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To Sell or Not to Sell: List Price, Transaction Price and Marketing Time in the Housing Market*

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Abstract

This paper specifies and estimates a structural model of home seller behavior. The model is an application of search theory to housing and is estimated using method of moments. The estimation method uncovers an analytical closed-form relationship between reduced-form coefficients of hedonic and marketing time equations and the structural parameters. Estimation can thus be performed using individual level or aggregate data. The model is first estimated using individual housing transaction data from a large suburb of the Washington D.C. metropolitan area during 2006, and it is used to analyze the relationship between list prices and marketing time. Then, for each year in the period 2002-2008, aggregate data are used to compute one structural parameter that measures home sellers' bargaining power. Trends of this estimate coincide with popular perceptions about the "heat" of the housing market in the area.

Keywords: Real Estate Market, Search Models, Asking Price, Time on the Market, Seller's Market Power, Bargaining Power, Market Heat Index

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1 Introduction

This paper specifies and estimates a structural model of home seller behavior. The model is an application of search theory to housing and is estimated using method of moments. The estimation method uncovers an analytical closed-form relationship between reduced-form coefficients of hedonic and marketing time equations and the structural parameters. Estimation can thus be performed using individual level or aggregate data.

The complicated relationship among list prices, transaction prices and marketing time has been analyzed in the literature from both theoretical and empirical perspectives.[1] Theory suggests that these three variables are jointly determined. That is, home sellers strategically choose a list price considering that a higher posting price may increase the final transaction price but also decrease the rate at which buyers arrive and consider buying the unit. Empirical papers typically propose exclusion restrictions to identify the impact of list prices on marketing time, and a few of them have estimated structural models to give additional insights about this relationship (Horowitz, 1992, and Carrillo, forthcoming). Despite these efforts, little is known about the relationship between the structural parameters of models that study home sellers' optimal pricing decisions and the reduced-form coefficients of hedonic and marketing time equations.[2] This paper aims to help fill this gap.

To explain the relationship among seller's list prices, transaction prices and marketing

[1] See, for example, Belkin, Hempel and McLeavey (1976), Kang and Gardner (1989), Horowitz (1992), Yavas and Yang (1995), Knight (2002), Anglin, Rutherford and Springer (2003), Allen, Rutherford and Thomson (2007), and Carrillo (forthcoming).

[2] Empirical works that exploit home sale data generally estimate separate reduced-form specifications of the pricing or the marketing time equation. This is a sensible approach because it allows researchers to tackle their question of interest without dealing with the biases resulting from adding an endogenous variable to the set of explanatory covariates. Thus, it is important to uncover the relationship between the reduced-form coefficients and the structural parameters of models that study sellers' optimal pricing decisions and marketing time.

time, a stylized model of home seller's behavior is developed. The theoretical model is a standard application of search theory to housing.[3] Every period, sellers wait for buyers to visit and inspect their housing units. If a buyer visits, the final transaction price is determined and trade may or may not occur. If trade does not take place, sellers may wait for a potential buyer next period. The posting price affects both the rate at which potential buyers arrive and the final transaction price. In particular, a higher posting price decreases the likelihood that a buyer arrives but increases the expected transaction price. We focus on the steady state solution where the seller optimally picks the listing price and reservation value that maximize her expected gains from searching and trade. This stylized model is parametrized to obtain a closed formed solution that facilitates comparative static analysis and the estimation process.

To estimate the model, four moment conditions are derived. The model could be estimated using the generalized method of moments (GMM). Instead, we use an alternative simpler approach that uses transformations from ordinary least squares (OLS) coefficients of four reduced-form models to compute consistent estimates of the structural parameters. Reduced-form equations are estimated for i) list prices, ii) transaction prices, iii) time on the market, and iv) the probability that the transaction price is below the list price. This method allows adding a very large set of covariates in the structural model and estimate its parameters at a low computational cost. It illustrates in a clean and clear manner the link between the coefficients of reduced-form models and the structural parameters of a home seller's search model. But, more importantly, given that the relationship between the lin-

[3] The earliest application of a search model in a formal analysis of real estate markets is attributed to Yinger (1981). Later developments can be found in Yavas (1992), Horowitz (1992), Yavas and Yang (1995), Haurin (1998), Arnold (1999), Ford, Rutherford, and Yavas (2005), Albrecht et al. (2007), Novy-Marx (2009) and Carrillo (forthcoming), among others.

ear reduced-form and the structural model has been uncovered, we show that some of the structural parameters can be computed using (readily available) aggregate data.

The model is first estimated using *individual-level* residential real estate transaction data from a large suburb of the Washington D.C. Metropolitan Area. The data contain more than 14,000 transactions of units that were listed on the Multiple Listing Services (MLS) during 2006 and include information about the asking price, transaction price, marketing time, and a comprehensive set of the home's and neighborhood's characteristics.[4] Most parameter estimates have the expected signs and have an intuitive interpretation. Moreover, the estimated model is able to replicate the pricing and duration data remarkably well. It is not surprising that the predicted means match the actual moments very closely. What is remarkable is that the model is able to simulate the whole *distribution* of time on the market with great accuracy. We highlight this point because marketing time is simulated using only the underlying assumptions of the model without imposing any other source of heterogeneity. The estimated structural model is used to predict the effects of list price on time on the market. We find that there is a substantially large effect of overpricing on marketing time; this effect is non-linear and increases exponentially as list price rises.

Then, for each year in the period 2002-2008, *aggregate* data from housing transactions in the same area, are used to compute one particular structural parameter of the model that measures home sellers' bargaining power. It is found that, between 2002 and 2005, sellers had most bargaining power in what appears to have been a very hot housing market. After 2006, sellers' bargaining power diminish depicting a much cooler and rather cold buyers' market.[5]

[4]We thank Metropolitan Regional Information Systems (MRIS) for sharing these data with us.

