Percentage Fees in Thin Markets: An Empirical Perspective *

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Note: Online Appendices begin on page 42.

Abstract

This paper estimates the cost of using simple percentage fees rather than optimal pricing using data for real estate transactions. This counterfactual analysis shows that intermediaries using a percentage fee achieve more than 99 percent of optimal pricing. Our results imply that for all practical intents and purposes, percentage fees can be assumed to be optimal when analyzing brokerage in thin markets. Arguments based on extreme value theory provide an explanation for why simplicity and optimality may be well aligned in thin markets. We also use our structural estimates for two additional counterfactuals: fee regulation and transfer taxes.

Keywords: brokerage, fee setting, percentage fees, thin markets, Pareto distributions.

JEL classification: C72, C78, L13

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1 Introduction

Real-world economic agents often employ simple mechanisms. Examples include uniform pricing by iTunes, cost-reimbursement contracts in procurement, and percentage fees employed by credit card companies and real estate brokers.[1] On its surface, this simplicity contrasts with the prescriptions and predictions of Bayesian mechanism design theory, which suggests that optimal mechanisms will in general be rather sophisticated. For example, simple percentage fees are optimal mechanisms (or, equivalently, optimal pricing or optimal second-degree price discrimination) for brokers if and only if the supply function brokers face is isoelastic. This raises the fundamental question of whether the choice of mechanisms is, in reality, driven by concerns of simplicity and practicality or primarily guided by insights from mechanism design theory.

In this paper, we investigate how much profit is sacrificed by the use of simple mechanisms rather than optimal ones in the case of real estate brokerage. Based on the data set of Genesove and Mayer (2001) and a novel structural model, we investigate how well the empirically observed 6 percent fees perform compared to a mechanism that maximizes a weighted average of the intermediary's and the seller's utility. Our counterfactual analysis shows that intermediaries who employ a 6 percent fee achieve more than 99 percent of the value of the objective function achieved by the optimal mechanism. Little to nothing is thus lost using simple mechanisms, suggesting that concerns of practicality and economic optimality may be well aligned. From a practical perspective, our results further suggest that for future research a simple approach can be taken for the empirical analysis of thin markets with fee-setting brokers: a family of functions – generalized Pareto distribution functions – turn out to be a good approximation of the seller's supply function. This family of functions allows for a closed-form solution for the problem at hand.

Our structural estimation is based on our theoretical companion paper (Loertscher and Niedermayer, 2017), which contributes to the growing literature that applies insights and methods from mechanism design to pertinent questions in industrial organization.

[1] See, respectively, Shiller and Waldfogel (2011), Rogerson (2003), Shy and Wang (2011), and Hsieh and Moretti (2003).

Recent and complementary contributions, such as Board (2008), Gomes (2014), Niedermayer and Shneyerov (2014),[2] Tirole (2016), and Garrett (2016), have applied multi-period mechanism design to intertemporal pricing and to optimal incentive schemes for platform participation. See also Jullien and Mariotti (2006) for theoretical work on a one-period mechanism design problem by an intermediary.

In terms of the structural estimation, our paper is closest to the literature on the structural estimation of auctions, such as Shneyerov (2006), Krasnokutskaya (2011), Aradillas-López, Gandhi, and Quint (2013), and Balat, Haile, Hong, and Shum (2016) because we model the bargaining procedure as a (sequential) auction. We differ by focusing on the fees charged by the intermediary. We expect that our methods, appropriately adjusted, can be applied to analyze the fee-setting behavior of auction houses and online auction platforms. In a wider sense, our paper is also related to the recent literature on the structural estimation of markets with two-sided platforms (see e.g. Lee (2013)), which, however, focuses on very different questions than the linearity of fees.

The performance of simple mechanisms has recently been analyzed in a variety of contexts. McAfee (2002), Rogerson (2003), and Chu and Sappington (2007) provide theoretical analysis of simple mechanisms for assortative matching, incentives in procurement, and cost-sharing, respectively.[3] Recent empirical work includes Shiller and Waldfogel (2011), who demonstrate that uniform pricing by iTunes is close to optimal, and Chu, Leslie, and Sorensen (2011), who study a simple form of bundling, called bundled-size pricing, with an application to the pricing of theater tickets. To the best of our knowledge, the present paper is the first to quantify the performance of simple fee-setting mechanisms by brokers.

By providing empirically based measures that quantify how well the simple mecha-

[2]Our theoretical companion paper is closest to the theoretical work in Niedermayer and Shneyerov (2014). The crucial difference is that Niedermayer and Shneyerov (2014) have a continuum of buyers and sellers arriving in each period, so that by the law of large numbers there is no uncertainty about the realized distribution of types. In contrast, our companion paper assumes a thin market with a small number of participants, which is technically more involved and yields fundamentally different results. The key difference between thin and thick intermediated markets is similar in flavor to the difference between thin and thick markets without intermediaries, i.e. between Walrasian equilibrium and the Myerson and Satterthwaite (1983) Theorem.

[3]Holmstrom and Milgrom (1987) analyze the optimality of simple, linear incentive schemes in an intertemporal principal-agent model.

nisms employed by real estate brokers fare, our paper also contributes to the literature on real estate and real estate brokerage, which has witnessed an upsurge of interest over the past decade or so; see, for example, Genesove and Mayer (1997, 2001), Hsieh and Moretti (2003), Hendel, Nevo, and Ortalo-Magné (2009a), Genesove and Han (2012), Merlo, Ortalo-Magné, and Rust (2015), and Barwick, Pathak, and Wong (2016).

The remainder of this paper is organized as follows. Section 2 provides a description of the real estate brokerage market. Section 3 summarizes the theory. Sections 4, 5, and 6 describe the data, the data generating process, and our identification strategy. Sections 7 and 8 estimate the structural model and describe counterfactual analyses based on the estimates. Sections 9 and 10 discuss our findings and conclude. Additional background material and proofs are in the appendix.

2 Description of Real Estate Brokerage Market

One of the puzzling features of real estate brokerage in the United States is that real estate brokerage fees have been close to 6 percent over a long time and across heterogenous regions (see e.g. Hsieh and Moretti, 2003). Transaction costs are usually described as negligible compared to the fees and cannot explain the fees (Barwick and Pathak, 2015). These fees have sometimes been viewed as the result of collusion, leading to multiple investigations by the Department of Justice in 1983 and 2007.[4] No matter whether these fees are a result of collusion or imperfect competition (imperfection being due to product differentiation or capacity constraints), their invariance is puzzling.

Another important feature of real estate markets is that they are illiquid (thin). For example, the literature reports time on market for properties to be around two to four months (see Genesove and Mayer (1997, 2001) Hendel, Nevo, and Ortalo-Magné (2009b), Merlo, Ortalo-Magné, and Rust (2015)). This is similar to what we have in our data set.

While bargaining between buyers and sellers is not standardized, the various descrip-

[4] An explanation of how such a collusion may be enforced has been provided in Department of Justice (2007): if a broker sets a low fee, other brokers in the Multiple Listing Service will refuse to cooperate with him. Barwick, Pathak, and Wong (2016) provide an explanation of how such a refusal is organized: in case that there is both a buyer's broker and a seller's broker, the buyer's broker's fee is proportional to the seller's broker's fee. Therefore, buyer's brokers have an incentive to stay clear of sellers with low-fee brokers.

tions of bargaining provide a similar picture. A commonly described bargaining procedure is what Han and Strange (2014) call an "informal auction" or a "quasi-auction": a buyer makes a price offer to the seller through his broker; if the seller agrees, the property is sold at that price. However, the seller may also reject the offer, either because the price is below his reserve price or because he has a better offer from another buyer. The seller's reserve price stems from a combination of his valuation of retaining the property (e.g. to rent it out) and his expectation of getting a better offer some time later. After a rejected offer, a buyer may either leave or make a higher price offer. This cycle of offers and rejections is repeated until either one of the offers is accepted or all buyers leave. If all buyers leave, the seller can continue to list his property and potentially meet other buyers. This bargaining procedure approximates a sequential English auction with a (secret) reserve price reasonably well.[5,6] There are also reports of real estate sales in North America that are literally auctions.[7]

The long time on market and bargaining lead to considerable price dispersion. The standard deviation of quality-adjusted prices is more than 18 percent of the mean in our data set.[8] In the period from April 1993 to April 1996, which is the period we analyze, the variance of prices due to cross-sectional dispersion of quality-adjusted prices was more than 50 times larger than variance due to changes of the price index.

Services of Real Estate Brokers A number of explanations have been provided for why the services of real estate brokers are being used. The services of brokers include "list[ing] the house on the Multiple Listing Service, assist[ing] sellers in staging and marketing the house, advis[ing] sellers on the listing price, help[ing] sellers evaluate offers and

[5]In a traditional English auction, all buyers would sit in the same room and see other buyers' bids. However, since in a (standard independent private values) English auction, a buyer's dominant strategy is to continue bidding up to his valuation, it is not important whether a buyer sees others' bids. Further, in a traditional English auction, the reserve price is usually public, whereas in the bargaining protocol described above it is secret. However, as is well known in the auction literature, a secret reserve price leads to the same outcome as a public reserve price in an English auction.

[6]Merlo, Ortalo-Magné, and Rust (2015) describe a similar bargaining protocol for the United Kingdom.

[7]While our focus is on the real estate market in North America, it is worth mentioning that in Australia, some real estate sales are formal auctions and not just bargaining that reasonably approximates an auction.

[8]We will describe in more detail later how quality adjustment is done. We will also discuss later issues of unobserved heterogeneity.

formulate counteroffers, help[ing] negotiate directly with the buyer or the buyer's agent, and provid[ing] assistance in closing a transaction" (Han and Strange, 2014, p. 851). Agents on the buyer's side "attempt to find houses that match buyers' tastes, show buyers prospective homes, advise them in making offers, and provide assistance in the negotiation process" (Han and Strange, 2014, p. 851). Various other reasons have been put forth for why real estate brokers' services are demanded; see Han and Strange (2014) for an excellent overview. Since these reasons are not mutually exclusive, one should also consider all possible combinations of these reasons. However, since these explanations are mostly orthogonal to the question of optimal pricing – which is the object of interest of this paper – it is worthwhile to focus on optimal pricing in the theory and simply assume that there is some reason why a seller wants to make use of the services of a broker. We will discuss some of these reasons in more detail later on.

3 Theory

We first provide a simplified version of the theory in our companion paper. It is based on the premise that a broker asks for a price when offering his services to a seller in order to raise revenues. The broker will have to give some surplus to the seller due to competitive pressure (or imperfect collusion). Our theory formalizes two trade-offs at the core of intermediated markets: the seller's trade-off between selling at a higher expected price versus selling faster or with a higher probability, and the broker's trade-off between earning a higher commission when a transaction occurs versus transactions occurring with a higher probability because of lower commissions.

Specifically, we assume that there is a seller with cost $c \sim G$. In the simplified version of our theory that we present first, we additionally assume $G(c) = c^{\sigma}$. This distribution corresponds to an isoelastic supply function with elasticity σ.[9] An intermediary enables the seller to sell using some sales technology that gives the seller the opportunity to target an expected sales price $\bar{p}$ and an associated discounted probability of sale $1-\bar{F}(\bar{p})$, where $\bar{F}$ takes into account the possibility that either there will be no sale or that sale

[9]To see this, note that, interpreting the probability of sale at price p as the quantity supplied $q(p)$, we have $q(p) = G(p)$. Consequently, with the price elasticity of supply being defined as $q'(p)p/q(p)$, we have $q'(p)p/q(p) = \sigma$.

will be delayed.[10] The seller's outside option (selling without a broker or renting out his apartment) is captured in c. c can also be viewed as capturing the sellers' impatience to sell. The intermediary charges the percentage b of the expected price as the fee.

Our key theoretical results do not depend on the specifics of the sales technology. They only require that there is a trade-off between a higher expected sales price $\bar{p}$ and a higher discounted probability of sale $1 - \bar{F}(\bar{p})$. However, in most of the analysis, we will assume a sales technology similar to what is described in Han and Strange (2014), a *sequential English auction with a reserve price*: In each period, the seller meets a random number of potential buyers and the bidding process described above ensues (buyers keep increasing their bids until the seller accepts or until the price is too high for all buyers, in which case there is no trade in this period). In case no trade occurs in a given period, the process is repeated in the next period.

For this sequential auction, there is a one-to-one mapping between the reserve price the seller sets in every period and the expected transaction price $\bar{p}$, so that one can think of $\bar{p}$ as being the seller's choice variable, rather than the reserve price. The discounted probability of sale is then given by the probability of sale in each period, with sales probabilities at later dates discounted.

The intermediary and the seller write a contract that maximizes a weighted average of the intermediary's profit and the joint profit of the intermediary and the seller, with weight α on the former and weight $1 - \alpha$ on the latter, where α can be thought of as a bargaining weight: The higher the α, the larger the intermediary's bargaining weight. Alternatively, and equivalently, α can be thought of as capturing the competitiveness of the brokerage industry in a reduced form with $\alpha = 0$ corresponding to perfect competition, $\alpha = 1$ to monopoly or perfect collusion between brokers, and $\alpha \in (0, 1)$ to imperfect competition (due to product differentiation between brokers' services, capacity constraints by brokers, and/or imperfect collusion).[11]

[10] The notion of "discounted probability of sale", first introduced in Satterthwaite and Shneyerov (2007), conveniently summarizes the net effect of probabilities and discounting. The idea is that the probability of sale will be discounted in the future. If discounting is viewed as the probability of dying (or dropping out of the market for exogenous reasons), the probability of trading at some point in the future has to be multiplied by the probability of not having dropped out by then.

[11] Taking a Ramsey pricing perspective, α can also be interpreted as related to a Lagrange multiplier associated with the constraint that the broker cover the fixed costs of operation.

The seller's utility is $W_S(c, \bar{p}, b) = ((1-b)\bar{p} - c)(1 - \bar{F}(\bar{p}))$. For a given fee b the seller chooses $\bar{p}$ such that it maximizes W_S. The seller's first-order condition $dW_S/d\bar{p} = 0$ can be rearranged to $\bar{\Phi}(\bar{p}) = c/(1-b)$, where

$$\bar{\Phi}(\bar{p}) := \bar{p} - \frac{1 - \bar{F}(\bar{p})}{\bar{f}(\bar{p})}$$

is the virtual valuation function. Denote the optimal price set by the seller as $P(c, b) := \bar{\Phi}^{-1}(c/(1-b))$. The broker's utility when interacting with a seller of type c is $W_I(c, P(c, b), b) = bP(c, b)(1 - \bar{F}(P(c, b)))$.

The objective function that the contract between the broker and the seller maximizes is the expected value of $\alpha W_I + (1-\alpha)(W_I + W_S) = W_I + (1-\alpha)W_S$, taking expectations over c. Formally, the objective function is

$$W_\alpha(b) = \int_0^{(1-b)\overline{v}} [W_I(c, P(c, b), b) + (1-\alpha)W_S(c, P(c, b), b)]\, dG(c).$$

Sellers with costs $c > (1-b)\overline{v}$ stay out of the market because they would sell with a loss even if they were to set the price $\overline{v}$, which explains the upper limit of the integral. Observe that maximizing $W_I + (1-\alpha)W_S$ is equivalent to maximizing $\tilde{\alpha}W_I + (1-\tilde{\alpha})W_S$ with $\tilde{\alpha} = 1/(2-\alpha)$.

The optimal fee b^* is such that $W'_\alpha(b^*) = 0$. It is surprisingly simple:

Proposition 1. *The optimal fee is* $b^* = \alpha/(\alpha + \sigma)$.

The comparative statics of b^* are intuitive: the more elastic the supply, that is, the larger the σ, the lower the fee. Further, fees are higher in less competitive environments, that is, when α is larger. However, there is also a surprising implication: the fee is independent of the sales technology (i.e. the way the seller meets buyers and the way bargaining happens). Further, for a proportional fee b^*, it does not matter whether it is levied on the expected transaction price $\bar{p}$ or on the realized transaction price.

A natural question is whether the restriction to percentage fees is without loss of generality. Should one not be able to do better with a non-linear fee $\bar{\omega}(\bar{p}) \neq b\bar{p}$? Interestingly, the answer is that for distribution functions of the form $G(c) = c^\sigma$, percentage fees are without loss of generality. However, for other functional forms of G, the fee would not be linear and would also depend on $\bar{F}$. Section 8.1 specifies the potentially non-linear fees that are optimal in general (that is, not only for $G(c) = c^\sigma$) for the model underlying the data-generating process described in Section 5.

4 Data

The data set we use is the one constructed by Genesove and Mayer (2001). In order to save space and given that Genesove and Mayer (2001) is one of the most cited empirical articles on real estate with one of the highest quality data sets, we provide a summary of the description of the data here and refer the reader to Genesove and Mayer (2001) for more details, rather than repeating a detailed description of the data here.

The data set includes property listings from January 6, 1990 to December 28, 1997 and property delistings (due to sale or withdrawal) from May 10, 1990 to March 16, 1998 with a total of 5792 observations from the Multiple Listing Service. The data track individual properties in the condominium market in downtown Boston and contain the date of the entry and exit of a property, listing price, and, if applicable, sale price, and property characteristics (square footage, number of bedrooms, number of bathrooms, assessed tax valuations).

A challenge when working with real estate data is the heterogeneity of properties. The data set of Genesove and Mayer (2001) is particularly appealing since it has three features that help to deal with heterogeneity. First, all properties considered are condominiums in downtown Boston, which by itself already means a certain level of homogeneity. Second, Genesove and Mayer (2001) construct a quality index from property characteristics using a standard hedonic pricing approach, that is, they run a regression of the form $\ln y_i = Z_i\beta + \epsilon_i$, where y is the transaction price of a property, Z_i a vector of characteristics of the property, and ϵ_i an error term. Here, $\exp(Z_i\beta)$ serves as a quality index. Third, besides the standard approach of hedonic pricing, Genesove and Mayer (2001) also merge the Multiple Listing Services data set with data from the registrar's office. The registrar's office contains data on the previous transaction price of a property, when it was sold several years before. The previous transaction price – adjusted by inflation and the change of the real estate price index – has the advantage that unobserved heterogeneity of the property plays a lesser role. They report an R^2 in the order of 0.85 across the board. We will discuss unobserved heterogeneity later on.

We construct quality-adjusted prices by taking the residual of the price that cannot be explained by the quality index. In the main part of this article we use the previous transaction price-based quality index. As a robustness check we have done the same analysis that we describe below with the quality index based on hedonic pricing, and obtained essentially the same results. We report robustness checks in the appendix.

