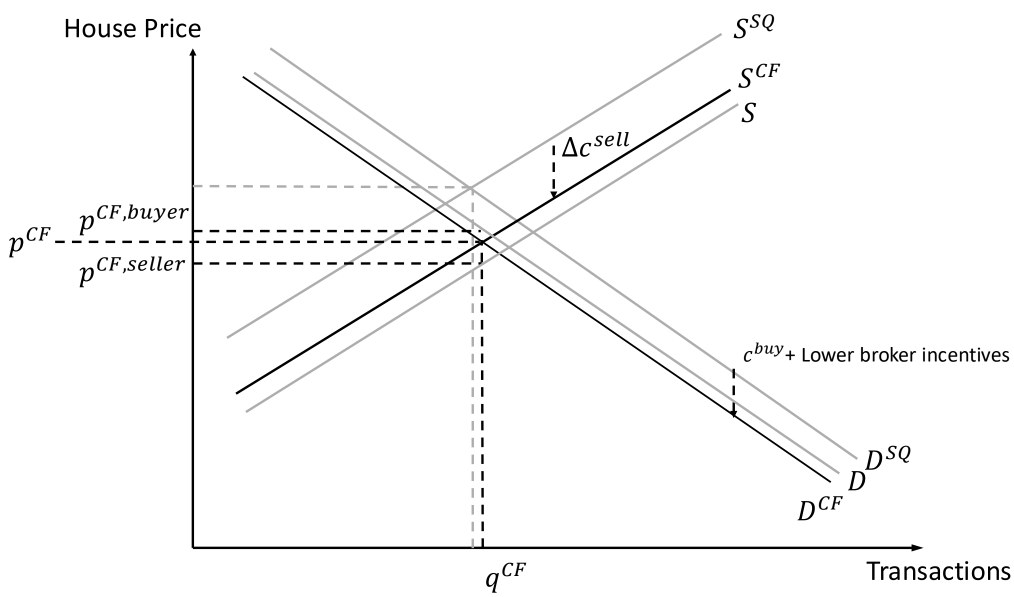
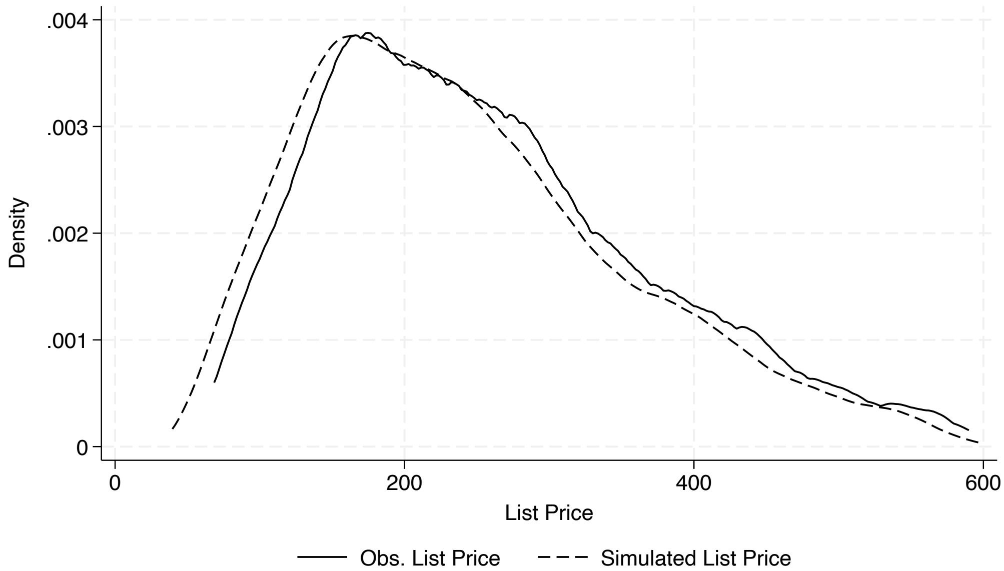
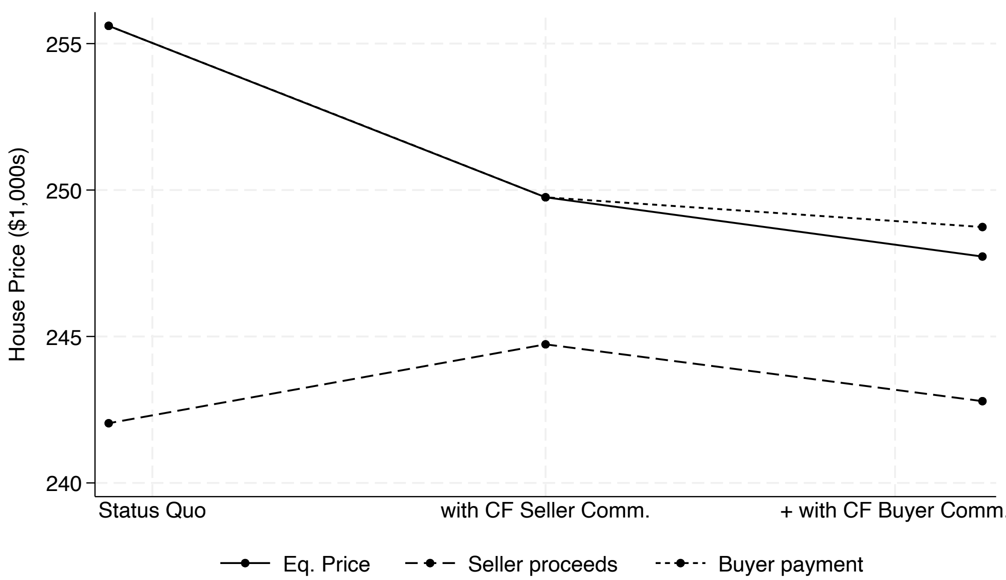