[5]Novy-Marx (2009) use a theoretical matching model to describe hot and cold housing markets.

These trends coincide with the up and downturns in home appreciation rates in the area and are consistent with popular perceptions about the "heat" of the housing market. More importantly, this estimate may have substantial utility in other applications where index numbers of housing market conditions are needed.[6]

The rest of this document is organized as follows. Section 3 presents the theoretical and empirical model. The estimation method is discussed in the fourth section. In section 4, we present the data. Section 5 describes the results including the effects of list price on marketing time and the computation of sellers' bargaining power. Finally, the last section concludes.

2 The model

2.1 A stylized theoretical model

The theory is a simplification of a model developed by Carrillo (forthcoming). The model below is a partial equilibrium search model where home sellers choose list prices and reservation strategies and is similar in spirit to the search model developed by Horowitz (1992). The model below ignores equilibrium effects and imposes specific functional form assumptions about housing demand. These additional assumptions facilitate finding analytical solutions to the seller's optimal strategies and its estimation.

Assume a market with infinitely-lived agents. The agents are households who either are actively searching for a home (buyers), or who have a vacant home for sale (sellers). A home is considered to be an indivisible good from which both buyers and sellers derive utility. The

[6]For instance, the real estate industry computes (and sells) a proprietary "market heat index" of the real estate market (www.marketheatindex.com) that is similar in spirit to the parameter estimated in this paper. Due to its proprietary nature, however, a comparison between these two indices cannot be provided.

home's characteristics are fully captured by an index s that measures the monetary value of a housing unit.[7]

A seller joins the housing market by placing a listing that informs all potential buyers: a) that her home is for sale, b) her list price P_s, and c) the home's characteristics (and thus s). Define $u(P, s)$ as the level of utility that sellers obtain by selling a type s home, which depends on the selling price P and the home's characteristics. We assume that u is a differentiable function strictly increasing in the first argument and decreasing in the second. Sellers wait for potential buyers to arrive at their home, and in the event that they engage in trade, they exit the market forever.

Let buyers observe a listing and visit a particular seller at rate $q(P_s, s)$, which depends on the posting price P_s, and the home's value s. In particular, it is assumed that this rate is decreasing in P_s and increasing in s.

When a buyer visits a home, she meets the seller and both bargain over the transaction price. The bargaining game is as follows. With probability θ, the seller is not willing to accept counter-offers, and the posting price P_s constitutes a take-it-or-leave-it offer to the buyer. With probability $(1-\theta)$, the buyer has the option to make a counter take-it-or-leave-it offer P_b to the seller. It will be assumed that once a buyer has visited a property, she has perfect information about the seller's preferences. That is, if she makes a counter take-it-or-leave-it offer, she will bid the seller's reservation value R_s (the minimum price at which she is willing to sell her property). The assumption of (ex-post) perfect information simplifies the nature of the bargaining game and has been used in other studies such as

[7] Notice that in a perfect competitive market with no search and transactions costs, every home should sell for s monetary units.

Albrecht et al. (2007), for example.[8]

During the meeting, buyers have the option to buy the home (paying either P_s or P_b), or to stay in the market. The buyer's optimal behavior is not modelled explicitly. Instead, we define $\gamma_s = \gamma(P_s, s)$ as the probability that a buyer is willing to buy a property given that she has visited it and did not have the opportunity to make a counter offer. γ_s depends on both P_s and s; in particular, we assume that γ_s is continuous, differentiable, and that $\gamma_{s1} \leq 0$ and $\gamma_{s2} \geq 0$, where the subscripts denote partial derivatives. If the buyer has visited a home and had the opportunity to make a counter offer, let $\gamma_b = \gamma(R_s, s)$ be the rate at which buyers are willing to engage in trade. γ_b is assumed to be a continuous, differentiable function with $\gamma_{b1} \leq 0$ and $\gamma_{b2} \geq 0$.

From a seller's point of view, trade occurs only if a buyer visits her property and is willing to trade, either at the posting price P_s or at her reservation value R_s. Using this consideration we are able to define the seller's expected gain from search and trading as

$$\Pi_t^e = q\left[\theta\gamma_s u(P_{st}, s) + (1-\theta)\gamma_b u(R_{st}, s)\right] + \left[1 - q(\theta\gamma_s + (1-\theta)\gamma_b)\right]\beta\Pi_{t+1}^e, \qquad (1)$$

where Π_t^e is the seller's value of having an opportunity to trade in each period t (her value of search), β is the seller's discount factor, and u captures the seller's net utility of selling her home.[9]

[8] This bargaining model simplifies the model's solution but it has several limitations. For instance, the bargaining model predicts that transaction prices occur either at the seller's posting price or reservation value and that buyers make at most one counteroffer to sellers. These implications are likely rejected by the data (Merlo and Ortalo-Magne 2004).

[9] One could argue that sellers in the housing market are not searching in the conventional way one thinks about search. Rather than actively searching and drawing buyers at random, they wait patiently for offers. Home sellers' behavior, however, can be and has been described by search models (see for example, Horoworitz 1992). They passively wait for random offers to arrive, incur high transaction costs and their behavior can be characterized by optimal reservation strategies. For these reasons we refer to Π^e as the seller's expected gain from search and trading.

Equation (1) states that, in every period, there is $q\theta\gamma_s$ probability that a seller sells her home for the posting price and obtains $u(P_{st}, s)$ profit when trading; with probability $q(1-\theta)\gamma_b$, trade occurs at the seller's reservation value, in which case her gain from trade is $u(R_{st}, s)$; finally, if trade does not happen, she returns to the market and keeps her value of search $\beta\Pi^e_{t+1}$(the discounted value of having an opportunity to trade next period).