Given that the novelty and the focus of our approach is in the cross-sectional variation of seller's opportunity costs of selling, we avoid adding excessive complexity to our structural model by using a stationary model for structural estimation. To make sure that the intertemporal variation in our data is small compared to the cross-sectional variation, we perform the structural estimation for each year separately. Further, we restrict attention to the period from April 1, 1993 to April 1, 1996, which exhibits only a modest change of real estate prices. In Appendix B we show that stationarity is a reasonable – even if not perfect – approximation for the years chosen for the estimation. In particular, the inter-temporal variation in quality-adjusted prices is less than 2 percent of the cross-sectional variation for the years considered. Excluding data for the years before 1993 and after 1995 has the additional advantage of avoiding truncation issues, which would occur for the first two and last two years in our data set. As a robustness check, we have also estimated the model for all the other years. As we will see, we find little variation in parameter estimates.

Of the 2455 observations between April 1, 1993 and April 1, 1996, we further exclude data with a quality-adjusted price larger than two and less than half, as well as properties that were on the market for more than two years. This applies to 5.0 percent of the observations and results in 2333 remaining observations. A property that is offered at less than half of or more than twice the previous transaction price (adjusted by the movement of the real estate price index) is likely to have undergone significant changes in quality or to constitute an error within the data set. Similarly, a property that is on the market for more than two years has probably not been seriously marketed. Table 1 contains descriptive statistics of the included data. The average ratio of transaction price over list price is remarkably similar to the one found by Merlo and Ortalo-Magné

(2004, Table 1), who use data from two regions in the United Kingdom.

Descriptive Statistics			
Variables	All Houses	Sold Houses	Unsold Houses
Observations	2333	1522	811
Listing Price	\$223,077 (\$177,736)	\$231973 (\$172,861)	\$206,383 (\$185,501)
Quality-Adjusted Listing Price	1.139 (0.219)	1.125 (0.220)	1.165 (0.215)
$100\frac{\text{Transaction Price}}{\text{Listing Price}}$		92%	
Time on Market	148 (134) days	130 (123) days	182 (147) days

Table 1: Sample means (standard deviations) of descriptive statistics

5 Data Generating Process

To specify the data generating process, we impose additional assumptions on how buyers and the seller transact. These are based on the general theoretical model in our theoretical companion paper with discrete time $t = 0, \tau, 2\tau, ..., \infty$, where τ denotes the length of a period (say, the number of days). The discount factor is $\delta \in [0, 1)$, where δ may represent time preferences or the period-to-period probability that the seller stays in the market, as in Satterthwaite and Shneyerov (2008), or a combination thereof. The seller's opportunity cost c is drawn from a distribution G with support $[\underline{c}, \overline{c}]$. In each period B buyers arrive, where B follows a Poisson distribution with arrival rate ξ, i.e. the probability mass function of B is $\pi_B = \xi^B e^{-\xi}/\xi!$. Each buyer's valuation v is drawn from the distribution F with support $[\underline{v}, \overline{v}]$. We further denote by $F_{(1)}$ and $F_{(2)}$, respectively, the distribution of the highest and the second-highest valuation in a given period.[12]

We impose the standard assumption that Myerson's regularity condition holds for F and G, i.e. that the virtual valuation function

$$\Phi(v) = v - \frac{1 - F(v)}{f(v)}$$

and the virtual cost function

$$\Gamma(c) = c + \frac{G(c)}{g(c)}$$

[12] These distributions are $F_{(1)}(v) := \sum_{B=0}^{\infty} \pi_B F(v)^B$ and $F_{(2)}(v) := F_{(1)}(v) + (1 - F(v)) \sum_{B=1}^{\infty} \pi_B B F(v)^{B-1}$.

are increasing. This assumption ensures quasiconcavity of the profit function, so that the first-order condition is sufficient. For our purposes, it will be useful to also define the weighted virtual cost function $\Gamma_\alpha(c) = \alpha\Gamma(c) + (1-\alpha)c$ and the dynamic virtual valuation function

$$\tilde{\Phi}(p) := \overline{v} - \int_p^{\overline{v}} \frac{1-\delta F_{(1)}(v)}{1-\delta} \Phi'(v)dv.$$

The functions Γ_α and $\tilde{\Phi}$ are best thought of as generalizations of virtual valuation and virtual cost, with $\Gamma_\alpha = \Gamma$ if all the weight is on the intermediary's profit ($\alpha = 1$) and $\tilde{\Phi} = \Phi$ for a static setup ($\delta = 0$). We show in our companion paper (equation (3) after Proposition 1) that for a 6 percent fee, the seller will choose a reserve price $P^*(c) = \tilde{\Phi}^{-1}(c/0.94)$. We provide a brief intuition here for the simplified case of a static model ($\delta = 0$) so that $\tilde{\Phi}$ simplifies to Φ and only one buyer. The seller's first-order condition is then $(p - 0.06p - c)(1 - F(p))$, which implies the pricing function P^*.

Observe that we allow arbitrary well-behaved distributions G for our data generating process and for our estimation technique and not only Generalized Pareto distributions. For our estimation, we take the empirically observed 6 percent fees as given and do not make any assumption on whether these fees are optimal or not.

The probability of sale in any given period is $(1 - F_{(1)}(p))$ while the discounted probability of not selling prior to period t with period length τ is $(\delta F_{(1)}(p))^{t/\tau}$. Consequently, the *discounted probability of sale* as a function of the reserve price p is

$$1 - F_\infty(p) := (1 - F_{(1)}(p)) \left(\sum_{t=0}^{\infty} \left(\delta F_{(1)}(p)\right)^{t/\tau} \right), \tag{1}$$

where $1 - F_\infty(p)$ corresponds to the discounted probability of sale $1 - \bar{F}(\overline{p})$ in the simple version of the theory, except that it depends on the reserve price p rather than the expected price $\overline{p}$.

In the companion paper, we allow the seller to choose a sequence of reserve prices over time and the intermediary to choose a sequence of fee schedules over time. However, as we show there, the intermediary wants to choose the same fee schedule in every period and the seller wants to choose the same price in every period. This allows us to simplify the exposition here by restricting attention to a stationary fee schedule $\omega(\breve{p})$ for a transaction price $\breve{p}$ and a stationary reserve price p.

For the data generating process we make sure not to assume that the 6 percent fees charged by brokers are optimal, but take them as given.[13] We assume that there is a large number of intermediaries and that a large number of buyers and sellers enter in every period. Each seller draws his cost c independently from the distribution G and is randomly matched to an intermediary who offers a fee-setting contract with a fee of 6 percent. These contracts offer exclusive dealership to the same intermediary, so a seller who accepts a contract is matched to the intermediary as long as he stays in the game. Buyers, in contrast, visit the house in one period and if they cannot buy in that period, leave and do not come back. A buyer's valuation already incorporates the option value of visiting another property and is drawn from a distribution F.[14]

At any intermediary, we model the arrival process of buyers, π_B, as a Poisson process with arrival rate ξ, which implies for the distribution of the highest valuation

$$F_{(1)}(p) = e^{-\xi(1-F(p))}. \tag{2}$$

The time on market t of a property has a geometric distribution with the distribution function $1-(\delta F_{(1)}(p))^{t/\tau}$ because of the assumption that the environment in a given year is stationary. The expected time on market $T(p)$ is

$$T(p) = \frac{\tau}{1-\delta F_{(1)}(p)}, \tag{3}$$

which is the mean of the geometric distribution with a probability of sale $(1-F_{(1)}(p))(\delta F_{(1)}(p))^{t/\tau}$ in period t.

Observed and Unobserved Heterogeneity To account for heterogeneity, we use the multiplicative quality index constructed by Genesove and Mayer (2001) based on previous transaction prices. A multiplicative quality index is the standard approach to correct for heterogeneity, see e.g. Genesove and Mayer (1997); Levitt and Syverson (2008); Hendel, Nevo, and Ortalo-Magné (2009a).

[13] See e.g. Hsieh and Moretti (2003) and Department of Justice (2007) for evidence on the almost universal use 6 percent fees.

[14] In a larger model, one would think of F as being endogenous and composed of a fundamental valuation of the buyer and an additional option value of buying from other sellers in the future.

The recent auction econometrics literature highlights the importance of taking into account unobserved heterogeneity additionally to observable heterogeneity (see e.g. Krasnokutskaya, 2011).[15] Therefore, despite the strengths of the quality index constructed by Genesove and Mayer (2001), we additionally take into account unobserved heterogeneity in quality besides the observable heterogeneity covered by the quality index.

Define the true quality index ϑ_i for each property i. This multiplicative quality index captures heterogeneity of properties, that is, a buyer's valuation is $\vartheta_i v$ and a seller's opportunity cost $\vartheta_i c$. All of our above theoretical analysis holds with the only modification that everything is multiplied by ϑ_i. The seller's reserve price is $\vartheta_i p$ and the transaction price $\vartheta_i \breve{p}$.

If the quality index ϑ_i were observed without noise, one could simply divide everything by ϑ_i to correct for heterogeneity. However, one should expect any observed quality index to be a noisy measure of the true quality index. For the quality measure used in the main text – the previous transaction price adjusted by the change of the real estate price index – the noise might be due to unobserved heterogeneity changing over time (that is, the price of an individual property might change differently than the overall price index). For the quality index used as a robustness check in the appendix – the index constructed from a hedonic regression – there may be characteristics of a property observable by market participants but unobservable by the econometrician.[16]

We make the standard assumption of multiplicative noise ϵ_i^Q, such that the observed quality index is $\hat{\vartheta}_i = \vartheta_i/\epsilon_i^Q$. Hence, dividing the observed transaction price $\hat{\breve{P}}_i = \vartheta_i \breve{p}_i$ by the observed quality index $\hat{\vartheta}_i$ gives the *observed quality-adjusted transaction price* $\breve{P}_i = \hat{\breve{P}}_i/\hat{\vartheta}_i = \breve{p}_i \epsilon_i^Q$, which is a noisy measure of the true quality-adjusted transaction price $\breve{p}_i$. For the quality index based on the previous transaction price, P_i should be viewed as the change of price not explained by a change of the real estate price index. For the

[15] Krasnokutskaya (2011) shows that for Michigan highway procurement auctions, 66 percent of the variation in estimated costs is explained by unobserved heterogeneity and 34 percent by private values.

[16] To be more specific, the main (previous transaction price-based) quality index constructed by Genesove and Mayer (2001) is $\hat{\vartheta}_i = \frac{P_q^{\text{index}}}{P_{q'}^{\text{index}}} \hat{P}_{iq'}$, where q' and q denote two different quarters and P_q^{index} is the real estate price index in quarter q constructed by Genesove and Mayer (2001). The alternative hedonic pricing-based quality index is $\hat{\vartheta}_i = \exp(Z_i\beta)$. Z_i are the characteristics of the property and β are the coefficients from the hedonic regression $\ln \hat{\breve{P}}_i = Z_i\beta + \epsilon_i$ with $\hat{\breve{P}}_i$ being the observed transaction price. See Genesove and Mayer (2001) for more details.

hedonic pricing based quality index, P_i should be viewed as the residual when projecting property prices on observable attributes.[17] We assume that unobserved heterogeneity ϵ_i^Q is independent of the quality index.[18]

For the reserve price, there is an additional complication: we observe the listing price the seller announces, which is a noisy measure of the reserve price below which the seller is not willing to sell, even if one were to correct for the true quality index. Taking into account this "discount noise" ϵ_i^D, the listing price is $\hat{P}_i = \vartheta_i p_i \epsilon_i^D$. Dividing the listing price $\hat{P}_i$ by the observed quality index $\hat{\vartheta}_i$ gives the *observed quality-adjusted listing price* $P_i = p_i \epsilon_i^D \epsilon_i^Q$. Our analysis will be simplified by using the "reserve noise" $\epsilon_i^P := \epsilon_i^D \epsilon_i^Q$ instead of the quality noise ϵ_i^Q in the following. This simplification is no restriction, since knowing the distribution of ϵ_i^P and ϵ_i^D, the distribution of ϵ_i^Q is only one deconvolution away.

We also assume that the true time on market t_i is observed with an error, denoted ϵ_i^T, and that the observed time on market of object i, denoted T_i, satisfies $T_i = t_i + \epsilon_i^T$. The error ϵ_i^T may arise because a broker starts to show the property some time after it has been listed or because a property is delayed in being delisted after the buyer and the seller agreed on a deal. In the data set we use, most properties are listed and delisted on a Sunday. Thus, we essentially have weekly data and delay happens at least until the end of the week. A typical observation is then given by $\boldsymbol{X}_i = (T_i, P_i, S_i, \breve{P}_i)$, where $S_i = 1$ if the object has been sold and $S_i = 0$ if the object has never been sold.

The Likelihood Function It is useful to first write down the likelihood function ignoring "noise" $(\epsilon_i^P, \epsilon_i^D, \epsilon_i^T)$, $\hat{l}(t, p, S, \breve{p}|\boldsymbol{\theta}) = h_{tpS}(t, p, S) h_{\breve{p}}(\breve{p}|p, S)$, where $\boldsymbol{\theta}$ is a vector of parameters determining the underlying distributions. The density h_{tpS} of the joint distribution of t, p, and S is given by G, the pricing function $p = \tilde{\Phi}^{-1}(c/0.94)$, and the

[17] This could be referred to as a "homogenized price" in analogy to the "homogenized bids" in Balat, Haile, Hong, and Shum (2016).

[18] This assumption is obviously weaker than assuming that there is no unobserved heterogeneity, which corresponds to a degenerate distribution of ϵ_i^Q. For the previous transaction price based quality index, our assumption means that unobserved heterogeneity may change over time, but this (proportional) change is independent of the previous transaction price. For the hedonic regression based quality index, our assumption means that the residual in the regression is independent of the quality index. It is reassuring that – as we will see later on – the estimates for both types of quality indices give almost the same result.

geometric distribution of t given the probability of sale per period $1 - F_{(1)}(p)$ and the probability of dropping out $1 - \delta$. The density $h_{\breve{p}}$ of the distribution of the transaction price $\breve{p}$ conditional on p and S is given by standard auction theoretical reasoning. We provide a formal derivation in Appendix C.1.

When taking into account noise, the likelihood $l(\boldsymbol{X}_i, \boldsymbol{\theta})$ of an observation $\boldsymbol{X}_i$ given parameters $\boldsymbol{\theta}$ is obtained by integrating and adding over the noise variables:

$$l(\boldsymbol{X}_i|\boldsymbol{\theta}) = \sum_{k=1}^{T_i/\tau} \int_0^\infty \int_0^\infty \hat{l}\left(T_i - k\tau, \frac{P_i}{\epsilon^P}, S_i, \frac{\epsilon^D \breve{P}_i}{\epsilon^P} \middle| \boldsymbol{\theta}\right) h_t(k\tau) h_P(\epsilon^P) h_D(\epsilon^D) d\epsilon^D d\epsilon^P, \quad (4)$$

where h_D and h_P are the densities of ϵ^D and ϵ^P, respectively; k is the summation variable of $\epsilon^T = k\tau$; and h_T is the probability mass function of ϵ^T.

6 Identification

Even though our estimation is based on a Bayesian approach, it is worth noting that our model is non-parametrically identifiable. This is easiest to see for the case without noise, that is, when ϵ^Q and ϵ^D are constant, and ϵ^T is zero. The basic idea of the identification is the following. We observe two functions empirically, the discounted probability of sale $F_\infty(p)$ and the expected time on market $T(p)$. Evaluating one of the functions at all values of p and the other function at two values $p \in \{p_1, p_2\}$, we can identify the distribution of the highest valuation $F_{(1)}$, the rematching time τ, and the dropout probability $1-\delta$. From this, we can construct the optimal price $p = \tilde{\Phi}^{-1}(c/0.94)$ a seller of type c would set. Using the inverse pricing function $c = 0.94\tilde{\Phi}(p)$ and the empirical distribution of prices, one can back out the distribution G of costs c.

When allowing for noise (ϵ^P, ϵ^D, and ϵ^T), the reasoning is more involved and makes use of the entire joint distribution of p and t, rather than only the expected time on market conditional on price $T(p)$, to identify the distributions of ϵ^P, ϵ^D, and ϵ^T. We provide formal results for identification in Appendix C.2.

7 Estimation

We parameterize the virtual type Φ and Γ as Chebyshev polynomials rather than taking the usual approach of parameterizing the distributions F and G. This has a number of advantages for our purposes. Most importantly, this class is a strict superset of (mirrored) generalized Pareto distributions, which correspond to linear virtual types functions. It also permits us to impose Myerson's regularity condition with a simple parameter restriction, that is, monotonicity of Φ and Γ. Note also that there is a one-to-one mapping between Φ and F and between Γ and G and that closed-form solutions can be obtained for F and G.[19]

As in the theoretical model, we impose the restriction $\underline{v} = \underline{c}$ and $\overline{v} = \overline{c}$ and only use the parameters $\underline{c}$ and $\overline{v}$ in the following. To reduce the complexity of the estimation procedure we use a parametric Bayesian estimation.[20] As we model virtual type functions as Chebyshev polynomials, there is in principle little loss in flexibility, as one can simply increase the number of polynomial terms considered for estimation at the cost of reducing the degrees of freedom and increasing the computational complexity. Specifically, let $y_B := \frac{2v-\underline{v}-\overline{c}}{\overline{v}-\underline{c}}$ and $y_S := \frac{2c-\underline{c}-\overline{v}}{\overline{v}-\underline{c}}$, be the valuation and cost that are normalized to the range $[-1, 1]$. The Chebyshev polynomials that parameterize the virtual type functions are then given by $\Phi(v) = \sum_{i=0}^{N} \phi_i \mathcal{T}_i(y_B)$ and $\Gamma(c) = \sum_{i=0}^{N} \gamma_i \mathcal{T}_i(y_S)$, where $\mathcal{T}_i(x)$ is the degree i Chebyshev polynomial and N is the degree of polynomial approximation.[21] Calligraphic font $\mathcal{T}$ is used to distinguish Chebyshev polynomials from time on market T.

The parameters ϕ_0 and γ_0 in the polynomial parameterization of Φ and Γ are pinned down by the constraints $\Phi(\overline{v}) = \overline{v}$ and $\Gamma(\underline{c}) = \underline{c}$.[22] The measurement error in the time on market ϵ^T has a geometric distribution with survival probability β_T. The reserve price noise ϵ^P and the discount noise ϵ^D are lognormally distributed with $\ln \epsilon^P \sim N(\mu_D, \sigma_P)$

[19] F can be obtained by solving the differential equation $\Phi(v) = v - (1 - F(v))/f(v)$ with initial condition $F(\underline{v}) = 0$. Similarly, G can be obtained by solving $\Gamma(c) = c + G(c)/g(c)$ with initial condition $G(\overline{c}) = 1$.

[20] A maximum likelihood estimator would suffer from errors in variables.

[21] The sequence of Chebyshev polynomials starts with $\{\mathcal{T}_i(y)\}_{i=0} = \{1, y, 2y^2 - 1, 4y^3 - 3y, 4y^4 - 8y^2 + 1, ...\}$.