Figure A4. Validation: Simulated List Prices vs. the Observed



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

Figure A5. Decomposing Changes in the Equilibrium Prices and Proceeds



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.

C Relaxing the Equal Split Assumption

Throughout the paper, I assumed that sellers pay twice as much as the commissions offered to buyers' brokers. In this section, I show that the takeaways from the theoretical framework introduced in Section 3 stand even if I allow brokers to set two "prices": one for sellers, and one to offer to buyers' brokers. I also explain how this can be taken to the empirical estimation.

Consider broker l setting two potentially different commission rates for seller h. Let c_l^S denote what seller pays in total, and c_l^B denote what they offer to buyers' brokers. I assume house price p_h stays exogenous in this model. The expected profit function of the broker is then:

$$\Pi_l(c_l^S, c_l^B) = s_{hl}^L(c_l^S, \phi_{hl}(c_l^B))\phi_{hl}(c_l^B)(p_h(c_l^S - c_l^B) - m_l). \tag{49}$$

Similar to Equation (2) in Section 3, $s_{hl}^L\phi_{hl}$ is the joint probability that seller h chooses to listing the broker, and the house getting sold. The seller's probability of choosing the broker, s_{hl}^L, depends on the total commission that the seller pays, c_l^S, and the sales probability the broker can generate, ϕ_{hl}, which now only depends on the commission offered to buyers' broker c_l^B. The broker then makes $p_h(c_l^S - c_l^B) - m_l$ profit for every potential transaction, $s_{hl}^L\phi_{hl}$. In this model, the broker can choose to charge the seller a higher or a lower commission, c_l^S, holding what will be offered to buyers' brokers, c_l^B, *fixed*.

The first-order conditions with respect to c_l^S and c_l^B are:

$$\begin{aligned}
[c_l^S] :& \frac{\partial \Pi_l}{\partial c_l^S} = \left(\frac{\partial s_{hl}^L}{\partial c_l^S}\phi_{hl}\right)(p_h(c_l^S - c_l^B) - m_l) + s_{hl}^L\phi_{hl}p_h = 0, \\
[c_l^B] :& \frac{\partial \Pi_l}{\partial c_l^B} = \left((\frac{\partial s_{hl}^L}{\partial c_l^S} + \frac{\partial s_{hl}^L}{\partial \phi_{hl}}\frac{\partial \phi_{hl}}{\partial c_l^B})\phi_{hl} + s_{hl}^L\frac{\phi_{hl}}{\partial c_l^B}\right)(p_h(c_l^S - c_l^B) - m_l) - s_{hl}^L\phi_{hl}p_h = 0.
\end{aligned} \tag{50}$$