Because time horizon is infinite, the seller's profit, posting price and reservation price are time independent. In particular, we conjecture that there exists a steady state where $\Pi^e_t = \Pi^e_{t+1} = \Pi^e$. Then, the seller's problem consists of choosing an optimal reservation value R^*_s and posting price P^*_s that maximize her value of search.[10]

First, notice that any optimal seller's behavior necessarily implies that

$$u(R^*_s, s) = \beta\Pi^e. \tag{2}$$

That is, the minimum price that the seller is willing to accept should be such that she is indifferent between selling and the option of continued search. We replace this condition in equation (1) and obtain that, for any R^*_s,

$$\Pi^e = \theta q\gamma_s u(P_s, s) + (1-\theta q\gamma_s)u(R^*_s, s). \tag{3}$$

Differentiating this equation with respect to P_s, we find that the optimal seller's posting price P^*_s solves:

$$\frac{u(P^*_s, s) - u(R^*_s, s)}{u_1(P^*_s, s)} = \frac{1-\phi(P^*_s, s)}{\phi_1(P^*_s, s)}. \tag{4}$$

Here the subscripts denote partial derivatives and, for notational simplicity, we have defined $1-\phi(P_s, s)$ as the probability that, given that the posting price is a take-it-or-leave-it offer to the buyer, a home sells for the posting price; that is: $1-\phi(P_s, s) = q(P_s, s)\gamma(P_s, s)$.

[10] This is a standard approach to solve infinite-horizon search models. For details, see Lipmann and McCall (1976).

Combining equations (2) and (3), we find a new optimality condition that P_s^* and R_s^* must satisfy

$$\frac{u(R_s^*, s)}{\beta} = \theta[1 - \phi(P_s^*, s)]u(P_s^*, s) + (1 - \theta[1 - \phi(P_s^*, s)])u(R_s^*, s). \tag{5}$$

The optimal steady state seller's posting price and reservation value are defined by the pair $\{P_s^*, R_s^*\}$ that solves equations (4) and (5). One could characterize the general properties of the solution.[11] Instead, we choose specific functional form assumptions for q, γ, and u that provide us some specific insights about the properties of the model.

In particular, we assume that

$$q(P_s, s) = (P_s/s)^{-\lambda^q}; P_s \geq s, \tag{6}$$

$$\gamma_s = \gamma(P_s, s) = (P_s/s)^{-\lambda^s}; P_s \geq s, \tag{7}$$

and

$$\gamma_b = \gamma(R_s, s) = (R_s/s)^{-\lambda^s}; R_s \geq s, \tag{8}$$

where λ^q, $\lambda^s > 0$. The interpretation of equations (6), (7), and (8) is straightforward. For instance, every period, there is a $(P_s/s)^{-\lambda^q}$ probability that a buyer visits a property with a relative markup of 100*$(P_s/s - 1)$ percent. Similarly, given that a buyer has visited a unit, the probability that trade occurs is $(P_s/s)^{-\lambda^s}$ if the posting price is the take-it-or-leave-it offer and $(R_s/s)^{-\lambda^s}$ otherwise. Notice that both the visiting rate as well as the probability of trade (conditional on a visit) decrease with posting prices. Moreover, the parameters λ^q, λ^s measure how responsive buyers are to changes in posting prices.

[11] In fact, if sellers are risk neutral ($u(x) = x$), it can be shown that as long as, a) the hazard function $h(P_s^*, s) = \frac{\phi'(P_s^*, s)}{1 - \phi(P_s^*, s)}$ is non-decreasing in P_s^*, and b) $\frac{\partial \phi(P_s^*, s)}{\partial s} < 0$, the optimal steady state seller's posting price and reservation value are well defined and unique. In addition, $P_s^*(\beta, s) \geq R_s^*(\beta, s) \geq s, \forall \beta, \forall s$ and these functions are increasing in both arguments.

We let sellers have a constant-relative-risk-aversion utility function. In particular, we assume that

$$u(P,s) = \frac{1}{1-\alpha}(P/s)^{1-\alpha}, \tag{9}$$

where P is the transaction price (either P_s or R_s), and the scalar α is a parameter that measures the seller's taste for risk.

Given these assumptions, we are able to provide a closed formed solution for the optimal seller's strategies. After some algebra (details are shown in Appendix 1), we find that

$$P_s^* = s \cdot \left\{ \frac{\theta}{r} \frac{1-\alpha}{(\lambda^q + \lambda^s - (1-\alpha))} \right\}^{\frac{1}{\lambda^q+\lambda^s}} \tag{10}$$

and

$$\begin{aligned} R_s^* &= P_s^* / \left\{ \frac{\lambda^q + \lambda^s}{\lambda^q + \lambda^s - (1-\alpha)} \right\}^{\frac{1}{1-\alpha}} & (11) \\ &= s \cdot \left\{ \frac{\theta}{r} \frac{1-\alpha}{(\lambda^q + \lambda^s - (1-\alpha))} \right\}^{\frac{1}{\lambda^q+\lambda^s}} \left\{ \frac{\lambda^q + \lambda^s}{\lambda^q + \lambda^s - (1-\alpha)} \right\}^{\frac{-1}{1-\alpha}}, & (12) \end{aligned}$$

where r is the per-period discount rate.