[22] The explicit expressions are $\phi_0 = \overline{v} - \sum_{i=1}^{N} \phi_i$ and $\gamma_0 = \underline{c} - \sum_{i=1}^{N} \gamma_i (-1)^i$.

and $\ln \epsilon^D \sim N(\mu_D, \sigma_D)$ with the restriction $\sigma_P > \sigma_D$.[23]

Given observations $\boldsymbol{X} = (\boldsymbol{X}_i)_{i=1}^n$ with $\boldsymbol{X}_i = (T_i, P_i, S_i, \breve{P}_i)$, the likelihood function $l(\boldsymbol{X}|\boldsymbol{\theta})$ is $l(\boldsymbol{X}|\boldsymbol{\theta}) = \prod_{i=1}^n l(\boldsymbol{X}_i|\boldsymbol{\theta})$, where $l(\boldsymbol{X}_i|\boldsymbol{\theta})$ is as given in (4) and $\boldsymbol{\theta} = ((\phi_i)_{i=0}^N, (\gamma_i)_{i=0}^N, \beta_T, \sigma_p, \delta, \underline{v}, \overline{v}, \underline{c}, \overline{c}, \xi, \mu_D, \sigma_D)$ is the vector of parameters over which we take Bayesian expectations. In other words, we take a parametric approach and integrate out over the parametric distribution of unobserved heterogeneity. We run a Bayesian estimation with an uninformative prior (i.e. $\pi(\boldsymbol{\theta})$ constant), which means that by Bayes' law our posterior

$$\pi(\boldsymbol{\theta}|\boldsymbol{X}) = \frac{l(\boldsymbol{X}|\boldsymbol{\theta})\pi(\boldsymbol{\theta})}{l(\boldsymbol{X})}$$

is proportional to the likelihood function. We compute Bayesian estimates using Markov chain Monte Carlo simulations. Since the computation is quite time intensive, we use a number of numerical techniques to improve the speed of the algorithm.[24] The Julia[25] code is available upon request from the authors.

Parameter Estimates Table 2 contains the posterior mean and standard deviations of the parameter estimates for 1993, 1994, and 1995. There is remarkably little variation in parameter estimates over time. Although the coefficient γ_2 is positive and about 0.13 for each year, which means that the virtual cost function is not exactly linear, it is only roughly one tenth of the coefficient γ_1 for the linear term in the Chebyshev polynomial.[26]

Robustness Checks Appendix D shows a number of robustness checks: (i) using a hedonic regression rather than previous transaction prices for the quality index, (ii) an estimation assuming that the brokers' empirically chosen fee is 5 percent or 5.5 percent rather than 6 percent, and (iii) using the excluded years (we only use the years 1993 to 1995 in the main text, since there is little price variation over time in these years).

[23] It is computationally more convenient to work with ϵ^P rather than ϵ^Q, but otherwise equivalent.

[24] We approximate functions with polynomials, which allows us to work with closed forms of polynomials for some calculations. Since we have parameterized the virtual type functions as polynomials, it is fast to numerically check whether the virtual type functions are increasing everywhere on the support by computing the roots of the derivatives of Φ and Γ. It further helps that the just-in-time compiler of the Julia programming language emits code with a speed within a factor 2 of Fortran.

[25] See `http://julialang.org/`.

[26] Because the extrema of all Chebyshev polynomials are either -1 or 1, such comparisons of the size of coefficients are meaningful.

Estimated Parameter Values						
Parameters	1993		1994		1995	
ϕ_1	1.15	(0.107)	1.11	(0.124)	1.06	(0.106)
ϕ_2	-0.0601	(0.0421)	-0.0177	(0.0469)	-0.0200	(0.0330)
γ_1	1.27	(0.0328)	1.25	(0.0272)	1.20	(0.0200)
γ_2	0.134	(0.0130)	0.138	(0.0109)	0.140	(0.00612)
$\underline{x}$	0.0165	(0.0159)	0.0151	(0.0145)	0.0122	(0.0119)
$\overline{x}$	1.30	(0.0266)	1.29	(0.0218)	1.23	(0.0133)
δ	0.945	(0.0112)	0.965	(0.0135)	0.984	(0.00113)
ξ	0.136	(0.0973)	0.321	(0.168)	0.175	(0.0914)
μ_D	0.0953	(0.00367)	0.0833	(0.00335)	0.0735	(0.00235)
σ_D	0.0747	(0.00262)	0.0738	(0.00234)	0.0572	(0.00167)
σ_P	0.243	(0.00724)	0.201	(0.00553)	0.191	(0.00514)
β_T	0.0701	(0.0170)	0.142	(0.0491)	0.385	(0.0585)
# Observations	736		840		793	

Table 2: Estimated parameter values for 1993 to 1995. Table entries read: Mean (standard deviation).

Robustness checks (i) and (ii) provide remarkably similar parameter estimates. Even for robustness check (iii) the estimates are relatively close to the main estimation results, despite the the fact that the additional years showed considerable price changes over time.

The most involved robustness check is provided in Appendix H, where we relax the independent private values assumption and allow the seller to have private information about the quality of the property. In particular, we assume there that the buyer's valuation is $v(x, c) = \lambda c + (1 - \lambda)x$, where $x \sim F$ is the buyer's private signal about his idiosyncratic valuation and $\lambda \in [0, 1)$ is the weight of the common value component c given by the seller's cost. This specializes to an independent private values setup for $\lambda = 0$. In order to structurally estimate such a model, we extend the informed seller auction model (where the seller's reserve serves as a signal) of Cai, Riley, and Ye (2007) by percentage fees and dynamics. To the best of our knowledge, this is the first paper to structurally estimate an informed seller auction model.[27] We find that independent

[27]See Niedermayer, Shneyerov, and Xu (2015) for a reduced-form estimation of reserve price signaling in foreclosure auctions, a setup very different from the current setup.

private values is a good approximation (λ is close to zero) and therefore relegate this robustness check to the Appendix to save space.

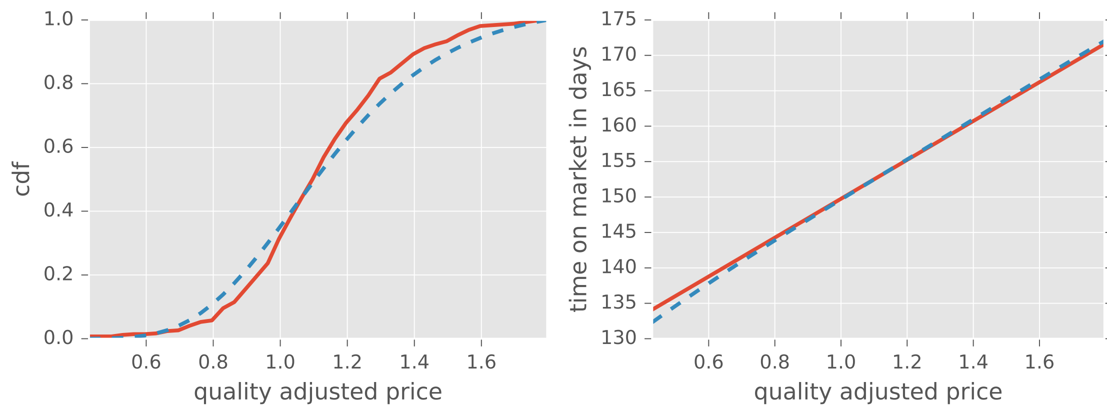
We conduct a further robustness check, in which we allow Φ and Γ to be third-degree rather than second-degree polynomials. We will discuss this robustness check once we get to the counterfactuals in Section 8.1.

Goodness of Fit Figure 1 compares the predictions of our structural model for quality-adjusted listing prices and time on market with reduced-form estimates. The figure suggests that the predictions of the model fit the data reasonably well. This suggests that our parametric restrictions are not too strong. Note that we could in principle fit any (analytical) functions F and G arbitrarily well by increasing the degree of the polynomials Φ and Γ. This also means that we could in principle fit the price distribution and the time on market as a function of price arbitrarily well. However, to avoid an excessive computational burden, we have chosen second-degree polynomials for Φ and Γ.

One may wonder what role our assumption of unobserved heterogeneity plays in fitting the data. The hedonic regression used as a quality index in robustness check (i) leads to quite different unobserved heterogeneity than the previous sales price-based quality index used in the main text. The fact that the resulting estimates are very similar should give us confidence in our method to deal with unobserved heterogeneity.

Backing out the Bargaining Parameter α We back out the bargaining parameter α by assuming that the 6 percent chosen is the result of a maximization in which the intermediary's profit has weight α. By inverting the first-order condition of this maximization problem, we find the value of α that rationalizes the 6 percent fees. It is crucial for the following counterfactual exercise that we rationalize only the *percentage value*, not the shape of the fee function ω (i.e., whether the fee is a percentage or some non-linear function). More formally, let $W(\alpha, b)$ denote the value of the objective when a percentage fee $\omega(p) = bp$ is used. Assuming that the empirically observed 6 percent fees are chosen to maximize $W(\alpha, b)$ over b, we can back out α^* by solving

$$\frac{\partial W(\alpha^*, b)}{\partial b}|_{b=0.06} = \alpha W_I'(b) + (1-\alpha)(W_I'(b) + W_S'(b))|_{b=0.06} = 0,$$



(a) Price Dispersion

(b) Time on Market

Figure 1: The structural model's predictions on the distribution of quality-adjusted listing prices and time on market (dashed lines). As a comparison, reduced-form estimates (solid lines) are provided: the empirical cdf of quality-adjusted listing prices (left panel) and an ordinary least squares estimate of the relation between quality-adjusted listing price and time on market (right panel).

for α, where $W_I(b)$ and $W_S(b)$ are the broker's and the seller's expected welfare given the percentage fee b. More details about the underlying procedure are provided in Appendix C.3. The results are displayed in Table 3.

Price Dispersion Before turning to the counterfactuals, we can look at a more immediate result following from our estimation: price dispersion. It is an old question in Economics to what extent prices are dispersed. Stigler (1961) argues that price dispersion is important in real-world markets, but notes that it is difficult to disentangle "true price dispersion" from unobserved heterogeneity in quality (which is observable to market participants but not to the econometrician).[28] Our structural estimates of the parameters $\underline{x}$ and $\overline{x}$ (and the parameters ϕ_1, ϕ_2, γ_1, γ_2) are in line with Stigler's claim that there is indeed true price dispersion: the underlying distributions of v and c and

[28]Stigler (1961, p. 214) writes: "Dispersion is a biased measure of ignorance because there is never absolute homogeneity in the commodity. Thus, some automobile dealers might perform more service, or carry a larger range of varieties in stock, and a portion of the observed dispersion is presumably attributable to such differences. But it would be metaphysical, and fruitless, to assert that all dispersion is due to heterogeneity." See also Pennerstorfer, Schmidt-Dengler, Schutz, Weiss, and Yontcheva (2014) for a paper that uses commuter data to estimate true price dispersion in the Austrian gasoline market.

hence also of true quality-adjusted prices are clearly non-degenerate.

8 Counterfactual Analyses

Our theoretical model and the empirical estimates of demand and supply lend themselves to a variety of insightful counterfactual exercises. In this section, we perform four such analyses. In turn, we compare the performance of 6 percent fees against the benchmark of the Bayesian optimal mechanism, compare observed average prices with prices in a counterfactual market in which sales are made directly by sellers, analyze fee regulation, and analyze the effects of introducing a transfer tax. These counterfactual exercises are based on a partial equilibrium analysis. In particular, we abstract away from any effects our experiments have on the arrival rate of buyers ξ and thereby on the distribution $F_{(1)}$. We also maintain the assumption that α does not vary with our policy experiments.

8.1 Nearly Optimal Percentage Fees

Our first counterfactual consists of comparing the value of the objective with the empirically observed percentage fee of 6 percent and with the unconstrained optimal fee, which we denote $\omega^{opt}_{\alpha^*}$. This requires, of course, that we first derive this optimal fee.

In general, that is, without requiring the fee function to be a percentage fee, the objective function W_α is the weighted average $\alpha W_I + (1-\alpha)(W_S + W_I)$, where $W_S = E_c[W_S(c,p,\omega)]$ is the seller's expected discounted utility and $W_I = E_c[W_I(c,p,\omega)]$ is the intermediary's expected discounted profit. These functions are the same as in the simple model of Section 3, except that they now depend on the fee schedule ω rather than a percentage b, that discounted present values have to be calculated, and that a seller chooses a reserve price p rather than an expected price $\bar{p}$. The optimal fee schedule ω^{opt}_α, which maximizes $\alpha W_I + (1-\alpha)(W_S + W_I)$ for some α, is described in the following proposition, whose proof is provided in the companion paper. Besides deriving the fee schedule, the proposition shows that there exists no incentive-compatible,[29] individually

[29]Incentive compatibility means that seller c_1 has no incentive to imitate the behavior of a seller with a different cost c_2, which would mean setting the reserve price the seller with cost c_2 would set. Analogous conditions apply for the buyers.

rational[30] mechanism that provides a higher value of the objective function than charging fees.

Proposition 2. *The objective function* $W_\alpha = \alpha W_I + (1-\alpha)(W_S + W_I)$ *is maximized by the fee*

$$\omega(p) = p - \frac{\int_p^{\overline{v}} \left[\Gamma_\alpha^{-1}(\tilde{\Phi}(v)) + \delta V(\Gamma_\alpha^{-1}(\tilde{\Phi}(v))) \right] f(v) dv}{1 - F(p)}, \tag{5}$$

where

$$V(c) = \int_c^{\Gamma_\alpha^{-1}(\overline{v})} (1 - F_\infty(\tilde{\Phi}^{-1}(\Gamma_\alpha(y))))dy.$$

is the expected discounted payoff of seller type c*. This fee induces a seller with cost* c *to set the reserve price* $\tilde{\Phi}^{-1}(\Gamma_\alpha(c))$*.*

Further, a sequential English auction combined with the fee ω *in* (5) *constitutes an optimal mechanism, i.e. there exists no incentive-compatible, individually rational mechanism that generates a higher objective* W_α*.*

Proposition 2 provides the optimal pricing strategy of a broker with a fee that is non-linear in general. However, in practice we see that many intermediaries (including real estate agents) use simple percentage fees as described in Proposition 1. Naturally, the question arises under what conditions percentage fees are optimal and – more importantly from a practical perspective – under what conditions percentage fees are *approximately* optimal. We are now going to provide such a theoretical explanation. Our argument, which we elaborate on in more details in the companion paper (Loertscher and Niedermayer, 2017), is based on extreme value theory. In particular, the reasoning is based on the idea that sellers' cost distribution is truncated from above, with truncation being based on the assumption that only the sellers who are most eager to sell participate in the market. This is consistent with the observation that at any given point in time the vast majority of properties are *not* on the market. According to this theory, the reason only the lowest-cost sellers enter the market is that there are additional costs of a transaction: costs of moving or the opportunity cost of renting out the apartment rather than selling. For sellers with high costs these additional transaction costs make it unprofitable to offer their property for sale. Based on this assumption, our result is informally the following.

[30] Individual rationality means that the neither the seller nor any of the buyers wish to walk away.

This truncation of sellers' costs implies that we only see the lower tail of the sellers' cost distribution. Extreme value theory implies that the lower tail of any regular distribution is well approximated by a (mirrored) generalized Pareto distribution. Proximity to a mirrored generalized Pareto distribution implies an approximately constant elasticity of supply, which in turn implies approximate optimality of linear fees.

Formally, we assume that there is a sequence of linear transformations indexed by j, such that the supports $[\underline{c}, \overline{c}]$ and $[\underline{v}, \overline{v}]$ are transformed into $[\underline{c}_j, \overline{c}_j]$ and $[\underline{v}_j, \overline{v}_j]$ and the potential gains from trade are positive, but converge to zero, that is, $\overline{v}_j > \underline{c}_j$ and $\overline{v}_j - \underline{c}_j \to 0$. We then consider the sequence of normalized fees $\tilde{\omega}_j(\tilde{p}) = \omega(p)/(\overline{v}_j - \underline{c}_j)$ as a function of the normalized price $\tilde{p} = (p - \underline{c}_j)/(\overline{v}_j - \underline{c}_j)$ and show that $\tilde{\omega}_j$ converges to a linear fee. Further, the distribution of the sellers' normalized cost $\tilde{G}_j(\tilde{c}) = G(u_j\tilde{c})/G(u_j)$ with $u_j = (\overline{v}_j - \underline{c}_j)/(\overline{c}_j - \underline{c}_j)$ converges to a generalized Pareto distribution.

Proposition 3. *Let $\underline{c}_j$ and $\overline{v}_j$ be arbitrary sequences satisfying $\underline{c}_j < \overline{v}_j$ for all j and $\overline{v}_j - \underline{c}_j \to 0$ as $j \to \infty$. Then, as $j \to \infty$, the distribution of the sellers' normalized cost distribution converges to a (mirrored) generalized Pareto distribution*

$$\lim_{j\to\infty} \tilde{G}_j(\tilde{c}) = \tilde{c}^{\sigma}$$

for some constant σ. Further, the normalized fee $\tilde{\omega}_j(\tilde{p})$ converges to a linear fee:

$$\lim_{j\to\infty} \tilde{\omega}_j(\tilde{p}) = \frac{\alpha}{\alpha+\sigma}\tilde{p}.$$

The companion paper provides additional details and intuition as well as numerical illustrations that the Pareto approximation is good away from the limit.

A discussion of this asymptotic result is in order, as asymptotic results in statistics are among the most often misunderstood concepts. A common misunderstanding is that asymptotic results are only applicable in one of two cases: either if one assumes very particular functional forms for distributions that are close to the limiting distribution, or if one is exactly in the limit. While for often-used asymptotic results, such as the central limit theorem, such misunderstandings (mostly based on a false dichotomy[31])

[31] For the central limit theorem, such a misinterpretation would mean the following. The central limit theorem is *supposedly* only applicable in one of two cases: (i) the distribution of a variable has a peculiar

are seldom, for other asymptotic results, such as extreme value theory, they are quite common.[32]

The correct interpretation is that if the underlying distribution is not too irregular (in our case, this means essentially that the elasticity does not change too much for different prices) and one is not too far from the limit, then the normalized distribution $\tilde{G}_j$ will be close to a generalized Pareto distribution and the fee $\tilde{\omega}_j$ will be close to a linear fee. In our theoretical companion paper we provide numerical examples that illustrate this. In the following, we will use our structural estimate of the distribution of c that demonstrates the near optimality of percentage fees.

Denote by $\omega_{\alpha^*}^{opt}$ the optimal fee provided in Proposition 2 for a given α^*, the backed-out bargaining weight. Our first counterfactual experiment consists of comparing the weighted joint surplus for 6 percent fees, $W(\alpha^*, 0.06)$, with the weighted joint surplus for the optimal fee schedule, $W(\alpha^*, \omega_{\alpha^*}^{opt})$. As Table 3 shows, for each of the three years, the 6 percent fee achieves more than 99 percent of the joint surplus that the seller and an intermediary can obtain given α^*.