Rearraging to solve for the optimal commission pair $(c_l^{S,*}, c_l^{B,*})$,

$$\begin{aligned}
c_l^{S,*} - c_l^{B,*} &= \frac{m_l}{p_h} - (\overbrace{\frac{\partial s_{hl}^L}{\partial c_l^S}}^{(i)<0}\phi_{hl})^{-1}s_{hl}^L\phi_{hl}, \\
c_l^{S,*} - c_l^{B,*} &= \frac{m_l}{p_h} + ((\overbrace{\frac{\partial s_{hl}^L}{\partial c_l^S}}^{(i)<0} + \overbrace{\frac{\partial s_{hl}^L}{\partial \phi_{hl}}\frac{\partial \phi_{hl}}{\partial c_l^B}}^{(ii)>0})\phi_{hl} + \overbrace{s_{hl}^L\frac{\phi_{hl}}{\partial c_l^B}}^{(iii)>0})^{-1}s_{hl}^L\phi_{hl}.
\end{aligned} \tag{51}$$

All tagged terms, (i), (ii), and (iii), correspond to the same economic forces from Equation (3) in Section 3. The difference is that the steering forces are now acting through the optimal commission *offer* to buyers' brokers, i.e. first-order condition with respect to c_l^B. Hence, it is still the case that the steering motives contribute to the supra-markup that brokers can charge under the current incentive structure.

Another observation is that the two first-order conditions in Equation (51) must be equal to each other at the optimal pair of commissions, $(c_l^{S,*}, c_l^{B,*})$:

$$\overbrace{-\left(\frac{\partial s_{hl}^L}{\partial c_l^S}\phi_{hl}\right)^{-1}}^{=:\mu_l^S(c_l^{S,*}, c^{B,*})} = \overbrace{\left((\frac{\partial s_{hl}^L}{\partial c_l^S} + \frac{\partial s_{hl}^L}{\partial \phi_{hl}}\frac{\partial \phi_{hl}}{\partial c_l^B})\phi_{hl} + s_{hl}^L \frac{\phi_{hl}}{\partial c_l^B}\right)^{-1}}^{=:\mu_l^B(c^{S,*}, c_l^{B,*})}, \tag{52}$$

Implying that the broker sets the pair of commissions such that the marginal revenue from increasing the commission charged to the seller (μ_l^S) equals to the marginal revenue from increasing the commission offered to buyers' brokers (μ_l^B). In other words, brokers set sellers' commissions such that they capture back their direct revenue loss from having to offer a commission to buyers' brokers. Hence the steering motives of buyers' brokers still indirectly inflates what sellers end up paying in whole, $c_l^{S,*}$, and the broker is still able to charge a supra-markup. The key economic mechanisms and the intuitions from the main analysis of the paper do not change.

Empirical Implementation I assumed what sellers had paid were double the observed commissions offered to buyers' brokers. I discuss how, in theory, the total commissions sellers had paid can be identified.

Consider Equation (52). From the data, I observe $c_l^{B,*}$, which is what was offered to buyers' brokers. Then I can solve for $c_l^{S,*}$ that satisfies Equation (52), by jointly estimating broker pricing and seller demand for brokers, $s_{hl}^L(c^S, c^B)$.

There are three main disadvantages to this approach. First, broker marginal costs, m_l, cannot be recovered from this approach because the term drops out from the system of first-order equations. Hence the counterfactual analysis needs to make an assumption on brokers' marginal costs. Second, the approach is computationally demanding. For every guess of c_l^S, the estimation procedure solves sellers' discrete game of choosing a broker and the ensuing pricing game among sellers. Lastly, this requires the researcher to have a firm stand on how brokers price. If such assumption is incorrect, this may exacerbate measurement errors in "inferring" the total commissions paid by sellers.