Proposition 1: Let $L = \frac{r}{\theta+r}(\lambda^q + \lambda^s)$ and $H = \frac{(1-\alpha)\ln\left\{\frac{\theta}{r}\frac{1-\alpha}{(\lambda^q+\lambda^s-(1-\alpha))}\right\}}{\ln\left\{\frac{\lambda^q+\lambda^s}{\lambda^q+\lambda^s-(1-\alpha)}\right\}}$. As long as $L < 1-\alpha < \lambda^q + \lambda^s < H$, then a) $P_s^* \geq R_s^* \geq s$, b) $\frac{\partial P_s^*}{\partial \theta} \geq 0$, c) $\frac{\partial P_s^*}{\partial r} \leq 0$, d) $\frac{\partial P_s^*}{\partial(\lambda^q+\lambda^s)} \leq 0$, e) $\frac{\partial(P_s^*-R_s^*)}{\partial(\lambda^q+\lambda^s)} \leq 0$, and f) $\frac{\partial P_s^*}{\partial \alpha} \leq 0$.

The bounds on the parameters guarantee that the solution is well defined and that proposition 1) holds.[12] The other statements in proposition 1 are derived from differentiating equations (10) and (11) with respect to each argument and are quite intuitive. For instance,

[12] In order to guarantee that $P_s^* \geq R_s^* \geq s$, certain conditions must hold. First, the term that multiplies s in equation (10) must be no less than one. This condition holds as long as $\frac{r}{\theta+r}(\lambda^q + \lambda^s) < 1-\alpha$. Second, it must be the case that both the numerator in equation (11) and the total factor multiplying s in equation (11) are no less than one. The first requirement is met as long as $0 < (1-\alpha) < \lambda^q + \lambda^s$; the second is met as long as $\lambda^q + \lambda^s < \frac{(1-\alpha)\ln\left\{\frac{\theta}{r}\frac{1-\alpha}{(\lambda^q+\lambda^s-(1-\alpha))}\right\}}{\ln\left\{\frac{\lambda^q+\lambda^s}{\lambda^q+\lambda^s-(1-\alpha)}\right\}}$. We combine these restrictions in Proposition 1.

the posting price and the markup increase with θ. In addition, more motivated sellers (with higher discount rates) choose lower markups. Finally, if demand for homes becomes more elastic (as $\lambda^q + \lambda^s$ rises) posting prices decrease.

2.2 An empirical model

Here we add seller's heterogeneity to the baseline model described in the previous section. There are N sellers in the market, and each seller i owns a home that is uniquely described by a vector of home characteristics X_i and a scalar u_i. The vector X_i includes features of the property that can be observed by both, the agents and the econometrician. These include the square footage, acreage and number of bathrooms, for example. The seller's value of other characteristics of the home that are not observed by the econometrician are captured by the variable u_i. It is assumed that $E[u_i|X_i] = 0$ and $E[u_i^2|X_i] = \sigma_u^2$. We let the monetary value of a home be a linear index of both observed and unobserved characteristics; that is, $\ln(s_i) = \delta^0 + X_i\delta + u_i$, where δ^0 is a scalar (the constant term) and δ is a vector of parameters.

Given these assumptions, X_i and a set of parameters δ, we may use equation (10) to define log-posting prices as

$$\ln P_{si}^* = \delta^0 + X_i\delta + \frac{1}{\lambda^q + \lambda^s} \ln \left\{ \frac{\theta}{r} \frac{1-\alpha}{(\lambda^q + \lambda^s - (1-\alpha))} \right\} + u_i. \tag{13}$$

Similarly, we may use equation (11) to compute the seller's log-reservation value as

$$\ln R_{si}^* = \ln P_{si}^* - \frac{1}{(1-\alpha)} \ln \left\{ \frac{\lambda^q + \lambda^s}{\lambda^q + \lambda^s - (1-\alpha)} \right\}. \tag{14}$$

These optimal pricing choices allow us to compute the seller's per-period unconditional probability of trade. For this, let us first work out the per-period probability that a buyer visits and is willing to trade given that the posting price is a take-it-or-leave-it offer

$$\begin{aligned}\Pr\{trade|P &= P^*_{si}\} = (P^*_{si}/s_i)^{-(\lambda^q+\lambda^s)} \\ &= \frac{r}{\theta}\frac{(\lambda^q+\lambda^s-(1-\alpha))}{1-\alpha}. \end{aligned} \tag{15}$$

Here, P is the (random) transaction price and we have used equation (13) to find the optimal relative markup P^*_{si}/s_i in terms of the structural parameters. Similarly, we may compute the per-period probability of trade if trade occurs at the seller's reservation value as

$$\begin{aligned}\Pr\{trade|P &= R^*_{si}\} = (P^*_{si}/s_i)^{-\lambda^q} * (R^*_{si}/s_i)^{-\lambda^s} \\ &= (P^*_{si}/s_i)^{-(\lambda^q+\lambda^s)} * (P^*_{si}/R^*_{si})^{\lambda^s} \\ &= \frac{r}{\theta}\frac{(\lambda^q+\lambda^s-(1-\alpha))}{(1-\alpha)}.\left(\frac{\lambda^q+\lambda^s}{\lambda^q+\lambda^s-(1-\alpha)}\right)^{\frac{\lambda^s}{1-\alpha}}. \end{aligned} \tag{16}$$

Thus, the seller's unconditional probability of trade in any given period is defined by

$$\begin{aligned}\omega &= \theta\Pr\{trade|P=P^*_s\}+(1-\theta)\Pr\{trade|P=R^*_s\} \\ &= \frac{r(\lambda^q+\lambda^s-(1-\alpha))}{\theta(1-\alpha)}\left[\theta+(1-\theta)\left(\frac{\lambda^q+\lambda^s}{\lambda^q+\lambda^s-(1-\alpha)}\right)^{\frac{\lambda^s}{(1-\alpha)}}\right].\end{aligned}$$

This finding along with the other assumptions about the trading mechanism implies that the time that property i stays on the market, T_i, follows a geometric distribution. That is,

$$\Pr\{T_i=t\}=\omega(1-\omega)^{t-1}. \tag{17}$$

3 Estimation

In this section, we derive a set of moment conditions that facilitate the estimation of the structural model. We assume at first that individual-level transaction data are available and develop an estimation method using this type of data. Then, we show how some structural parameters can be estimated using aggregate data.