An explanation sometimes given for linear pricing is that competition makes price discrimination impossible. One may wonder whether this is also an explanation for linear fees. Leaving aside the issue that linear fees are fundamentally different from linear prices,[33] we can take a closer look at the effect of decreasing the bargaining parameter α^* of the intermediary, which can be seen to capture competitive pressure in a reduced form.

There are two effects that move linear fees closer to optimality (by moving $\Gamma_{\alpha^*}(c) =$

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functional form that is very close to a normal distribution to start with, or (ii) one is (almost) exactly in the limit, which means taking the average of an infinite number of random draws. One would then *falsely* believe either that one has to make an overly restrictive assumption on functional forms (case (i)) or that the variance of the average is (almost exactly) zero (since we are taking the average of an infinite number of random draws, case (ii)). However, the distinction of cases (i) and (ii) is a false dichotomy: the applicability of the central limit theorem is due to the middle ground between cases (i) and (ii).

[32] For extreme value theory, the misinterpretation is that asymptotic results apply in only one of two cases: (i) the distribution is close to generalized Pareto to begin with, or (ii) the mass in the tail of the truncated distribution is (close to) zero. Again, a false dichotomy.

[33] Linear pricing refers to a *linear transformation*, i.e., the price increasing proportionally with the quantity bought. Contrary to this, *linear fees* refer to fees that are an *affine transformation* of the transaction price, i.e., they are the sum of a fixed transaction fee and a fee that is proportional to the transaction price.

$\alpha^*\Gamma(c)+(1-\alpha^*)c$ closer to linearity): Γ being close to linear and α^* being less than 1. To make the point that the former effect is important, we make an additional counterfactual with a hypothetical monopolist (i.e. $\alpha = 1$ and $\Gamma_\alpha(c) = \Gamma(c)$). In particular, we compute the optimal percentage fee b_1^* a monopoly would set for each of the years considered, and the ratio of monopoly profit with the optimal percentage fee over monopoly profit with the optimal fee ω_1^{opt}, $W(1, b_1^*)/W(1, \omega_1^{opt})$. As shown in Table 3, for each year this ratio is 0.996. Because the linearity ω_1^{opt} is driven by the linearity of $\Gamma(c)$, these results demonstrate that the remarkable performance of percentage fees is indeed driven by the near linearity of Γ. Numerical simulations, which we do not display because of space constraints, further show that percentage fees are robust mechanisms insofar as the respective objective functions vary only little in the neighborhood of 1 or 2 percentage points of the maximizer.

Bargaining Parameter and Counterfactual Fees and Welfare			
Variable	1993	1994	1995
α^*	0.089	0.083	0.077
Performance of 6 percent Fee: $\frac{W(\alpha^*,0.06)}{W(\alpha^*,\omega_{\alpha^*}^{opt})}$	0.992	0.995	0.997
Optimal Percentage Fee for a Monopoly: b_1^*	35.6%	36.0%	36.2%
Performance of b_1^*: $\frac{W(1,b_1^*)}{W(1,\omega_1^{opt})}$	0.996	0.996	0.996

Table 3: α^* and counterfactual fees and welfare for the three years 1993 to 1995.

One way to interpret the parameters in Tables 2 and 3 is to first consider a linear approximation of Γ with $\gamma_2 = 0$ and $\underline{x} = 0$. For the corresponding approximating Pareto distribution $G(c) = (c/\overline{x})^{\gamma_1}$, a percentage fee $\omega(p) = \alpha/(\alpha + \gamma_1)$ is exactly optimal. For the estimated values of γ_1 and α, the implied percentage fee is close to 6 percent. How far away a percentage fee is from the optimal fee is driven by how much γ_2 and $\underline{x}$ differ from 0.

As mentioned, our analysis is based on a parameterization with Φ and Γ as second-degree polynomials to avoid excessive computational complexity. One may wonder to what extent results would change if one were to increase the degree of the polynomials. We describe a robustness check in Appendix E in which we allow Φ and Γ to be third-degree polynomials. While our Markov chain Monte Carlo simulations take much longer to converge, we find that moving to third-degree polynomials has a negligible effect on our main finding: 6 percent fees still achieve 99.3 percent to 99.6 percent of the weighted joint surplus achieved by the optimal schedule.

8.2 For-Sale-By-Owner vs Multiple Listing Service

Our data set is from Boston in the early 1990s, a market in which the vast majority of real estate was sold via the Multiple Listing Service (MLS) of real estate brokers. However, in other markets, e.g. the real estate market in Madison, Wisconsin, starting from the late 1990s, a sizable minority of properties – so called for-sale-by-owner (FSBO) properties – have also been sold directly from sellers to buyers. It is natural to ask what would happen if all properties were sold through FSBO platforms rather than brokers. A related question concerns comparisons of FSBO sales and MLS sales if the two forms of sales coexist. While a detailed analysis of each of these questions warrants an article of its own, there are some answers that fall out quite naturally from our preceding analysis.

In the following, we will analyze a setup in which all properties are sold without a commission, keeping all other parameters of the model fixed, including the distribution of buyers' and sellers' valuations. We will then also conduct a calibration exercise, in which we allow for the fact that FSBO properties take longer to sell than MLS listed properties. The simplest interpretation of this analysis is that it concerns a hypothetical world in which all properties are sold without commissions. An alternative interpretation is that we are analyzing the coexistence of MLS and FSBO under the assumption that there is no selection effect., i.e. that some sellers have no other choice than to sell through a broker (because they have limited time or sales skills) whereas others can sell without a broker, but the distributions of c are the same for both types of sellers. A further underlying assumption is that the distribution of buyers is the same for both platforms, which can be justified by the idea that buyers multihome. An obvious limitation of the second interpretation is that there may be a correlation between a seller's time constraints and his opportunity cost of selling c.

Such an analysis is valuable since it can provide a possible explanation for a surprising observation that has been made in the literature comparing sales through a broker with direct sales. As documented by Hendel, Nevo, and Ortalo-Magné (2009a), the average prices charged on FSBO platforms are not significantly different from the gross prices in intermediated trade, although the sellers bear the broker's fees only in the latter case. Similarly, Barwick, Pathak, and Wong (2016) find that average sales prices do not vary with commission fees.[34,35] In light of the double marginalization that occurs in intermediated trade, this finding is puzzling at first sight.[36] Note, however, that the question at hand is more complicated than standard double marginalization: we are not simply dealing with one upstream and one downstream monopolist setting markups which result in a single price, but rather with a distribution of heterogeneous sellers' costs and an implied distribution of heterogeneous prices. Thus, in general, one has to compare average prices for FSBO sellers and sellers selling through an intermediary. However, it turns out that with the limiting generalized Pareto distribution, the analysis becomes tractable. Moreover, it provides a natural explanation for this otherwise puzzling empirical observation.

Formally, consider an MLS market in which sellers face a percentage fee $\omega(p) = bp$ with $b \in [0, 1]$ and an FSBO market in which sellers face no fees. Observe that the marginal seller type who is active in the sense of setting a reserve price that at least one buyer type would accept is given by $c_b^* := (1 - b)\overline{v}$ in the intermediated market and by $c_{FSBO}^* = \overline{v}$ on the FSBO platform. Let $G_{p,b}(p)$ denote the distribution of reserve prices set by sellers who are active in the intermediated market with percentage fee b and denote by $G_{FSBO,p}(p)$ the distribution of reserve prices set by active sellers on the FSBO platform. The following proposition shows that, surprisingly, the predicted distributions

[34] As noted before, there is very little variation in commission fees. However, a small fraction of brokers offer lower fees.

[35] Rutherford, Springer, and Yavas (2005) and Levitt and Syverson (2008) make a different, but somewhat related comparison: they compare real estate brokers selling their own houses with real estate brokers selling other people's houses. While the results are difficult to directly compare, since real estate brokers are likely to be a different demographic group of sellers than the general population, these papers also find that the asking price is not lower for brokers selling their owner properties. It is actually somewhat higher. A way to reconcile the findings of these articles with those of Hendel, Nevo, and Ortalo-Magné (2009a) is that real estate brokers are a different demographic group than average sellers and have higher opportunity costs of selling (i.e. their c is higher on average). Note that we have shown that the distribution of opportunity costs G is non-parametrically identified in our setup, so that one could in principle test whether the distribution is different for different demographic groups.

[36] In intermediated trade, a seller of type c optimally sets the price $\tilde{\Phi}^{-1}(\Gamma_\alpha(c)) > \tilde{\Phi}^{-1}(c)$, where $\tilde{\Phi}^{-1}(c)$ is the price set by the same seller when selling directly.

$G_{p,b}$ and $G_{FSBO,p}$ are identical.

Proposition 4. *Assume that the sellers' cost distribution is a mirrored generalized Pareto distribution of the form $G(c) = (c/\overline{c})^\sigma$ for both the intermediated market and the FSBO platform and that buyers' distributions are identical in both markets. Then we have*

$$G_{p,b}(p) = G_{FSBO,p}(p).$$

Proposition 4 provides a parsimonious explanation for the puzzling empirical observation documented by Hendel, Nevo, and Ortalo-Magné (2009a) and Barwick, Pathak, and Wong (2016).[37] Intuitively, mirrored generalized Pareto distributions are invariant to truncation from the right and to re-scaling. Such re-scaling is exactly what happens with additional seller entry as linear fees decrease. While we have stated the above results for $\underline{c} = 0$ because this assumption is consistent with the use of percentage fees, which are observed empirically in real estate, these results generalize to arbitrary values of $\underline{c}$ with the adjustment that the optimal fee will be linear with a non-zero fixed component when $\underline{c}$ is different from zero. The distribution $G(c) = (c/\overline{c})^\sigma$ is a simple way of modeling isoelastic supply and does not literally mean that there are sellers with costs close to zero.[38]

The above results show that the price-decreasing effect of a lower fee (or no fee) is exactly offset by the price-increasing effect of additional seller entry if G is exactly generalized Pareto and the arrival rate of buyers is exactly the same for the intermediated and the direct market. Of course, empirically one would expect approximate rather than exact statements to hold, since G is not exactly generalized Pareto and the arrival rate of buyers has been reported to be higher in the intermediated market (which can be seen in the shorter time on market; see Hendel, Nevo, and Ortalo-Magné (2009a)). We conduct three counterfactual exercises with our structural estimates to deal with these issues, which are described in detail in Appendix F.1. First, we take into account that the

[37] As mentioned in footnote 35, a comparison with Rutherford, Springer, and Yavas (2005) and Levitt and Syverson (2008) is more difficult. But our results can be interpreted as the price-increasing effect of fees being offset by the price-decreasing effect of less entry by high cost sellers, so that the price differences described in Rutherford, Springer, and Yavas (2005) and Levitt and Syverson (2008) would be explained by different distributions of c in different demographic groups.

[38] Our estimates suggest that the elasticity of supply is close to isoelastic, yet less than 0.5 percent of sellers have a cost less than $0.2\overline{c}$.

distribution G is not exactly Pareto, but only approximately, and assume everything to be equal for the FSBO and the MLS market except for the fees. We find that the predicted average prices are 0.1 to 0.32 percent lower in the FSBO market for the years 1993 to 1995 than in the MLS market. Second, we calibrate the parameters to match the finding of Hendel, Nevo, and Ortalo-Magné (2009a) that properties listed on the FSBO platform take 19.47 fewer days to sell than properties listed on the MLS. Predicted average prices are 0.55 to 4.73 percent lower on the FSBO platform. Third, we calibrate the parameters to match the difference in both time on market and probability of sale between the FSBO and the MLS reported by Hendel, Nevo, and Ortalo-Magné (2009a), who find that properties listed on the FSBO platform have a probability of sale 2 percentage points higher than properties sold through the MLS. Predicted average prices are 0.01 to 0.05 percent *higher* for FSBO sales than for MLS sales. These counterfactual predictions are reasonably close to Hendel, Nevo, and Ortalo-Magné (2009a)'s findings that the average price of FSBO properties was 0.45 to 0.75 percent higher for FSBO sales than for MLS sales.

8.3 Regulated Fees

One way of intervening in markets that are perceived as insufficiently competitive is by regulating prices, which in our setup means regulating fees. To model such fee regulation, we assume that the government can directly determine the fee a broker can charge, in particular that the government can cap fees. This is the policy currently in effect in Austria.[39] The effect of a fee cap can be decomposed into three effects: a direct effect (assuming market participants do not change their behavior), an indirect inframarginal seller effect (sellers active in the market change their reserve prices), and a marginal seller effect (additional sellers enter the market). We provide formal results and detailed numerical calculations in Appendix F.2 and only provide a brief summary here. A cap on fees has only a small effect on prices (a 1 percent decrease in fees reduces the average price by less than 0.05 percent), which is consistent with the findings in the previous section: for a distribution close to a mirrored generalized Pareto distribution, the average

[39]The regulation of real estate brokerage fees ("Immobilienmaklerverordnung") in Austria caps brokerage fees at 6 percent, excluding a VAT of an additional 1.2 percent.

price changes little as fees change, since the three effects approximately cancel out.

We also make a welfare comparison. One view of real estate brokerage is that there is inefficient free entry by real estate brokers; see e.g. Hsieh and Moretti (2003). In its most extreme form this view can be interpreted to mean that any payments to real estate brokers are burned money, since brokers would simply spend the payment to cover inefficient fixed costs of operating their business. If brokerage fees were lower, some brokers would leave the real estate brokerage industry and participate in productive employment. The opposite extreme view would be that a payment to the broker is a transfer and does not reduce welfare per se (of course there is still the welfare loss associated with some gains from trade between a seller and a buyer not being realized due to the fee).

To remain agnostic on this issue, we conduct two counterfactual analyses. In the first analysis, we assume that payments to real estate brokers are wasteful, so that total welfare should be viewed as the sum of sellers' and buyers' surplus. We find that a decrease of the fee by 1 percent increases the seller's surplus by 2.45 percent as a fraction of total welfare and the buyer's surplus by 0.277 percent as a fraction of total welfare. In the second analysis, we assume that payments to real estate brokers are not wasteful, so that total welfare is the sum of the brokers', sellers', and buyers' surplus. According to this analysis, sellers benefit the most (a 1 percent decrease of the fee changes the seller's surplus by 2.33 percent as a fraction of total welfare before the change), intermediaries lose nearly as much as sellers gain (2.25 percent of total welfare), and buyers are least affected (a gain of 0.25 percent of total welfare).

8.4 Transfer Taxes

Transaction taxes are an important source of revenue for governments around the globe, generating at times controversial policy debates, as, for example, in the case of the financial transaction tax in the European Union. Transfer taxes on real estate transactions vary across countries and, in some cases, across states and other jurisdictions within a country. For example, in the United States, marginal real estate transfer taxes range from zero in Alaska to more than 2.6 percent in New York City according to the National

Conference of State Legislatures.[40] We provide an analysis of the equilibrium effects of such transfer taxes on consumer surplus, and the welfare of intermediaries and sellers in Appendix F.3, and provide a brief summary here. For transfer taxes, there is an additional effect besides the three effects described above (direct effect, inframarginal seller effect, marginal seller effect): the adjustment of fees charged by intermediaries.

Using our estimated parameters, we find that an increase of the transfer tax by 1 percent decreases intermediaries' surplus by 0.4 percent as a fraction of total welfare before taxes and decreases the surplus of buyers by 0.2 percent. Sellers are hit most severely (a decrease of surplus by 1.4 percent). We also find that the first-order effect of the endogenous adjustment of fees to the changes of taxes is a redistribution from intermediaries to sellers.

9 Discussion

Our analysis has been about how brokers extract revenues by choosing the *fee structure*, that is, how the fee depends on the transaction price. There are other aspects of real estate brokerage contracts which are orthogonal to the fee structure, such as exclusivity clauses, whether the seller or the buyer pays the fee (for the rental market: the landlord versus the tenant paying), and in-house transactions.[41] Moreover, regardless of their exact structure and magnitude, transaction fees provide incentives to exert effort because they are only paid if a transaction occurs.

As mentioned, our analysis is deliberately agnostic about the various (competing) explanations that have been put forth for why the services of real estate brokers are demanded. We briefly discuss some of the other aspects of real estate brokerage fees and why they are mostly orthogonal to our analysis.

[40] See http://www.ncsl.org/research/fiscal-policy/real estate-transfer-taxes.aspx

[41] See Bar-Isaac and Gavazza (2015) for an intriguing analysis of the latter two points for the rental market in New York, where there is more variation of contractual forms than for the sales market. See also Han and Hong (2016) for an analysis of in-house transactions of brokerage firms. We hope that future work can combine insights on such additional features of brokerage contracts with insights on transaction fees as optimal pricing.

Incentivizing Brokers In our analysis, we have considered real estate brokerage fees as brokers pricing their services. Another, common explanation for real estate brokerage fees is that they serve to incentivize brokers to exert effort. There are two aspects of fees incentivizing brokers: fees are only paid if a transaction occurs so that a broker exerts effort to increase the probability that a transaction occurs ("enabling transactions" incentive); and a fee that increases with price may incentivize the broker to drive up the price ("price-inflation" incentive). Our analysis is orthogonal to the "enabling transaction" incentive. To illustrate this, assume in a setting with percentage fees that the broker can exert effort e, which affects the probability $\pi(e)$ that the seller meets suitable buyers, where $\pi' > 0$, $\pi'' < 0$. The broker chooses effort to maximize his expected profit $\pi(e)E[W_I] - e$, where $E[W_I] = \left[\int_0^{(1-b)\overline{v}} W_I(c, P(c,b), b)dG(c)\right]$ is the broker's expected profit in case that suitable potential buyers are found. The broker's equilibrium effort is then given by the first-order condition $e^* = (\pi')^{-1}(E[W_I])$. The choice of the weight α on the broker's profit is hence a trade-off between two distortions. Putting more weight on the broker's profit (increasing α) increases the $E[W_I]$ and hence gives the broker more incentive to exert effort, but has the downside that it increases the probability the seller cannot reach an agreement with any of the buyers he meets. Our assumption is then that no matter how much rents are given to the broker to incentivize him to choose the optimal level of effort e, the seller and the broker will write their contract such that these rents are extracted in the least distortionary way.

One could also think of a more complicated "enabling transactions" principal-agent model in which not only the probability of sale, but also the distribution of the time on market depend on the broker's effort. In such a model it may not be optimal to only condition the fee on whether the property was sold, but also on the time-on-market. Then it appears puzzling from a principal-agent perspective why the empirically observed fees do not depend on the time on market. However, there is no puzzle from the optimal-pricing perspective described in the main part of this paper: the optimal fee derived in Proposition 2 does not depend on the time on market. Further, transaction fees are shown to be an optimal mechanisms, therefore, conditioning on time on market (or any other additional clause in the contract) could not improve the objective function W_α.