3.1 Moment conditions

Assume that individual transaction data are available, and let p_{si}, p_{mi}, t_i and X_i be the actual posting price, transaction price, time on the market and observed characteristics of property $i, i = 1..n$.

We start by using equation (13) to derive the first moment equation

$$E[\ln P_{si}^*|X_i] = \delta^0 + X_i\delta + \frac{1}{\lambda^q + \lambda^s} \ln \left\{ \frac{\theta}{r} \frac{1-\alpha}{(\lambda^q + \lambda^s - (1-\alpha))} \right\}. \tag{18}$$

The second moment condition is derived by computing the expected value of the transaction price. Let P_i be the (random) transaction price of a unit. Then,

$$\begin{aligned} E[\ln P_i|X_i] &= \tilde{\theta} E[\ln P_{si}^*|X_i] + (1-\tilde{\theta}) E[\ln R_{si}^*|X_i] \\ &= E[\ln P_{si}^*|X_i] - (1-\tilde{\theta}) E[\ln P_{si}^* - \ln R_{si}^*|X_i] \\ &= E[\ln P_{si}^*|X_i] - (1-\tilde{\theta}) \frac{1}{1-\alpha} \ln \left\{ \frac{\lambda^q + \lambda^s}{\lambda^q + \lambda^s - (1-\alpha)} \right\}, \end{aligned} \tag{19}$$

where we have used equation (14) to compute $E[\ln P_{si}^* - \ln R_{si}^*|X_i]$. Here $\tilde{\theta}$ is the probability that the posting price is the transaction price given that trade occurs; that is $\tilde{\theta} = \Pr\{P = P_{si}^*|trade\}$. We may use Bayes' rule to compute $\tilde{\theta}$ as a function of the structural parameters

$$\begin{aligned} \tilde{\theta} &= \frac{\theta \Pr\{trade|P = P_s^*\}}{\theta \Pr\{trade|P = P_s^*\} + (1-\theta) \Pr\{trade|P = R_s^*\}} \\ &= \frac{\theta \frac{r}{\theta} \frac{(\lambda^q + \lambda^s - (1-\alpha))}{1-\alpha}}{\theta \frac{r}{\theta} \frac{(\lambda^q + \lambda^s - (1-\alpha))}{1-\alpha} + (1-\theta)(\frac{r}{\theta} \frac{(\lambda^q + \lambda^s - (1-\alpha))}{1-\alpha} \cdot \left(\frac{\lambda^q + \lambda^s}{\lambda^q + \lambda^s - (1-\alpha)} \right)^{\frac{\lambda^s}{1-\alpha}})} \\ &= \frac{1}{1 + \frac{(1-\theta)}{\theta} \left(\frac{\lambda^q + \lambda^s}{\lambda^q + \lambda^s - (1-\alpha)} \right)^{\frac{\lambda^s}{1-\alpha}}}. \end{aligned}$$

Define Y_i as one if the transaction price was below the posting price and zero else. Then, the third moment equation is defined by

$$E[Y_i = 1 - \tilde{\theta}]. \tag{20}$$

Let us derive one additional moment condition. Since time on the market follows a geometric distribution, the expected value of the time T that property i stays on the market is defined by

$$E[T_i] = \frac{1}{\omega}. \tag{21}$$

Notice that time on the market depends entirely upon the structural parameters (does not depend on X_i).

We use the moment conditions (18), (19), (20), and (21) to estimate the model. In particular, our estimates are the ones that minimize the distance between the observed and predicted moments so that, if possible, the following conditions hold:

$$\begin{aligned} E[\ln p_{si} - \ln P^*_{si}|X_i] &= 0, \\ E[\ln p_{mi} - \ln P_i|X_i] &= 0, \\ E[1(p_{si} > p_{mi}) - Y_i] &= 0, \end{aligned}$$

and

$$E[t_i - T_i] = 0,$$

where 1(.) is the indicator function.

3.2 Identification

The structural parameters of the model are α, λ^q, λ^s, δ^0, δ, r, θ and σ^2_u. First, notice that σ^2_u and δ are identified by the covariation between the home's characteristics and prices. We remain then with six parameters to be identified (that can shift the predicted means) and four moment conditions. Hence, some normalization is needed.

Because we do not observe the number of visits (nor the time period between visits) that a seller receives before she trades her home, it seems natural to make assumptions about the value of λ^q. In addition, we choose to calibrate the discount rate r because it is easier to select a plausible value for this coefficient than it is for the other parameters. The main results of the paper are robust to these normalization choices.

3.3 GMM vs. OLS

A standard method to estimate the model is GMM. Instead, we use an alternative simpler approach that uses transformations from the OLS coefficients to compute consistent estimates of the structural parameters. This method is straightforward. A pooled OLS regression of the four moment equations directly identifies σ_u^2 and δ. We are left with four constant terms (from the OLS regression) and four structural parameters that remain to be identified. After some algebra, we find a closed formed solution for the structural parameters as a function of the constant terms of the OLS regressions.[13] For instance, let $\hat{\kappa}^{p_s}, \hat{\kappa}^{p_m}, \hat{\kappa}^d$, and $\hat{\kappa}^T$ be the estimates of the constant terms of the (reduced-form) moment conditions 1, 2, 3 and 4, respectively. The structural parameters are then estimated as follows:

$$\hat{\alpha} = 1 - \frac{\hat{\kappa}^d}{\hat{\kappa}^{p_s} - \hat{\kappa}^{p_m}} \ln \left\{ 1 + \frac{\hat{\kappa}^T r}{1 - \hat{\kappa}^d} \right\}, \tag{22}$$

$$\hat{\lambda}^s = (1 - \hat{\alpha}) \left(1 + \frac{1 - \hat{\kappa}^d}{\hat{\kappa}^T r} \right) - \lambda^q, \tag{23}$$

$$\hat{\theta} = \frac{1}{1 + \frac{\hat{\kappa}^d}{1 - \hat{\kappa}^d} \exp\left\{ -\hat{\lambda}^s \frac{\hat{\kappa}^{p_s} - \hat{\kappa}^{p_m}}{\hat{\kappa}^d} \right\}}, \tag{24}$$

$$\hat{\delta}^0 = \hat{\kappa}^{p_s} - \frac{1}{\lambda^q + \hat{\lambda}^s} \ln \left\{ \frac{\hat{\theta}}{r} \frac{1 - \hat{\alpha}}{\lambda^q + \hat{\lambda}^s - (1 - \hat{\alpha})} \right\}. \tag{25}$$