There are a number of reasons why the second explanation of real estate brokerage fees ("price-inflation" incentive) is unconvincing. Among the many pieces of evidence contradicting the "price-inflation" explanation, the most damning is that when the brokerage fee is split between a seller's agent and a buyer's agent, both agents get 3 percent. This means that the buyer's agent is paid *more* if the outcome is *less* favorable to the buyer, that is, the price is higher. This is despite the fact that buyer's agents are contractually obliged to act in the buyer's fiduciary interests.[42] Therefore, a "price-inflation" theory cannot explain why a buyer would write such a contract with his agent. We discuss additional empirical findings that illustrate that a "price-inflation" theory cannot explain the fee structure in Appendix G.

Observe that in contrast to the "price-inflation" incentive theory our optimal pricing theory is to a large extent orthogonal to the institution of having both a buyer's agent and a seller's agent for some transactions: as long as the buyer's agent and the seller's agent can avoid double marginalization, it is jointly optimal for the two agents to have a total fee of 6 percent.

Collusion Over the years, suspicion has been repeatedly voiced that there may be collusion in real estate brokerage. This is a difficult question and a challenge the empirical literature has faced is that there is no theoretical model of collusion in transaction fees yet (see Han and Strange, 2014, p. 862). We will not attempt to give a complete answer to this question here, but want to point out that one can view our bargaining weight α as capturing the degree of competitiveness in a reduced form: $\alpha = 0$ for perfect competition, $\alpha = 1$ for a monopoly, and $\alpha \in (0, 1)$ for imperfect competition (either due to service differentiation/geographical differentiation or due to collusion).[43] As an illustration, the

[42] Since the 1990s, buyer agency has become common, that is, agents on the buyer's side are contractually obliged to act in the buyer's interest. It should be noted that before the 1990s, agents on the buyer's side were typically so-called cooperating agents, who worked with the buyer, but were obliged to act in the seller's interest. Both buyer's agents and cooperating agents typically get a 3 percent fee. See Han and Strange (2014, p. 873ff) for an overview of the literature on buyer agency.

[43] The problem is actually even more difficult than one might initially think: it is not only that there is so far no way to structurally estimate collusion; there is not even a way to structurally estimate competition. This is because transaction fees are very similar to non-linear pricing and it is well known that the structural estimation of competitive non-linear pricing (without making strong parametric assumptions on endogenous price schedules) is an unsolved problem in the literature. A difficulty to start with is that even theoretically, non-linear pricing with product differentiation is quite involved; see

roughly 2 percent real estate brokerage fees reported for the UK could be explained in light of our theory as the UK market being more competitive ($\alpha^{UK} \approx 0.0255$ in the UK versus $\alpha^{US} \approx 0.08$ in the US)[44], which may be due to collusion in the US or due to brokerage services in the US being more differentiated.

Our analysis complements the literature that deals with the question of how possible collusion might be sustained by real estate brokers (see Barwick, Pathak, and Wong, forthcoming), by focusing on what the optimal collusive (or imperfectly competitive) fee is rather than how collusion may be sustained at the optimal fee.

Large Shocks to Seller's Opportunity Costs One possible objection to our extreme value theory explanation of linear fees is the following. The reason that a seller wants to sell their property may be that they get hit by a large shock of their opportunity costs (e.g. because they are moving out of town). Hence, there may be no truncation of the opportunity cost of selling: a seller either has no other choice than to sell or does not consider selling at all. However, the data are inconsistent with this objection: for approximately 35 percent of the properties listed, the seller withdraws the property without selling after some time, so sellers who are actively trying to sell their properties do in fact have the choice not to sell. Further, the data reveal that the probability of sale decreases with the price, so that some sellers choose to aim for a higher price while taking into account the risk of not being able to sell the property. While our theory is novel, internally consistent, and consistent with the data, we do not claim that it is impossible to develop alternative theories, truncation-based or other, that fail along some or all of these dimensions.

Rochet and Stole (2002). We think that the current paper can serve as a starting point for an analysis of collusion, but several additional steps are needed, including dealing with problems that are so far unsolved in the literature.

[44]From the perspective of our theory, an explanation for the difference between fees in the UK and the US can be seen by considering a Pareto approximation of the distribution (which is equivalent to taking a first-degree approximation of the Chebyshev polynomial Γ) $G(c) = c^{\gamma_1}$, which implies a percentage fee $\omega(p)/p = \alpha/(\alpha + \gamma_1)$. Our estimates ($\alpha^{US} \approx 0.08$ and $\gamma_1^{US} \approx 1.25$) correspond to a percentage fee of 6 percent. The lower fees in the UK could be explained by the real estate market in the UK being more competitive ($\alpha^{UK} \approx 0.0255$ and $\gamma_1^{UK} = \gamma_1^{US}$).

Alternative Explanations Linear pricing is ubiquitous and many explanations have been provided for it in the economic literature, such as the possibility of arbitrage, simplicity, and competition. Hence one may wonder whether any of these explanations would apply to the linear fees used by intermediaries. It should first be noted that linear fees and linear pricing are only superficially similar and that there is a fundamental difference: linear fees are linear in the *price* whereas linear pricing is linear in *quantity*. This difference is crucial since it is often reasonable to believe that a firm's costs are proportional to the quantity produced, so that non-linear pricing corresponds to price discrimination. However, it is hard to believe that an intermediary's costs are proportional to the transaction price.[45]

In a similar vein, the possibility of arbitrage is clearly not applicable for linear fees.[46] Simplicity, however, is indeed a possible explanation, and our counterfactual suggests that only little optimality has to be sacrificed for the sake of simplicity. It is also worth noting that simplicity does not seem to concern other intermediaries, e.g., Amazon has an elaborate pricing scheme in which it charges different fees for 38 different categories of goods (for 33 of these categories the fees are linear). The idea that competitive pressure prohibits price discrimination (see Armstrong and Vickers, 2001 and Rochet and Stole, 2002) would, in our setting, imply flat fees that are independent of the price rather than percentage fees that increase with the price, i.e. percentage fees *are* a form of price discrimination. Apart from this, competition as an explanation has been discussed in Section 8.1.

Stationarity and the Bargaining Protocol Part of our analysis relies on two assumptions: stationarity and the details of the bargaining protocol. As mentioned in the theory section of this paper, our core theoretical results do not depend on these two as-

[45]As an example, consider that in many cities in the US, real estate prices doubled in a relatively short time, then dropped down again to close to the original level. The relative fee (6 percent) remained constant, which effectively means that the absolute fee doubled and then dropped down to the original level. It is unlikely that this reflects cost fluctuations of real estate brokers. This is also true for other types of intermediaries. It is unlikely that a bidding war that doubles the auction price at Sotheby's, Christie's, or eBay, will double the intermediary's costs. The same holds for a seller choosing to double his price for an item sold through Amazon.

[46]E.g. it is not possible to split a $300,000 property sale into a $200,000 transaction through one broker and a $100,000 transaction through another broker.

sumptions, the proofs in Loertscher and Niedermayer (2017) contain more details on this. However, our structural estimation does depend on the two assumptions to deal with the issue of unobserved heterogeneity. We think that this dependence is unproblematic, since the bargaining protocol is a plausible approximation of real world bargaining and since the three years we analyze exhibit stationary prices. Further, a modified version of our approach should be applicable even without the two assumptions.[47]

10 Conclusions

In this paper we have used a structural model based on Loertscher and Niedermayer (2017) to estimate demand and supply parameters for a data set constructed by Genesove and Mayer (2001), which covers the Boston condominium market in the 1990s. Using our parameter estimates for a counterfactual analysis, we have found that the empirically observed 6 percent fee achieves more than 99 percent of the objective (that is, a weighted average of the intermediary's and the seller's profit) that can be achieved with an optimal Bayesian mechanism. Even well-informed brokers will face non-trivial uncertainty about the relevant parameter values and hence about the optimal mechanism, be it linear or unconstrained. With isoelastic supply, the optimal fee is a percentage fee that is independent of these specific parameter values and the finer details of the design problem, such as the objective quality of a property and demand parameters. Thus, percentage fees resemble robust mechanisms in the sense of Wilson (1987).

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Online Appendix

A Proofs

Proof of Proposition 1. The broker's expected profit can be rearranged to

$$\begin{aligned}\int_0^{(1-b)\overline{v}} W_I(c, P(c,b), b) dG(c) &= \int_0^{\overline{v}} b\bar{\Phi}^{-1}\left(\frac{c}{1-b}\right)\left(1 - \bar{F}\left(\bar{\Phi}^{-1}\left(\frac{c}{1-b}\right)\right)\right) dG(c) \\ &= \int_0^{\overline{v}} b\bar{\Phi}^{-1}(x)(1-\bar{F}(\bar{\Phi}^{-1}(x)))g((1-b)x)(1-b)dx \\ &= b(1-b)^{\sigma} \underbrace{\int_0^{\overline{v}} \bar{\Phi}^{-1}(x)(1-\bar{F}\left(\bar{\Phi}^{-1}(x)\right))\sigma x^{\sigma-1}dx}_{=:Z}, \qquad (6)\end{aligned}$$

where the second equality is due to a change of variables ($x = c/(1-b)$) and the third makes use of the function form of $g(c) = \sigma c^{\sigma-1}$. Observe that the expression Z does not depend on b.

Consider next the derivative of the expected value of W_S with respect to b:

$$\begin{aligned}&\frac{d}{db}\int_0^{(1-b)\overline{v}} W_S(c, P(c,b), b) dG(c) \\ &= \int_0^{(1-b)\overline{v}} \frac{\partial}{\partial b} W_S(c, P(c,b), b) dG(c) \\ &+ \int_0^{(1-b)\overline{v}} \underbrace{\frac{\partial}{\partial \bar{p}} W_S(c, P(c,b), b)}_{=0} dG(c) - \underbrace{W_S((1-b)\overline{v}, P((1-b)\overline{v}, b), b)}_{=0} \\ &= -(1-b)^{\sigma} Z. \qquad (7)\end{aligned}$$

In the first equality, two of the expressions evaluate to zero due to an envelope theorem type of argument. The first zero expression is due to the seller's first-order condition. The second zero expression is because a seller with cost $c = (1-b)\overline{v}$ sells with probability zero. The second equality can be obtained by plugging in W_S and P and observing that the resulting expression is the same as in (6) except for the b multiplier. With equations (6) and (7) at hand, the first-order condition for the objective function simplifies to

$$W'_\alpha(b) = [b(1-b)^\sigma]' Z - (1-\alpha)(1-b)^\sigma Z = 0.$$

Solving for b yields $b^* = \alpha/(\alpha+\sigma)$. □

Proof of Proposition 4. Because demand is the same across the two platforms and because $G_{FSBO,p}(p) \equiv G_{0,p}(p)$, to prove the proposition it suffices to show that $G_{p,b}(p)$ does not vary with b. This is what we do in the following. Recall that given a distribution $G(c) = c^\sigma$, the optimal fee given α is $\omega(p) = \frac{\alpha}{\alpha+\sigma}p$. We are now going to show that $G_p^\alpha(p) := G_{p,\alpha/(\alpha+\sigma)}(p)$ does not vary with α.

To see that $G_p^\alpha(p)$ does not vary with α, notice first that a seller can only sell with positive probability if his cost is less than $\Gamma_\alpha^{-1}(\overline{v})$. Since a seller with cost c sets a reserve price $\tilde{\Phi}^{-1}(\Gamma_\alpha(c))$ by Proposition 2, $\tilde{\Phi}^{-1}(\overline{v}) = \overline{v}$ and $\Gamma_\alpha(0) = 0$, it follows that $[\tilde{\Phi}^{-1}(0), \overline{v}]$ is the support of reserve prices for any $\alpha \in [0,1]$. For any p in the support, we then have $G_p^\alpha(p) = \frac{G(\Gamma_\alpha^{-1}(\tilde{\Phi}(p)))}{G(\Gamma_\alpha^{-1}(\overline{c}))}$. The result then follows if we can show that for any $p \in [\tilde{\Phi}^{-1}(0), \overline{v}]$, $\frac{G(\Gamma_\alpha^{-1}(p))}{G(\Gamma_\alpha^{-1}(\overline{c}))}$ is independent of α. We now show that in fact

$$\frac{G(\Gamma_\alpha^{-1}(p))}{G(\Gamma_\alpha^{-1}(\overline{c}))} = G(p). \tag{8}$$

To see that this is true, observe first that $\Gamma_\alpha^{-1}(p) = \frac{\sigma}{\sigma+\alpha}p$. Therefore,

$$G(\Gamma_\alpha^{-1}(p)) = \left(\frac{\sigma}{\sigma+\alpha}\right)^\sigma \left(\frac{p}{\overline{c}}\right)^\sigma.$$

Consequently, $G(\Gamma_\alpha^{-1}(\overline{c})) = \left(\frac{\sigma}{\sigma+\alpha}\right)^\sigma$, whence (8) follows. □

B Approximate Stationarity of Data

While the data are not perfectly stationary in the considered time period from April 1993 to April 1996, stationarity is a reasonable approximation. In particular, cross-sectional variation rather than variation over time is the first-order issue, as we will discuss below.

A calendar year appears to be the appropriate choice for the time interval on the ground that the standard deviation of the price index within a year between 1993 and

1995 is much smaller than the standard deviation of the quality-adjusted price. A further indicator is a measure stemming from a widely documented stylized fact in real estate markets: the correlation between price and time on market is weakly positive in cross-sectional data and negative in longitudinal data.[48] An intuitive explanation for the former observation is that expensive houses need more time to sell. An explanation for the latter is that in times of booms, houses sell faster and at higher prices. Time on market increases in quality adjusted price for the years we include in our estimation. Further, the relative change of the real estate price index is generally small for the years considered. Table 4 shows the variance of the price index divided by its mean squared, V_I, within the time interval; the variance of quality-adjusted prices, V_P, divided by the square of the mean in a given time interval; the ratio of these mean-adjusted variances V_I/V_P, the relative change of the price index Δ_I; and the slope of a regression of the time on market on the quality-adjusted price. Figure 2 displays the movement of the real estate price index. The table and the figure suggest that for the time period 1993 to 1995, a time interval of one year appears to be sufficiently short to be considered cross-sectional. Excluding data for the years before 1993 and after 1995 has the additional advantage of avoiding truncation issues.

The variation in quality-adjusted prices is a measure of cross-sectional variation while the changes in the price index are related to intertemporal variation because the index uses quarterly data. For the three years considered, the cross-sectional variation exceeds the intertemporal variation by a factor of roughly fifty.

[48] Kang and Gardner (1989) provide empirical evidence that time on market increases with price in cross-sectional data – both based on their own data set and on a review of other empirical work. Similar findings are reported in Genesove and Mayer (1997, 2001). The empirical literature typically finds a negative correlation between prices and vacancies – the latter can be seen as a proxy for time on market. Quigley (1999) investigates the effect of economic cycles on the housing market using international data on housing. He finds a negative correlation between vacancies and prices. See also the overview about empirical findings on the relation of vacancies and prices provided in Wheaton (1990).

Cross-sectional and Intertemporal Variation					
Year	V_I/mean^2 Price Index	V_P/mean^2 QAP	$\frac{V_I/mean^2}{V_P/mean^2}$	Relative Δ_I	Slope of Time on Market Qual. Adj. Price Coeff. (Std. Err.)
1990	0.012	0.0396	0.31	-0.241	-87.6 (28.2)
1991	0.00044	0.0416	0.011	-0.030	39.0 (20.9)
1992	0.0026	0.0458	0.057	0.131	67.0 (21.5)
1993	0.00026	0.0412	0.0062	0.006	21.3 (22.0)
1994	0.00040	0.0342	0.012	-0.003	19.2 (22.0)
1995	0.00068	0.0361	0.019	0.067	40.1 (20.2)
1996	0.0017	0.0416	0.040	0.097	-7.6 (15.6)
1997	0.00040	0.0404	0.0099	0.044	7.2 (9.8)

Table 4: Variance V_I over squared mean of the real estate price index in a given time interval, variance V_P over mean squared of the quality-adjusted price in a given time interval, the ratio V_I/V_P, the change of the price index divided by the price index at the beginning of the interval Δ_I, and the slope β_1 of time on market T on quality-adjusted price P in the regression $T = \beta_0 + \beta_1 P + \epsilon$.

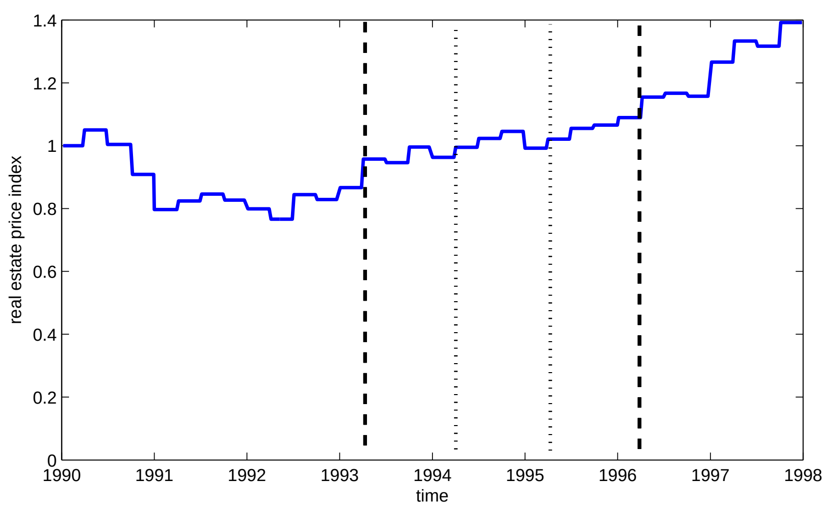


Figure 2: Development of the real estate price index in Boston. Data between the two dashed lines were used for estimations.

C Likelihood Function and Identification

C.1 Likelihood Function

We denote by $g_p(p) := g(P^{-1}(p))[P^{-1}(p)]'$ the density of reserve prices, where g is the density associated with the sellers' cost distribution $G(c)$ and $P^{-1}(p)$ is the inverse of the optimal pricing function $P^*(c) = \tilde{\Phi}^{-1}(c/0.94)$ derived in equation (3) after Proposition 1 in the companion paper. Given reserve p the probability mass function for time on the market t with $t = 0, \tau, 2\tau, ..., \infty$ is then given by $[\delta F_{(1)}(p)]^{t/\tau}(1 - F_{(1)}(p))$ for properties that sell and by $[\delta F_{(1)}(p)]^{t/\tau}(1-\delta)F_{(1)}(p)$ for properties that do not sell. We denote by $h_{tpS}(t, p, S)$ the likelihood function for observing (t, p, S). This function is given by

$$h_{tpS}(t,p,S) = \begin{cases} [\delta F_{(1)}(p)]^{t/\tau}(1-F_{(1)}(p))g_p(p) & \text{if } S=1 \\ [\delta F_{(1)}(p)]^{t/\tau}(1-\delta)F_{(1)}(p)g_p(p) & \text{if } S=0 \end{cases}.$$

Next we consider transaction prices $\breve{p}$. Denote by $\breve{f}(\breve{p}|p)$ the density of the transaction price $\breve{p}$ given the reserve price p. This density can be written as

$$\breve{f}(\breve{p}|p) = \begin{cases} 0 & \text{if } \breve{p} < p \\ \frac{F_{(2)}(p)-F_{(1)}(p)}{1-F_{(1)}(p)}\Delta(\breve{p}-p) & \text{if } \breve{p} = p \\ \frac{f_{(2)}(\breve{p})}{1-F_{(1)}(p)} & \text{if } \breve{p} > p \end{cases},$$

where $\Delta(.)$ is the Dirac delta function. Denote by $h_{\breve{p}}(\breve{p}|p, S)$ the likelihood of observing $\breve{p}$ given (p, S) and set $\breve{p} = 0$ if $S = 0$. Under stationarity $h_{\breve{p}}(\breve{p}|p, S)$ is independent of t. By the previous arguments,

$$h_{\breve{p}}(\breve{p}|p,S) = \begin{cases} \breve{f}(\breve{p}|p) & \text{if } S=1 \\ \Delta(\breve{p}) & \text{if } S=0 \end{cases}.$$

For a given observation $\boldsymbol{X}_i = (t_i, p_i, S_i, \breve{p}_i)$, the likelihood function absent unobserved heterogeneity in quality, discount noise, and measurement error in time on the market $l(\boldsymbol{X}_i|\boldsymbol{\theta})$ would be given by

$$l(\boldsymbol{X}_i|\boldsymbol{\theta}) = h_{tpS}(t_i, p_i, S_i)h_{\breve{p}}(\breve{p}_i|p_i, S_i),$$

where $\boldsymbol{\theta}$ is the vector of parameters determining the shapes of h_{tpS} and $h_{\breve{p}S}$.

The likelihood function $l(\boldsymbol{X}_i|\boldsymbol{\theta})$ for an observation $\boldsymbol{X}_i = (T_i, P_i, S_i, \breve{P}_i)$ that accounts for unobserved heterogeneity and measurement error in time on market is then given by

$$l(\boldsymbol{X}_i|\boldsymbol{\theta}) = \sum_{k=1}^{T_i/\tau} \int_0^\infty \int_0^\infty h_{tpS}(T_i - k\tau, P_i/\epsilon^P, S_i)h_{\breve{p}}(\breve{P}_i/\epsilon^Q|P_i/\epsilon^P, S_i)h_t(k\tau)h_Q(\epsilon^Q)h_D(\epsilon^D)d\epsilon^Q d\epsilon^D, \tag{9}$$

where $\breve{P}_i$ is the constructed transaction price; $h_j(\epsilon^j)$ is the density of the error term ϵ^j with $j \in \{Q, D\}$; and k is the summation variable and $\epsilon^T = k\tau$. It will be convenient for our estimation to rewrite (9) in terms of ϵ^D and ϵ^P using $\epsilon^Q = \epsilon^P/\epsilon^D$:

$$l(\boldsymbol{X}_i|\boldsymbol{\theta}) = \sum_{k=1}^{T_i/\tau} \int_0^\infty \int_0^\infty h_{tpS}(T_i - k\tau, P_i/\epsilon^P, S_i) h_{\breve{p}}(\breve{P}_i/(\epsilon^P/\epsilon^D)|P_i/\epsilon^P, S_i) h_t(k\tau) h_P(\epsilon^P) h_D(\epsilon^D) d\epsilon^D d\epsilon^P,$$

where $h_P(\epsilon^P)$ is the density of ϵ^P.

C.2 Formal Identification Results

First, consider the case without unobserved heterogeneity, discount noise, and measurement error in time on market, that is, when ϵ^Q and ϵ^D are constant, and ϵ^T is zero. Rearranging (3) and (1), the expressions for time on market as a function of the quality-adjusted price $T(p)$ and for the discounted probability of sale $1 - F_\infty(p)$, we obtain

$$F_{(1)}(p) = 1 - \frac{1 - F_\infty(p)}{T(p)/\tau} \quad \text{and} \quad \delta = \frac{T(p_2) - T(p_1)}{T(p_2)(1 - F_\infty(p_1)) - T(p_1)(1 - F_\infty(p_2))},$$

and

$$\tau = \frac{T(p_1)F_\infty(p_2) - T(p_2)F_\infty(p_1)}{F_\infty(p_2) - F_\infty(p_1)},$$

where p_1 and p_2 are two arbitrary prices (or – with some modification of the equations – price segments). This makes $F_{(1)}(p)$, the discount factor δ, and the period length τ non-parametrically identifiable over the range of prices that are set in equilibrium. Given $F_{(1)}(p)$ and the observable distribution of reserve prices $G_p(p)$, the sellers' cost distribution is non-parametrically identifiable via the relationship $G(c) = G_p(\tilde{\Phi}^{-1}(c/0.94))$, where $\tilde{\Phi}^{-1}(c/0.94)$ is the optimal price a seller of type c sets when facing a 6 percent fee.[49]

With unobserved heterogeneity and measurement errors in the time on market ϵ^T, the argument is more involved, but identification is still possible. Redefine the observed discounted probability of sale $1 - F_\infty(P_i/\vartheta_i)$ and the time on market of sold and unsold houses $T^s(P_i/\vartheta_i)$ and $T^u(P_i/\vartheta_i)$ as functions of the observed quality-adjusted listing price P_i/ϑ_i rather than the true (quality- and discount-adjusted) reserve price p_i. Further, let

[49] In Appendix D, we show that our estimation is robust to the alternative assumptions that brokers' fees are, maybe because of unobserved discounts, 5.5 percent or 5 percent.

$\hat{T}^s(P_i/\vartheta_i) := T^s(P_i/\vartheta_i) + E[\epsilon^T]$ and $\hat{T}^u(P_i/\vartheta_i) := T^u(P_i/\vartheta_i) + E[\epsilon^T]$ be the observed average times on market. The discounted probability of sale given P_i/ϑ_i and ϵ_i^P is $\text{Prob}(s = 1|P_i/\vartheta_i, \epsilon_i^P) = (1-F_{(1)}(P_i/(\vartheta_i\epsilon_i^P)))/(1-\delta F_{(1)}(P_i/(\vartheta_i\epsilon_i^P)))$ and the probability of never selling $\text{Prob}(s = 0|P_i/\vartheta_i, \epsilon_i^P) = (1-\delta)F_{(1)}(P_i/(\vartheta_i\epsilon_i^P))/(1-\delta F_{(1)}(P_i/(\vartheta_i\epsilon_i^P)))$. Given the unconditional density $h_p(\epsilon^P)$, the conditional densities are $h_p(\epsilon^P|P_i/\vartheta_i, s = 1) \propto h_p(\epsilon^P)/\text{Prob}(s = 1|P_i/\vartheta_i, \epsilon^P)$ and $h_p(\epsilon^P|P_i/\vartheta_i, s = 0) \propto h_p(\epsilon^P)/\text{Prob}(s = 0|P_i/\vartheta_i, \epsilon^P)$ by Bayes' law. This gives us

$$\begin{aligned} 1 - F_\infty(P_i/\vartheta_i) &= E_{\epsilon_i^P \sim H_p}\left[\frac{1 - F_{(1)}(P_i/(\vartheta_i\epsilon_i^P))}{1 - \delta F_{(1)}(P_i/(\vartheta_i\epsilon_i^P))}\right], \qquad (10) \\ \hat{T}^s(P_i/\vartheta_i) &= E_{\epsilon_i^P \sim H_p(\cdot|P_i/\vartheta_i, s=1)}\left[\frac{\tau}{1 - \delta F_{(1)}(P_i/(\vartheta_i\epsilon_i^P))}\right] + E[\epsilon^T], \\ \hat{T}^u(P_i/\vartheta_i) &= E_{\epsilon_i^P \sim H_p(\cdot|P_i/\vartheta_i, s=0)}\left[\frac{\tau}{1 - \delta F_{(1)}(P_i/(\vartheta_i\epsilon_i^P))}\right] + E[\epsilon^T]. \end{aligned}$$

Note that (10) and $\hat{T}^u(P_i/\vartheta_i) - \hat{T}^s(P_i/\vartheta_i)$ do not require any knowledge about the distributions of ϵ^T and c and identify $F_{(1)}$ and H_p for given ϵ and τ. The density of time on market t conditional on a particular price P_i/ϑ_i, $E_{\epsilon^P \sim H_p, \epsilon^T \sim H_t}[(\delta F_{(1)}(P_i/(\vartheta_i\epsilon^P)))^{t/\tau - \epsilon^T}|\epsilon^T \leq t/\tau]$, identifies H_t. This uses only one price P_i/ϑ_i. The different densities of t for two additional prices P_j/ϑ_j and P_l/ϑ_l pin down ϵ and τ. The sellers' distribution $G(c)$ is then non-parametrically identifiable in the same way as without unobserved heterogeneity via the relationship $G(c) = G_p(\tilde{\Phi}^{-1}(c/0.94))$.

Equation (2) means that we can express $F(p)$ as $F(p) = 1 + \ln(F_{(1)}(p))/\xi$, which allows us to write the virtual valuation function as

$$\Phi(v) = v + \frac{F_{(1)}(v)}{f_{(1)}(v)} \ln(F_{(1)}(v)).$$

This relates $F_{(1)}$ to Φ without knowledge of ξ, which means that we cannot identify ξ from Φ. Intuitively, by observing the distribution of the highest bid $F_{(1)}$ one cannot tell the extent to which it is driven by F or by the arrival rate ξ. Note that this is not a problem; it turns out that all the counterfactuals also only depend on $F_{(1)}$ and not on ξ and F separately. Further note that in our estimation ξ and F will be *parametrically* identified.

It is worthwhile mentioning that while the above reasoning is the most elegant identification proof we could find, it is not necessarily the best estimation technique, since it essentially relies on the fact that even if we "throw away" data, the underlying distributions are still identifiable. We throw away data for example by using the expected time on market $T(p)$ rather than the distribution of the time on market conditional on p and by not using the distribution of transaction prices $\breve{p}$. For finite sample sizes, it is preferable to make use of all the data, which we do with our Bayesian estimation.

C.3 Backing Out the Bargaining Parameter α

In the following, we describe the procedure to back out α. Let

$$\begin{aligned} W_I(b) &= bE_c[\tilde{\Phi}^{-1}(c/(1-b))(F_{(2)}(\tilde{\Phi}^{-1}(c/(1-b))) - F_{(1)}(\tilde{\Phi}^{-1}(c/(1-b)))) \\ &+ \int_{(\tilde{\Phi}^{-1}(c/(1-b)))}^{\overline{v}} y f_{(2)}(y)dy], \end{aligned}$$

be the expected payoff to an intermediary given percentage fee b and let

$$\begin{aligned} W_S(b) &= (1-b)E_c[\tilde{\Phi}^{-1}(c/(1-b))(F_{(2)}(\tilde{\Phi}^{-1}(c/(1-b))) - F_{(1)}(\tilde{\Phi}^{-1}(c/(1-b)))) \\ &+ \int_{(\tilde{\Phi}^{-1}(c/(1-b)))}^{\overline{v}} y f_{(2)}(y)dy - c/(1-b)(F_{(1)}(\tilde{\Phi}^{-1}(c/(1-b))))] \end{aligned}$$

be the expected profit of the seller. The maximum of the objective function $W(\alpha, b) = \alpha W_I(b) + (1-\alpha)(W_I(b) + W_S(b))$ with respect to b is given by the first-order condition $\alpha W_I'(b^*) + (1-\alpha)(W_I'(b^*) + W_S'(b^*)) = 0$. To back out the value of α that rationalizes the observed b^*, we invert the first-order condition, which yields

$$\alpha^* = \frac{W_I'(\hat{b}) + W_S'(b)}{W_S'(\hat{b})}$$

as the value of α consistent with the empirically observed fee $\hat{b} = 0.06$.

D Robustness Checks

Using Physical Characteristics for Estimation As a robustness check of our estimation using previous transaction prices as a proxy for the quality-adjusted price, we also estimate the model using physical characteristics as a proxy for quality. Table 5 shows that the parameters estimates are basically the same.

Estimated Parameter Values						
Parameters	1993		1994		1995	
ϕ_1	1.15	(0.106)	1.11	(0.126)	1.07	(0.104)
ϕ_2	-0.0596	(0.0420)	-0.0171	(0.0468)	-0.0209	(0.0328)
γ_1	1.27	(0.0326)	1.25	(0.0274)	1.20	(0.0201)
γ_2	0.134	(0.0130)	0.138	(0.0109)	0.140	(0.00609)
$\underline{x}$	0.0168	(0.0162)	0.0155	(0.0149)	0.0123	(0.0120)
$\overline{x}$	1.30	(0.0265)	1.29	(0.0216)	1.23	(0.0134)
δ	0.945	(0.0113)	0.966	(0.0133)	0.984	(0.00112)
ξ	0.136	(0.0978)	0.323	(0.169)	0.175	(0.0896)
μ_D	0.0952	(0.00363)	0.0833	(0.00331)	0.0735	(0.00235)
σ_D	0.0746	(0.00258)	0.0738	(0.00231)	0.0572	(0.00166)
σ_P	0.243	(0.00721)	0.201	(0.00550)	0.191	(0.00512)
β_T	0.0705	(0.0182)	0.143	(0.0486)	0.385	(0.0575)
# Observations	736		840		793	

Table 5: Estimated parameter values for 1993 to 1995 using physical characteristics. Table entries read: Mean (standard deviation).

Estimation Using 5 Percent and 5.5 Percent Fees In the main text, we estimate the distribution of sellers' costs using the observed distribution of reserve prices $G_p(p)$ and assuming $p = \tilde{\Phi}^{-1}(c/0.94)$, which is the optimal price for a seller of type c to set if the brokers employ 6 percent fees. While there is strong evidence that 6 percent are the empirically relevant fees (see e.g. Hsieh and Moretti, 2003), it is also important to check the robustness of our estimates if we assume that brokers use 5 percent or 5.5 percent fees, perhaps because of unobserved discounts. In this appendix, we show that our estimation is robust in these regards by estimating $G(c)$ using $G_p(p)$ and assuming $p = \tilde{\Phi}^{-1}(c/0.945)$ and $p = \tilde{\Phi}^{-1}(c/0.95)$, respectively. Tables 6 and 7 give the parameter estimates for the private values model when fees are 5.5 percent and 5 percent, respectively, and unobserved heterogeneity is controlled for using previous transaction prices. The estimates are almost the same as for the model with 6 percent fees in the main text (see Tables 6 and 7).

Other Years As an additional robustness check, we also estimated the model for the other years (using previous transaction prices and 6 percent fees as in the main model).

Estimated Parameter Values						
Parameters	1993		1994		1995	
ϕ_1	1.14	(0.0980)	1.11	(0.114)	1.02	(0.0995)
ϕ_2	-0.0724	(0.0395)	-0.0346	(0.0463)	-0.0207	(0.0315)
γ_1	1.24	(0.0353)	1.23	(0.0318)	1.15	(0.0208)
γ_2	0.133	(0.0125)	0.135	(0.0108)	0.134	(0.00588)
$\underline{x}$	0.0181	(0.0176)	0.0167	(0.0161)	0.0123	(0.0120)
$\overline{x}$	1.28	(0.0281)	1.26	(0.0260)	1.18	(0.0144)
δ	0.946	(0.0108)	0.956	(0.0168)	0.984	(0.00114)
ξ	0.110	(0.0891)	0.244	(0.176)	0.170	(0.0880)
μ_D	0.0984	(0.00499)	0.0841	(0.00340)	0.0736	(0.00234)
σ_D	0.103	(0.00355)	0.0739	(0.00238)	0.0572	(0.00168)
σ_P	0.263	(0.00793)	0.236	(0.00650)	0.232	(0.00632)
β_T	0.0693	(0.0158)	0.116	(0.0517)	0.380	(0.0576)
# Observations	727		830		787	

Table 6: Estimated parameter values for 1993 to 1995 assuming 5.5 percent fees. Table entries read: Mean (standard deviation).

Estimated Parameter Values						
Parameters	1993		1994		1995	
ϕ_1	1.16	(0.0980)	1.10	(0.119)	1.02	(0.101)
ϕ_2	-0.0839	(0.0437)	-0.0333	(0.0474)	-0.0206	(0.0317)
γ_1	1.25	(0.0405)	1.22	(0.0325)	1.15	(0.0213)
γ_2	0.134	(0.0129)	0.135	(0.0108)	0.134	(0.00603)
$\underline{x}$	0.0195	(0.0188)	0.0183	(0.0177)	0.0128	(0.0126)
$\overline{x}$	1.29	(0.0332)	1.26	(0.0258)	1.18	(0.0145)
δ	0.945	(0.00980)	0.956	(0.0168)	0.984	(0.00114)
ξ	0.129	(0.103)	0.241	(0.177)	0.171	(0.0891)
μ_D	0.0983	(0.00496)	0.0841	(0.00342)	0.0736	(0.00236)
σ_D	0.103	(0.00350)	0.0739	(0.00235)	0.0573	(0.00168)
σ_P	0.263	(0.00791)	0.236	(0.00662)	0.232	(0.00630)
β_T	0.0677	(0.0119)	0.117	(0.0519)	0.379	(0.0576)
# Observations	727		830		787	

Table 7: Estimated parameter values for 1993 to 1995 using 5 percent fees. Table entries read: Mean (standard deviation).

The parameter estimates appear to be fairly robust in this regards as well, as shown by the results in Table 8. As show in Figure 2, real estate prices declined substantively in 1990 and 1991 and experienced a strong increase in the last two years for which we have data. Because the estimated parameter values are roughly the same for all years, this suggests that there is little if any bias arising from non-stationarity. The notable variation in the price discount μ_D, and the way it differs from the years 1993 to 1995, is as one would expect because the discount is likely to be overestimated (underestimated) when the overall real estate price index is decreasing (increasing).