Standard errors can be computed using the delta method.

While GMM would allow the estimation of the current and more complicated versions of

[13] Details of the derivation are provided in Appendix 2.

the model (for example, when other types of seller's heterogeneity are introduced), we choose to keep the model as simple as possible and estimate it with OLS for the following reasons. This approach allows the parameters of a large set of covariates in the structural model to be estimated at low computational cost. It illustrates in a clean and clear manner the link between the coefficients of hedonic and time-on-the-market reduced-form equations and the structural parameters of a home seller's search model. More importantly, the proposed method can be used to recover some of the structural parameters even if only *aggregate* data were available.

3.4 Estimation using aggregate data

Micro data on individual housing transactions are generally not readily available. Instead, aggregate data such as average posting prices, average transaction prices and average time on the market are often published by regional MLS associations to measure the performance of local real estate markets over time. Because the relationship between reduced-form coefficients and the structural parameters of the seller's search model has been uncovered, some structural parameters can be computed using readily available aggregate data. This is particularly useful given the necessity to assess current housing market conditions.

To estimate structural parameters using aggregate data from housing transactions one needs the following information: (i) mean log posting prices, (ii) mean log transaction prices, (iii) the share of transactions that occurred at a price below the list price, and (iv) mean number of days that a property stays on the market. Notice that these are unconditional means. Because there are no covariates to consider, variables (i)-(iv) are equivalent to the coefficients $\hat{\kappa}^{p_s}$, $\hat{\kappa}^{p_m}$, $\hat{\kappa}^{d}$, and $\hat{\kappa}^{T}$, respectively. Equations (22)-(25) can be then used to recover the structural parameters of interest.

4 Data

To estimate the structural model, we require real estate transactions data including information on asking prices, transaction prices, time on the market, and home's characteristics. Such data have been collected for all residential real estate transactions in Fairfax County, which is located in Northern Virginia and is part of the Washington, D.C., metropolitan area. VA, that were listed on the local Multiple Listing Service (MLS) between January and December 2006 and sold before July 2007.[14]

The data come from the regional multiple listing service (MLS) and have information about units' list and transaction prices, number of days on the market, and detailed property characteristics. The MLS data is complemented with information from other sources. For instance, using geocode information, we match the MLS records with Fairfax County's assessor database. The assessor database contains a complete set of the unit's characteristics that were not always available in the MLS listings.[15] In addition, most of the observations could be matched with U.S. Census data at the Block-Group level and include several Census variables that may explain neighborhood desirability.

Table 1 shows a list of the relevant variables. The posting price, the sale price and the time that the unit was on the market provide information about the transaction.[16] The property characteristics include the unit's square footage, number of bathrooms, number of

[14] Our sample excludes properties a) not listed on the MLS, b) listed on the MLS and withdrawn from the market, and c) listed on the MLS and still active by June 30 2007.

[15] For example, a large percentage of our MLS data lacked information on square footage. By using the assessors database, we were able to obtain this information and use this variable in our models.

[16] We record the original asking price at the time the listing was posted. Time on the market is defined as the number of days from the date when the unit is listed until the contract is signed.

bedrooms and age, among others. In addition, we identify if the unit is a detached residence or a townhome.[17] Finally, we compute seven variables from the U.S. Census that capture the demographic composition of the Census Block Group where the unit is located. They include the population density, proportion of Blacks and Hispanics and median household income, among others. Our final matched database consists of 14,182 records.

[Insert Table 1]

Descriptive statistics are shown in Table 2. The average transaction price was $528,400 with a minimum of $125,000 and a maximum of $1,995,000.[18] In addition, most properties (about two thirds) sold below the asking price. In this sample, most homes were sold relatively quickly. While the mean time that a home stayed on the market was 55 days, 14 percent of the properties sold in less than one week, and fifty percent sold in less than 38 days. On the other hand, a small number of homes (about 10 percent) stayed on the market for more than four months. A typical home in Fairfax County is about 26 years old, has 1,709 square feet, two bathrooms, and 0.2 acres of land. In addition, an average home in our sample is located in a U.S. Census block-group where 8 percent of its population is black and 8 percent of the population is older than 65.[19] There is significant dispersion in the characteristics of the neighborhoods. For example, while there are many areas in our sample with virtually no Blacks or Hispanics living in them, there are several Census block-groups that are populated by these groups only.

[17] We use the information on the field "type" on the MLS listing to identify if the housing unit is a detached single family home or a townhome.

[18] To avoid biases in our analysis produced by outliers, we exclude from our database properties that were sold for more than $2,000,000.

[19] Notice, however, that the Census variables' statistics are weighted by the number of homes sold in each Census block-group and do not necessarily represent an accurate description of the whole population of Fairfax County. Instead, they describe only those locations where real estate transactions were made.

[Insert Table 2]

The model can also be estimated using aggregate data. For this reason, we have computed aggregate indicators of the Fairfax County housing market using information from the MLS for each year in the period 2002-2008.[20] Average (log) posting prices, (log) transaction prices, marketing time, and the share of transactions where the market price was below the list price have been computed.

Figures 1 and 2 show how these variables have evolved over time. Housing market conditions during the 2002-2005 period contrast with those in 2007 and 2008. Between 2002 and 2005, average posting prices are only about 1 percent higher than transaction prices and the mean home price appreciation is close to 70 percent. Price discounts below the asking price are not often granted, and the average home seller waits for about 3 weeks before selling her home. Presumably, these conditions are consistent with a hot housing market where sellers have most of the bargaining power (a seller's market). After 2006, the market cools down significantly, housing prices collapse and the gap between list and market prices increases. About 80 percent of sellers are willing to trade at a price lower than the asking price while average marketing time increases to more than 3 months.

[Insert Figure 1]

[Insert Figure 2]

5 Results

In this section, the model is first estimated using individual-level housing transaction data and it is used to analyze the relationship between list prices and marketing time. Then,

[20] 2008 data include transactions that occurred between January and April, only.

aggregate data are used to compute one structural parameter that measures home sellers' bargaining power.

5.1 List prices and marketing time

Individual-level data described in the previous section are used to estimate the model, and parameter estimates are shown in Tables 3a and 3b.[21] Table 3a displays the first set of structural parameters. The estimate of α is positive suggesting that home sellers dislike risk. For the relevant range of values, however, this function is quite linear.[22] λ^s is positive and quite large, suggesting that buyers are quite responsive to changes in posting prices. The estimate of θ is close to 0.5. This means that in about 50 percent of the buyer-seller meetings, the posting price was a take-it-or-leave-it offer to the buyer. We return to these points later.

[Insert Table 3a]

[Insert Table 3b]

In the first column of Table 3b we show estimates for δ^0 and δ. The second column presents coefficients of a standard hedonic model where the dependent variable is the log of the transaction price and the independent variables include the same set of controls used in the structural equations. The coefficients of the hedonic model show the marginal willingness to pay for each of the home's characteristics. The structural parameter δ describes how the intrinsic *value* of a home changes when the features of the housing unit vary. Thus, we expect δ to be close to the coefficients of a hedonic model. As expected, every coefficient has

[21] For estimation, we have normalized the values of the annual discount rate r and λ^q to 0.04 and 1, respectively.

[22] The relevant variable for the utility function is the ratio of the asking price to the value of the home. Our model suggests that the average ratio is 0.26. The estimated function $u(x)$ is essentially linear when $x \epsilon [0, 1]$.

the same sign and is quite close in magnitude.

Notice from Proposition 1 that the model is well defined for a bounded set of parameters. Although the estimation method does not impose any restrictions, the estimates lie within the required bounds. We interpret this as (informal) evidence that the model is correctly specified.

Before we use the estimated model to perform comparative statics, it is useful to assess its ability to fit the data. Within our sample, we use the estimates of the structural model and simulation methods to predict posting prices, transaction prices, and time on the market. Mean log-posting prices and mean log-transaction prices can be directly computed using equations (18) and (19). We simulate time on the market using the estimated coefficients and the structure imposed by the model. That is, marketing is simulated by obtaining independent realizations of a random variable with a probability distribution defined by equation (17). Results are shown on Tables 4a and 4b.

[Insert Table 4a]

[Insert Table 4b]

Given our estimation method, it is not surprising that the predicted means match the actual moments very closely. What is remarkable is that the model is able to simulate the whole *distribution* of time on the market with great accuracy. This is evidenced in Table 4b and in Figure 3. We highlight this point because marketing time is simulated using only the underlined assumptions of the model without imposing any other source of heterogeneity.

[Insert Figure 3]

How do list prices affect the marketing process of a housing unit? The large estimate of λ^s suggests that buyers are quite responsive to changes in posting prices. To get more insights on this, the estimated model is used to compute the effects of changing the list price on time on the market. To perform this exercise, we pick a representative unit with a posting price of $530,000 that expects to be sold in 55 days. We vary the posting price and use the structural model to calculate the expected marketing time. Results are shown in Figure 4. We find that there is a substantially large effect of overpricing on marketing time. This effect is non-linear and increases exponentially as the markup rises. For instance, if the markup, the ratio of the asking price to the expected transaction price, increases by 1 percentage point, the expected time on the market rises by about 10 days; if the mean ratio raises by 10 percentage points, however, marketing time is expected to increase by approximately 200 days.

The effects of list prices on marketing time found here are larger than similar effects documented by other studies (Belkin, Hempel and McLeavey 1976, Kang and Gardner 1989, Yavas and Yang 1995, Knight 2002, Anglin, Rutherford and Springer 2003, and Allen, Rutherford and Thomson 2007, for example).[23] Due to unobserved heterogenetity, however, it is likely that results from previous studies understate the impact of list prices on marketing time.[24] The structural model we estimate solves this problem by explicitly modeling and controlling for unobserved housing heterogeneity.

[Insert Figure 4]

[23]The common empirical approach used by many of these studies is intuitive and straightforward. In a duration model, an explanatory variable that measures the seller's "markup," the (percentage) difference between the posting price and the true value of the home, is included. Since the true value of the unit is unobserved, it is usually replaced by the expected price estimated using a hedonic equation. The coefficient on the markup variable estimates the effects of misspricing on time on the market.

[24]For instance, it is likely that the unexplained residual in a hedonic equation is negatively correlated with the unexplained portion of a time-on-the-market model. That is, a home that has desirable "unobserved" features may sell at at higher price and, other things equal, faster. Since list prices and transaction prices are highly correlated, the markup variable may be negatively correlated with the error term of the duration equation as well. Thus, the coefficient on the markup variable could have a negative bias understating the effects of overpricing.