Estimated Parameter Values					
Parameters	1990	1991	1992	1996	1997
ϕ_1	1.17 (0.170)	1.24 (0.162)	1.23 (0.131)	0.992 (0.0983)	0.985 (0.106)
ϕ_2	0.0611 (0.0630)	−0.0192 (0.0616)	−0.0579 (0.0534)	−0.0163 (0.0313)	0.00198 (0.0370)
γ_1	1.39 (0.0453)	1.44 (0.0437)	1.38 (0.0441)	1.12 (0.0214)	1.11 (0.0283)
γ_2	0.141 (0.0212)	0.148 (0.0194)	0.141 (0.0175)	0.128 (0.00700)	0.119 (0.0113)
$\underline{x}$	0.0292 (0.0275)	0.0224 (0.0215)	0.0208 (0.0209)	0.0122 (0.0121)	0.0179 (0.0172)
$\overline{x}$	1.44 (0.0313)	1.49 (0.0355)	1.42 (0.0365)	1.15 (0.0153)	1.15 (0.0191)
δ	0.956 (0.00484)	0.950 (0.00766)	0.934 (0.0129)	0.979 (0.00151)	0.953 (0.00388)
ξ	0.755 (0.107)	0.476 (0.146)	0.233 (0.118)	0.169 (0.0845)	0.209 (0.0936)
μ_D	0.191 (0.0115)	0.169 (0.00916)	0.128 (0.00640)	0.0605 (0.00234)	0.0546 (0.00267)
σ_D	0.153 (0.00818)	0.161 (0.00657)	0.118 (0.00454)	0.0532 (0.00169)	0.0491 (0.00190)
σ_P	0.233 (0.00903)	0.283 (0.00932)	0.288 (0.00929)	0.248 (0.00723)	0.231 (0.00775)
β_T	0.0637 (0.00621)	0.0643 (0.00758)	0.0602 (0.0108)	0.657 (0.114)	0.650 (0.127)
# Observations	497	668	671	704	543

Table 8: Estimated parameter values for the years other than 1993 to 1995. Table entries read: Mean (standard deviation).

E Additional Robustness Check: Third-Degree Polynomials

Our flexible polynomial parameterization of Φ and Γ in principle allows us to approximate arbitrary (analytical) distribution functions. However, due to computational complexity, we have assumed second-degree Chebyshev polynomials in the main text. One may wonder to what extent this simplification affects our results. For this purpose, we have estimated our structural model with third-degree Chebyshev polynomials and provide the results in Tables 9 and 10.

Table 9 shows that the estimated parameters are reasonably close to the parameters estimated with second-degree polynomials. The second row in Table 10 shows that that moving to third-degree polynomials has a negligible effect on our main finding: 6 percent fees still achieve 99.3 to 99.6 percent of the weighted joint surplus achieved by the optimal schedule.

Estimated Parameter Values						
Parameters	1993		1994		1995	
ϕ_1	1.09	(0.0883)	1.06	(0.0934)	1.06	(0.0612)
ϕ_2	-0.00200	(0.0509)	0.0443	(0.0423)	0.0538	(0.0346)
ϕ_3	-0.0450	(0.0177)	-0.0463	(0.0234)	-0.0578	(0.0176)
γ_1	1.20	(0.0322)	1.17	(0.0255)	1.13	(0.0221)
γ_2	0.298	(0.0402)	0.341	(0.0211)	0.321	(0.0226)
γ_3	0.116	(0.0297)	0.145	(0.0158)	0.133	(0.0183)
$\underline{x}$	0.0140	(0.0133)	0.0131	(0.0135)	0.0117	(0.0108)
$\overline{x}$	1.23	(0.0279)	1.20	(0.0183)	1.16	(0.0170)
δ	0.944	(0.0139)	0.972	(0.00702)	0.985	(0.00118)
ξ	0.221	(0.129)	0.391	(0.160)	0.289	(0.134)
μ_D	0.0977	(0.00497)	0.0828	(0.00321)	0.0734	(0.00237)
σ_D	0.103	(0.00355)	0.0738	(0.00236)	0.0573	(0.00169)
σ_P	0.266	(0.00765)	0.239	(0.00660)	0.234	(0.00652)
β_T	0.0730	(0.0269)	0.180	(0.0378)	0.407	(0.0623)
# Observations	727		830		787	

Table 9: Estimated parameter values for 1993 to 1995. Φ and Γ are parameterized as third-degree Chebyshev polynomials. Table entries read: Mean (standard deviation).

Bargaining Parameter and Counterfactual Fees and Welfare			
Variable	1993	1994	1995
α^*	0.186	0.164	0.135
Performance of 6 percent Fee: $\frac{W(\alpha^*,0.06)}{W(\alpha^*,\omega_{\alpha^*}^{opt})}$	0.993	0.993	0.996
Optimal Percentage Fee for a Monopoly: b_1^*	21.4%	20.0%	21.7%
Performance of b_1^*: $\frac{W(1,b_1^*)}{W(1,\omega_1^{opt})}$	0.980	0.956	0.971

Table 10: α^* and counterfactual fees and welfare for the three years 1993 to 1995 for Φ and Γ as third-degree Chebyshev polynomials.

F Details for Additional Counterfactuals

F.1 For-Sale-By-Owner vs Multiple Listing Service

In Proposition 4 we have established that if the distribution of the seller's opportunity cost G is a Pareto distribution, then the average prices for a market with a 0 percent transaction fee (FSBO) and for markets with a 6 percent transaction fee (MLS) are the same, given that all else is equal in these two markets. This result leaves two open questions. First, how much do the two average prices differ if G is not exactly, but only approximately Pareto? Second, how do the two average prices compare if the FSBO market and the MLS market differ by more than just the transaction fee? The second question is particularly relevant, since Hendel, Nevo, and Ortalo-Magné (2009a) find that, controlling for heterogeneity in properties, not only is property initially listed on a FSBO platform sold at the same average price as property listed on the MLS, but such properties also take 19.47 days longer to sell and are sold with a probability 2 percentage points higher than for MLS.

We use our structural estimates to answer these questions. For the first question, we simply compute the counterfactual average price if the fee were 0 percent. For the second question, we have to explore possible reasons why the time on market and the probability of sale differ between FSBO and MLS listings. One possible source of difference is that the arrival rate of buyers may be different, e.g. one may believe that properties listed on the MLS are viewed by more potential buyers. Another possible source is that the non-sales time on market may be shorter for MLS properties, for example, because it takes less time until the first buyers start viewing the property or it takes less time from initial agreement to sale and to the point at which the contract is signed and the property is delisted. There are further sources of differences between FSBO and MLS, such as the distributions of buyers' and sellers' valuations being different. For the sake of simplicity, we will focus our counterfactual exercises on the first and the second source. In our "arrival rate-adjusted counterfactual", we calibrate the arrival rate of buyers ξ such that we match the 19.47-day difference in time on market between FSBO and MLS properties reported by Hendel, Nevo, and Ortalo-Magné (2009a). In our "arrival rate and non-sales delay counterfactual" we calibrate both the arrival rate ξ and the non-sales delay parameter β_T to match the 19.47-day difference in time on market and the 2 percentage point difference in probability of sale.

Results are reported in Table 11. It shows the average quality-adjusted price $E[P]$ under different counterfactuals for FSBO sales. In the third column all parameters are assumed to be the same for FSBO and MLS, except for the fee. The predicted average price for FSBO is 0.1 to 0.32 percent lower than for MLS. In the fourth column, the arrival rate ξ is calibrated such that the time on market is the same as for the extrapolation based on Hendel, Nevo, and Ortalo-Magné (2009a). The average price for FSBO is 0.55 percent to 4.72 percent lower for FSBO than for MLS. In the fifth column, the arrival rate and the non-sale delay parameter are calibrated to fit the time on market and the probability of sale of the extrapolated values. The average price for FSBO is 0.01 to 0.05 percent higher than the price for MLS.

F.2 Regulated Fees

We assume that the government can directly determine the percentage fee $\bar{b}$ brokers can charge, with the natural focus being on regulated fees $\bar{b} \leq 0.06$.[50] In the following we will conduct a counterfactual analysis based on a partial equilibrium analysis: we assume that buyers' valuation distributions do not change as the policy changes. This is certainly an imperfect approximation of reality: if for example the distribution of house prices

[50] Besides being the natural counterfactual, it also means that the optimal prices of all sellers are well defined after a fee decrease even in scenarios that do not allow for entry (or exit). That said, when allowing for entry, we need to extrapolate because in the data we do not observe sellers with higher costs.

Year		MLS	FSBO			
			Extrapolated	Unadjusted	ξ-adjusted	(ξ, β_T)-adjusted
1993	$E[P]$	1	1.0045	**0.9968**	**0.9527**	**1.0001**
	$E[T]$	159.23	178.70	158.09	*178.70*	*178.70*
	$E[Prob.Sale]$	0.5714	0.5914	0.5804	0.4186	*0.5914*
	ξ	2.1930	-	2.1930	*0.6450*	*2.4069*
	β_T	0.0669	-	0.0669	0.0669	*0.0553*
1994	$E[P]$	1	1.0045	**0.9973**	**0.9684**	**1.0005**
	$E[T]$	141.37	160.84	140.15	*160.84*	*160.84*
	$E[Prob.Sale]$	0.6114	0.6314	0.6184	0.4998	*0.6314*
	ξ	1.4531	-	1.4531	*0.6584*	*1.5888*
	β_T	0.0952	-	0.0952	0.0952	*0.0725*
1995	$E[P]$	1	1.0045	**0.9990**	**0.9945**	**1.0004**
	$E[T]$	99.78	119.25	98.98	*119.25*	*119.25*
	$E[Prob.Sale]$	0.8163	0.8363	0.8181	0.7720	*0.8363*
	ξ	1.7909	-	1.7909	*1.3308*	*2.0362*
	β_T	0.3691	-	0.3691	0.3691	*0.1482*

Table 11: Counterfactual FSBO market. The first column contains values from our data set. The second columns is constructed by modifying our estimates by the FSBO-MLS differences reported by Hendel, Nevo, and Ortalo-Magné (2009a). The remaining columns contain counterfactuals assuming that the fee is 0 percent with no adjustments of parameters (third column), adjustments to fit time on market (fourth column), and adjustments to fit time on market and probability of sale (fifth column). Calibrated values are shown in *italics*.

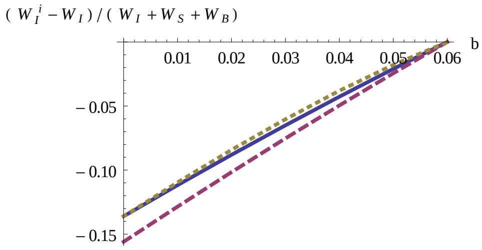
changes, then buyers' option value of future trade is likely to change as well. There are a number of reasons why we think that these counterfactuals simulations provide useful insights nonetheless. First, it turns out that the distribution of prices changes only by a small amount (which is in line with Proposition 4 and the arguments in its proof), so that the option value of future trade of buyers should only change moderately. Second, the sellers' cost distribution seems to be relatively close to a mirrored generalized Pareto distribution. For G mirrored generalized Pareto, the optimal fee is independent of the buyers' distribution. Therefore, even if the buyers' distribution changed, the effect of this change on the optimal fee structure should be small. Third, one can interpret our counterfactual analysis as a change of regulation in a small (open) jurisdiction, in which buyers' option values are mostly determined by trade opportunities outside of the jurisdiction.

It is instructive to decompose the effect of a decrease in fees into three effects: (1) a *direct effect* consisting of the "mechanical" price adjustments that occur if sellers' net prices are kept the same, (2) an indirect *inframarginal seller effect*, which occurs because sellers who are active before and after the reduction in fees change their prices, and (3) an indirect *marginal seller effect*, which stems from the fact that additional sellers with high costs will enter the market. To distinguish between these three effects, we calculate average prices and welfare for three counterfactual scenarios that correspond to this decomposition.

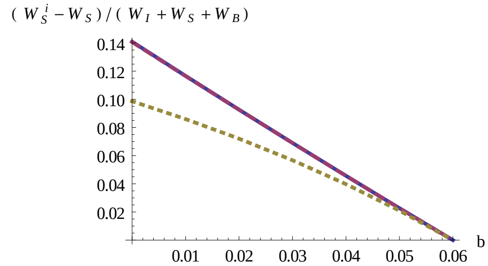
Let $p^i(c)$ be the reserve price a seller of type c sets in scenario $i \in \{1, 2, 3\}$ and let $\overline{c}^i$ be the least efficient seller type who enters the market in this scenario. Expected welfare of buyers, sellers, and intermediaries in scenario i is denoted, respectively, by W_B^i, W_S^i and W_I^i. The detailed derivations of these expressions are provided at the end of this section. The assumption underlying W_B^i is that buyers are short-lived and participate in one period only, so that changes in fees have no effect on their future payoffs.

The average reserve price EP^i in scenario i is given by $EP^i = \int_{\underline{c}}^{\overline{c}^i} p^i(c) \frac{dG(c)}{G(\overline{c}^i)}$. As mentioned before, an analogous conditional expectation underlies the estimation of average prices of active sellers in the analysis of Hendel, Nevo, and Ortalo-Magné (2009a).

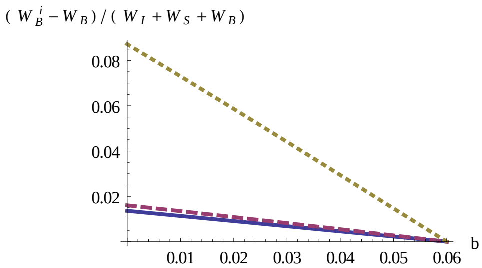
We write W_B, W_I, W_S and EP to denote the variables absent fee regulation, that is, when $\bar{b} = 0.06$. Figure 3 plots the results, expressed as percentages, for 1993 for $\bar{b}$ between 0 and 0.06.



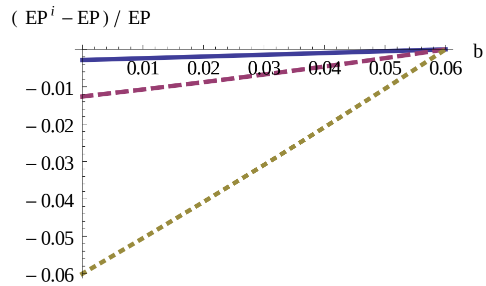
(a) Intermediary's profit W_I



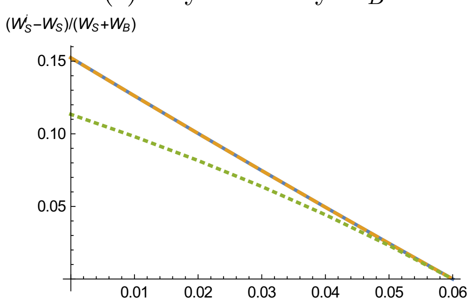
(b) Seller's utility W_S



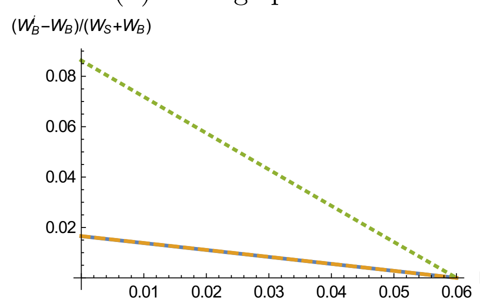
(c) Buyer's utility W_B



(d) Average price EP



(e) Seller's utility W_S (change as fraction of buyer and seller surplus)



(f) Buyer's utility W_B (change as fraction of buyer and seller surplus)

Figure 3: The percentage change of different variables $(y^i - y)/y$ as a function of the regulated fee $\bar{b} \in [0, 0.06]$ for scenarios $i = 1$ (dotted), $i = 2$ (dashed), and $i = 3$ (solid) for $y \in \{W_I, W_S, W_B, EP\}$ for 1993. Subfigures (e) and (f) show the change of buyer and seller welfare as a fraction of joint buyer-seller surplus.

From Proposition 4 we know that if the sellers' costs are drawn from a mirrored generalized Pareto distributions with $\underline{c} = 0$, then the direct effect (1) and the indirect inframarginal seller effect (2) on EP^3 are exactly offset by the marginal seller effect (3). Because empirically the distribution of the sellers' cost is not exactly mirrored generalized Pareto, the extent to which these effects wash out empirically is an open question. Panel

(d) in Figure 3 shows that a fee decrease to $\bar{b} = 0$ would, by construction, reduce average prices by 6 percent if only the direct effect (1) is accounted for. Additionally taking into account effects (2) and (3), one finds a decrease of the average price close to zero, in accordance with the analysis in Section 8.2. In contrast, in panels (b) and (c) the difference between the dashed and solid lines, that is, between scenarios 2 and 3, is almost negligible as far as agents' welfare is concerned. The difference between the dotted and the dashed line, that is between scenarios 1 and 2, is pronounced and shows a large and negative impact of the price endogeneity effect on buyers' welfare and a positive effect of similar size on the sellers' welfare.

Panels (e) and (f) contain the same calculations as (b) and (c) with the only difference being that changes are normalized by the buyer-seller joint surplus rather than the buyer-seller-intermediary surplus. If one believes that there is inefficient free entry by real estate brokers (so that the intermediary's profit is simply wasteful spending on fixed costs of operation), then the buyer-seller surplus should be viewed as total welfare and panels (e) and (f) should be viewed as the relevant welfare comparison.

Technical Details Because $p(c) = \tilde{\Phi}^{-1}(c/0.94)$ is the reserve price sellers of type c set with a 6 percent fee, the reserve price set in scenario 1, denoted $p^1(c)$, is $p^1(c) = 0.94\tilde{\Phi}^{-1}(c/0.94)/(1-\bar{b})$. In scenarios 2 and 3, sellers of type c set the price $p^i(c) = \tilde{\Phi}^{-1}(c/(1-\bar{b}))$ with $i \in \{2,3\}$. In scenarios 1 and 2, the least efficient active seller type has a cost equal to $\bar{c}^i = 0.94\bar{v}$ with $i = 1,2$ while in scenario 3 the least efficient active seller has a cost of $\bar{c}^3 = \bar{v}/(1-\bar{b})$.

Assuming that buyers are short-lived and participate only for one period, the expected buyer surplus generated in any given period by a seller of type c who sets the reserve price $p^i(c)$ is

$$\int_{p^i(c)}^{\bar{v}} v[f_{(1)}(v) - f_{(2)}(v)]dv - \left(F_{(2)}(p^i(c)) - F_{(1)}(p^i(c))\right) p^i(c).$$

Because such a seller fails to trade in any given period with probability $F_{(1)}(p^i(c))$ and enters the subsequent period with probability $\delta F_{(1)}(p^i(c))$, the expected discounted buyer surplus such a seller generates is

$$\sum_{t=0}^{\infty}(\delta F_{(1)}(p^i(c)))^{t/\tau}\left[\int_{p^i(c)}^{\overline{v}} v[f_{(1)}(v)-f_{(2)}(v)]dv-\left(F_{(2)}(p^i(c))-F_{(1)}(p^i(c))\right)p^i(c)\right]$$

$$= \frac{\int_{p^i(c)}^{\overline{v}} v[f_{(1)}(v)-f_{(2)}(v)]dv-\left(F_{(2)}(p^i(c))-F_{(1)}(p^i(c))\right)p^i(c)}{1-\delta F_{(1)}(p^i(c))}.$$

Consequently, taking the expectation over the relevant seller types, the expected discounted buyer surplus in scenarios $i \in \{1,2,3\}$ gives

$$W_B^i = \int_{\underline{c}}^{\overline{c}^i} \frac{\left[\int_{p^i(c)}^{\overline{v}} v[f_{(1)}(v)-f_{(2)}(v)]dv-\left(F_{(2)}(p^i(c))-F_{(1)}(p^i(c))\right)p^i(c)\right]}{1-\delta F_{(1)}(p^i(c))}dG(c).$$

The expected intermediary surplus W_I^i in scenario i is

$$W_I^i = \overline{b}\int_{\underline{c}}^{\overline{c}^i} \frac{p^i(c)(F_{(2)}(p^i(c))-F_{(1)}(p^i(c)))+\int_{p^i(c)}^{\overline{v}} yf_{(2)}(y)dy}{1-\delta F_{(1)}(p^i(c))}dG(c).$$

Expected sellers' surplus in scenario i, denoted W_S^i, can be written as

$$W_S^i = (1-\overline{b})\int_{\underline{c}}^{\overline{c}^i} \frac{(p^i(c)-\frac{c}{1-\overline{b}})(F_{(2)}(p^i(c))-F_{(1)}(p^i(c)))+\int_{p^i(c)}^{\overline{v}}\left[y-\frac{c}{1-\overline{b}}\right]f_{(2)}(y)dy}{1-\delta F_{(1)}(p^i(c))}dG(c).$$

F.3 Transfer Taxes

We now provide an analysis of the equilibrium effects of transfer taxes on consumer surplus, and the welfare of intermediaries and sellers, assuming that a small local government imposes a percentage transfer tax $\kappa \geq 0$.[51]

Again it proves useful to distinguish various layers through which the policy experiment can affect outcomes. We look at the effect of imposing a tax $\kappa > 0$ when there was none before. High-cost sellers that absent the tax barely broke even would now make a loss if they did not adjust their prices. To circumnavigate this problem, the first scenario we consider is the exit of sellers. Before the introduction of the tax, sellers with costs $c \leq (1-b)\overline{v}$ entered the market. After the introduction of the tax, sellers would enter only if their cost is below $\overline{c}^0 := (1-b)\overline{v}/(1+\kappa)$, which we refer to as scenario (0). Scenarios (1) and (2) are then analogous to (1) and (2) under fee regulation

[51] The assumption of a percentage tax is imposed for analytical tractability and because of its practical relevance. For example, in the United States roughly one-third of the states impose a percentage transfer tax.

with the exception that scenario (2) is now subdivided into (2.a) fees do not change, and (2.b) fees adjust optimally to the tax. In scenario (1) sellers with costs $c \leq \overline{c}^0$ set the same reserve price $\tilde{\Phi}^{-1}(c/(1-b))$ as they did before the tax was imposed. Accordingly, the reserve price $p^1(c)$ bidders face in this scenario given a seller type c satisfies $p^1(c) = (1+\kappa)\tilde{\Phi}^{-1}(c/(1-b))$. Of course, the least efficient seller type who is active in scenario (1) has the same cost $\overline{c}^1 = (1-b)\overline{v}/(1+\kappa) = \overline{c}^0$ as in scenario (0).

In scenario (2.a), the fee is still b but now for given b and κ all seller types set the optimal after-tax pre-fee reserve price $p^{2.a}_{\kappa}(c) = \tilde{\Phi}^{-1}\left((1+\kappa)c/(1-b)\right)/(1+\kappa)$. Accordingly, the reserve price $p^{2.a}(c)$ bidders face with a seller of type c is $p^{2.a}(c) = \tilde{\Phi}^{-1}\left((1+\kappa)c/(1-b)\right)$ while the least efficient active seller type has the cost $\overline{c}^{2.a} = (1-b)\overline{v}/(1+\kappa) = \overline{c}^1 = \overline{c}^0$. Lastly, in scenario (2.b), the fee adjusts optimally to κ to induce a seller of type c to set the reserve price $p^{2.b}_{\kappa}(c) = \tilde{\Phi}^{-1}((1+\kappa)\Gamma_{\alpha}(c))/(1+\kappa)$ because the optimal allocation rule given a transfer tax κ is such that the seller of type c sells to the bidder with the highest virtual value if and only if this buyer's value exceeds $\tilde{\Phi}^{-1}\left((1+\kappa)\Gamma_{\alpha}(c)\right)$. Accordingly, the reserve price faced by buyers who are matched to a seller of type c is $p^{2.b}(c) = \tilde{\Phi}^{-1}\left((1+\kappa)\Gamma_{\alpha}(c)\right)$ and the least efficient active seller has the cost $\overline{c}^{2.b} = \Gamma^{-1}_{\alpha}(\overline{v}/(1+\kappa))$.

In all scenarios other than (2.b) the fees ω^{κ}_i are simple percentage fees with $b = 0.06$. In scenario (2.b) the fee $\omega^{\kappa}_{2.b}(p_{\kappa})$ is given by the expression in (14) in the technical details part at the end of this section, which also contains details on the other derivations. As in the analysis of regulated fees, we assume that buyers are short-lived and denote expected buyer surplus in scenario i by W^i_B, the expression for which is identical to the one under regulated fees. As before, expected seller and intermediary welfare in scenario i are denoted W^i_S and W^i_I, while K^i denotes tax revenue in scenario i. These expressions are derived at the end of this section. Variables without superscripts i denote the benchmark scenario when $\kappa = 0$. .

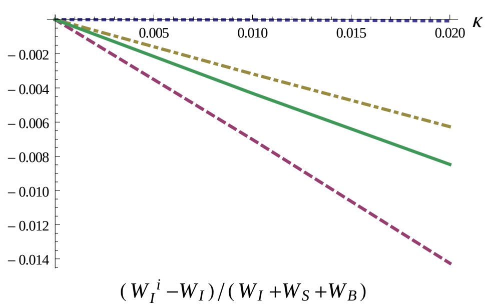
Figure 4 depicts the results for 1993. All agents – buyers, sellers, and intermediaries – are adversely affected by the introduction of the transfer tax in the small local jurisdiction as shown by the solid lines. Remarkably, sellers are most severely hit by the transfer tax and incur a decrease in welfare roughly ten times as large as the corresponding decreases for buyers and intermediaries. All agents benefit from the additional adjustments that occur because sellers and intermediaries adjust their choice variables, as shown by the difference between the solid line (total effect) and the dotted line (exit and mechanical price adjustment). Interestingly, the additional adjustment in fees (difference between scenarios (2.a) and (2.b)) has almost zero effect on the welfare of buyers (and the local government) while its effect on intermediaries and sellers is substantive with opposite signs. Thus, the first-order effect of the adjustment in fees is how the pie is split between the intermediaries and the sellers while the first-order effect of the sellers' adjustment of prices is to increase the size of the pie to be shared between the buyers, sellers, intermediaries, and government.[52]

Technical Details We assume that the government imposes a percentage transfer tax $\kappa \geq 0$. We denote by $p_\kappa(c)$ the "after-tax pre-fee" reserve price the seller of type c sets. That is, if the intermediary charges a percentage fee b and the government collects a transfer tax κ, the seller's net reserve price is $p_\kappa(c)(1-b)$. Accordingly, if a bidder buys at the reserve price, she pays $p := (1+\kappa)p_\kappa$ and the intermediary receives bp_κ. Given p_κ and κ, the probability that a given bidder is willing to buy the property is $F^\kappa(p_\kappa) := F(p_\kappa(1+\kappa))$ with density $f^\kappa(p_\kappa) := f(p_\kappa(1+\kappa))(1+\kappa)$. Accordingly, for $h = 1, 2$ we let $F^\kappa_{(h)}(p_\kappa) := F_{(h)}(p_\kappa(1+\kappa))$ and $f^\kappa_{(h)}(p_\kappa) := f_{(h)}(p_\kappa(1+\kappa))(1+\kappa)$. Denoting by $v^\kappa := v/(1+\kappa)$ the transaction-relevant valuation and by $\Phi^\kappa(v^\kappa) := v^\kappa - \frac{1-F^\kappa(v^\kappa)}{f^\kappa(v^\kappa)}$ the associated virtual valuation, we get $\Phi^\kappa(v^\kappa) = \Phi(v)/(1+\kappa)$ as the virtual valuation relevant for the static mechanism design problem with $v = (1+\kappa)v^\kappa$. Analogously, the virtual valuation relevant for the dynamic setup given transfer tax κ, denoted $\tilde{\Phi}^\kappa(v^\kappa)$, satisfies

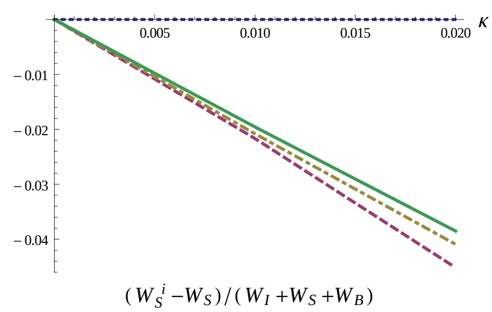
$$\tilde{\Phi}^\kappa(v^\kappa) = \frac{\tilde{\Phi}(v)}{1+\kappa},$$

where $\tilde{\Phi}(v)$ is given by the expression in Proposition 1 in the companion paper evaluated at $\omega = 0$.

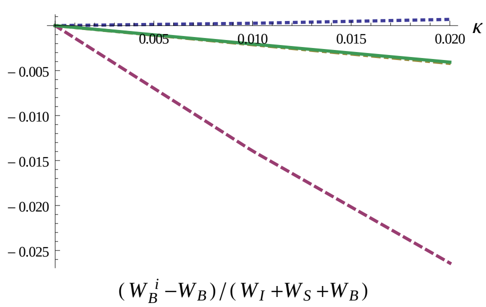
[52] That the adjustment of the fee – scenario (2.b) (solid) versus scenario (2.a) (dash-dotted) – is to the detriment of the intermediaries and to the benefit of the sellers is due to the fact that $\alpha^* \approx 0.08$ puts little weight on the intermediaries' welfare.



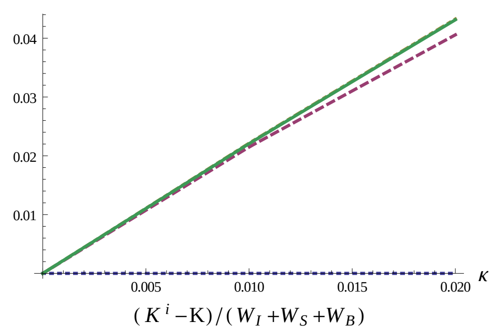
(a) Intermediary's profit W_I



(b) Seller's utility W_S



(c) Buyer's utility W_B



(d) Tax revenue K

Figure 4: The percentage change of different variables $(y^i - y)/y$ as a function of the transaction tax κ for scenarios $i = 0$ (dotted), $i = 1$ (dashed), $i = (2.a)$ (dash-dotted), and $i = (2.b)$ (solid) for $y \in \{W_I, W_S, W_B\}$. For variable K (tax revenues), the absolute normalized change is given, since the starting value of K is 0.

The expected intermediary surplus in scenario i is denoted W_I^i and given by

$$W_I^i = \frac{\int_{\underline{c}}^{\overline{c}^i} \omega_i^\kappa(p_\kappa^i(c))(F_{(2)}^\kappa(p_\kappa^i(c)) - F_{(1)}^\kappa(p_\kappa^i(c))) + \int_{p_\kappa^i(c)}^{\overline{v}^\kappa} \omega_i^\kappa(y)dF_{(2)}^\kappa(y)}{1-\delta F_{(1)}^\kappa(p_\kappa^i(c))} dG(c),$$

where $F_{(i)}^\kappa(y) := F_{(i)}(y(1+\kappa))$ for $i = 1, 2$.

Expected sellers' surplus in scenario i is

$$W_S^i = \frac{\int_{\underline{c}}^{\overline{c}^i} [p_\kappa^i(c) - \omega_i^\kappa(p_\kappa^i(c)) - c](F_{(2)}^\kappa(p_\kappa^i(c)) - F_{(1)}^\kappa(p_\kappa^i(c))) + \int_{p_\kappa^i(c)}^{\overline{v}^\kappa} [y - \omega_i^\kappa(y) - c]dF_{(2)}^\kappa(y)}{1-\delta F_{(1)}^\kappa(p_\kappa^i(c))} dG(c),$$

and government's expected tax revenue in scenario i, denoted K^i, is

$$K^i = \kappa \int_{\underline{c}}^{\overline{c}^i} \frac{p_\kappa^i(c)(F_{(2)}^\kappa(p_\kappa^i(c)) - F_{(1)}^\kappa(p_\kappa^i(c))) + \int_{p_\kappa^i(c)}^{\overline{v}^\kappa} y dF_{(2)}^\kappa(y)}{1-\delta F_{(1)}^\kappa(p^i(c))} dG(c).$$

Next we derive the optimal fee given κ. Let

$$\begin{aligned}
v^\kappa &:= v/(1+\kappa), \quad \overline{v}^\kappa := \overline{v}/(1+\kappa) \quad \text{and} \quad \underline{v}^\kappa := \underline{v}/(1+\kappa) \\
F^\kappa(v^\kappa) &:= F(v^\kappa(1+\kappa)) \quad \text{and} \quad F_{(1)}^\kappa(v^\kappa) := F_{(1)}(v^\kappa(1+\kappa)) \\
F_{(2)}^\kappa(v^\kappa) &:= F_{(2)}(v^\kappa(1+\kappa)) \quad \text{with support} \quad [\underline{v}^\kappa, \overline{v}^\kappa] \\
1 - F_\infty^\kappa(v^\kappa) &:= \frac{1 - F_{(1)}^\kappa(v^\kappa)}{1 - \delta F_{(1)}^\kappa(v^\kappa)} \\
R^\kappa(p) &:= \frac{p[F_{(2)}^\kappa(p) - F_{(1)}^\kappa(p)] + \int_p^{\overline{v}^\kappa} y dF_{(2)}^\kappa(y)}{1 - F_{(1)}^\kappa(p)} \\
1 - \overline{F}^\kappa(k) &:= 1 - F_\infty^\kappa(R^{\kappa-1}(k)) \\
f^\kappa(v^\kappa) &:= [F^\kappa(v^\kappa)]', \quad f_{(1)}^\kappa(v^\kappa) := [F_{(1)}^\kappa(v^\kappa)]', \quad \text{and} \quad \overline{f}^\kappa(v^\kappa) := [\overline{F}^\kappa(v^\kappa)]' \\
\Phi^\kappa(v^\kappa) &:= v^\kappa - \frac{1 - F^\kappa(v^\kappa)}{f^\kappa(v^\kappa)} \quad \text{and} \quad \tilde{\Phi}^\kappa(p) := \overline{v}^\kappa - \int_p^{\overline{v}^\kappa} \frac{1 - \delta F_{(1)}^\kappa(y)}{1-\delta} [\Phi^\kappa(y)]' dy \\
\overline{\Phi}^\kappa(v^\kappa) &:= v^\kappa - \frac{1 - \overline{F}^\kappa(v^\kappa)}{\overline{f}^\kappa(v^\kappa)}.
\end{aligned}$$

A direct application of Lemma 1 in Loertscher and Niedermayer (2017)[53] implies that the optimal allocation rule is such that there is trade in period t from the seller to the buyer b_t with the highest virtual valuation $\tilde{\Phi}^\kappa(v_{bt})$ if $\tilde{\Phi}^\kappa(v_{bt}) \geq \Gamma_\alpha(c)$. Otherwise, there

[53] Lemma 1 in Loertscher and Niedermayer (2017) states that in any optimal mechanism, the good is sold to the buyer with the highest valuation present, in the earliest period t for which $\max_{b_t} \tilde{\Phi}(v_{b_t}) \geq \Gamma_\alpha(c)$, and the expected payoff of every buyer of type $\underline{v}$ and of the seller of type $\overline{c}$ is 0.

is no trade in period t. This allocation rule can be implemented with fee setting if a seller of type c can be induced to set the (after-tax pre-fee) reserve price

$$p_\kappa^{2.b}(c) := \tilde{\Phi}^{\kappa-1}(\Gamma_\alpha(c)). \tag{11}$$

Next, let

$$\overline{\omega}^\kappa(k) := k - \frac{\int_p^{\overline{v}^\kappa} \Gamma_\alpha^{-1}(\overline{\Phi}^\kappa(y))\overline{f}^\kappa(y))dy}{1-\overline{F}^\kappa(p)} \tag{12}$$

and

$$V^\kappa(c) := (1-\overline{F}^\kappa(k^\kappa(c)))(k^\kappa(c) - \overline{\omega}^\kappa(k^\kappa(c)) - c), \tag{13}$$

where

$$k^\kappa(c) := \overline{\Phi}^{\kappa-1}(\Gamma_\alpha(c)).$$

In a stationary environment, the optimal transaction fee $\omega^\kappa(p_\kappa)$ is then given by

$$\omega^\kappa(p_\kappa) := p_\kappa - \frac{\int_{p_\kappa}^{\overline{v}^\kappa}\left[\Gamma_\alpha^{-1}(\tilde{\Phi}^\kappa(y)) + \delta V^\kappa(\Gamma_\alpha^{-1}(\tilde{\Phi}^\kappa(y)))\right] f^\kappa(y)dy}{1-F^\kappa(p_\kappa)}, \tag{14}$$

which follows as a direct implication of Proposition 2 in the companion paper and an application of the various definitions.

G "Price-Inflation" Theory of Real Estate Brokerage Fees

We describe additional reasons why a "price-inflation" explanation of the structure of brokerage fees is unconvincing.

The theory is contradicted by the findings of Hendel, Nevo, and Ortalo-Magné (2009a) that sellers selling directly through a for-sale-by-owner platform get on average the same gross price as those who sell through a broker. The theory could be defended by the claim that this is due to the 6 percent fee contract not giving sufficient incentives to the broker to get a higher price. However, this leads to the question of why brokers do not get more high-powered incentives – a marginal fee close to 100 percent and possibly an inframarginal fee below 6 percent. The usual explanation in a principal agent setting is that incentives are insufficiently steep because the principal provides insurance to the agent. However, the larger brokerage firms have hundreds of transactions per year (even individual brokers have half a dozen transactions per year, see Hsieh and Moretti, 2003), whereas an individual seller has a sale every couple of years. This would suggest that the seller should be more rather than less risk averse than the broker and hence not provide insurance to him.

The empirical literature on real estate brokerage has documented a number of other puzzles when viewing brokerage fees from a “price-inflation” perspective.[54]

Online Supplement

Appendix H is provided in the online supplement, see `http://andras.niedermayer.ch/research/`.

[54] We thank François Ortalo-Magné for pointing out to us some of the difficulties of the “price-inflation” explanations of real estate brokerage fees and for providing anecdotes of real estate brokers who consider their value-added to be in making transactions more convenient (reducing search frictions, legal uncertainty, etc.) rather than driving up the price. Brokers seem to view it as important to get both the seller and the *buyer* on board; a reputation of driving up the price is hence viewed bad for business, especially for buyer’s brokers. See also the discussion in Levitt and Syverson (2008, p. 610) about the puzzles created by a “price-inflation” explanation of brokerage fees and Han and Strange (2014) for an overview of the findings of the empirical literature on real estate brokerage fees.