5.2 Buyers' market? Sellers' market?

In hot housing markets home sellers have the ability to set prices. In cold housing markets the opposite is true: home buyers are the ones who can influence transaction prices the most. Clearly, sellers have most of the bargaining power in hot markets, and viceversa.[25] The structural model developed in this paper provides a natural measure of the seller's bargaining power: θ. A value of θ close to one would suggest that in most meetings the posting price is a take-it-or-leave-it offer to the buyer. This case would be consistent with a "seller's market" where sellers have the ability to set prices, and discounts below the asking price are rarely granted. Similarly, a low value of θ may be consistent with the opposite, a "buyer's market" where buyers set prices and take enough time to consider all their options before engaging in trade.

The estimate of θ using the individual-level data is about 0.5 suggesting that home buyers and home sellers had a similar amount of bargaining power in 2006. How does this estimate change over time? If individual transaction records were available, one could easily replicate the calculations above and estimate θ for other periods. As we mentioned in an earlier discussion, individual housing transaction data are not always available. Given the properties of our estimation method, θ may be computed using readily available aggregate data.

θ is estimated using aggregate data from housing transactions in Fairfax County, VA. For each year in the period 2002-2008, (i) mean log posting prices, (ii) mean log transaction prices, (iii) the share of transactions that occurred at a price below the list price, and (iv) mean number of days that a property stays on the market are used to compute $\hat{\theta}$, the estimate

[25] For a excellent theoretical discussion of hot and cold markets see Novy-Marx (2009).

of the Fairfax County seller's bargaining power.[26]

Results are displayed in Figure 5. Between 2002 and 2005, sellers had most bargaining power in what appears to have been a very hot housing market. After 2006, low values of $\hat{\theta}$ are consistent with a much cooler and rather cold buyers' market. These trends coincide with the swings in home appreciation rates in the area and are consistent with popular perceptions about the "heat" of the housing market.

[Insert Figure 5]

6 Conclusions

This paper illustrates the relationship between the structural parameters of a home seller search model and the coefficients of four linear reduced-form equations that explain a) log list prices, b) log transaction prices, c) marketing time and d) the share of transactions below the list price. This approach is useful because it allows adding a very large set of covariates into the structural model and estimate its parameters at a low computational cost. Moreover, this method allows estimation of structural parameters using individual-level or aggregate data.

The model is first estimated using individual-level housing transaction data and it is used to analyze the relationship between list prices and marketing time. Despite its simplicity, the model is able to replicate the data remarkably well. Results suggest that, the effects of overpricing are large and non-linear. For instance, if the list price to expected price ratio increases by 1 (10) percentage point, the expected time on the market rises by about 10 (200) days. Aggregate data from housing transactions are then used to compute a structural

[26] To be consistent, in all calculations the values of the annual discount rate r and λ^q have been set to 0.04 and 1, respectively.

parameter that measures home sellers' bargaining power for each year in the period 2002-2008. Estimates suggest that sellers had most of the bargaining power before 2006; in later years, the opposite is true. These trends are consistent with popular perceptions about the "heat" of the housing market in the area. We hope that this estimate is useful in other applications where (low budget) index numbers of housing market conditions are needed.

Appendix 1

Given our functional form assumptions $1-\phi(P_s,s)=\left[\frac{P_s}{s}\right]^{-(\lambda^q+\lambda^s)}$, $u(P_s,s)=\frac{1}{1-\alpha}\left[\frac{P_s}{s}\right]^{1-\alpha}$, and $u(R_s,s)=\frac{1}{1-\alpha}\left[\frac{R_s}{s}\right]^{1-\alpha}$. Then, equation (4) becomes

$$
\begin{aligned}
\frac{\left[\frac{P_s}{s}\right]^{1-\alpha}-\left[\frac{R_s}{s}\right]^{1-\alpha}}{(1-\alpha)\left[\frac{P_s}{s}\right]^{-\alpha}} &= \frac{\left[\frac{P_s}{s}\right]}{(\lambda^q+\lambda^s)} \\
\frac{1-\left[\frac{P_s}{R_s}\right]^{-(1-\alpha)}}{1-\alpha} &= \frac{1}{\lambda^q+\lambda^s} \qquad (26) \\
1-e^{-(1-\alpha)\ln\left[\frac{P_s}{R_s}\right]} &= \frac{1-\alpha}{\lambda^q+\lambda^s} \qquad (27) \\
-(1-\alpha)\ln\left[\frac{P_s}{R_s}\right] &= \ln\left\{1-\frac{1-\alpha}{\lambda^q+\lambda^s}\right\} \\
\ln\left[\frac{P_s}{R_s}\right] &= \frac{1}{(1-\alpha)}\ln\left\{\frac{\lambda^q+\lambda^s}{\lambda^q+\lambda^s-(1-\alpha)}\right\}. \qquad (28)
\end{aligned}
$$

Similarly, equation (5) becomes

$$
\begin{aligned}
\frac{1}{1-\alpha}\left[\frac{R_s}{s}\right]^{1-\alpha} &= \beta\theta\frac{1}{1-\alpha}\left[\frac{P_s}{s}\right]^{-(\lambda^q+\lambda^s)+(1-\alpha)} \\
&\quad +\beta\left(1-\theta\left[\frac{P_s}{s}\right]^{-(\lambda^q+\lambda^s)}\right)\frac{1}{1-\alpha}\left[\frac{R_s}{s}\right]^{1-\alpha} \\
\frac{1-\beta}{\beta}\left[\frac{R_s}{s}\right]^{1-\alpha} &= \theta\left[\frac{P_s}{s}\right]^{-(\lambda^q+\lambda^s)+(1-\alpha)}-\theta\left[\frac{P_s}{s}\right]^{-(\lambda^q+\lambda^s)}\left[\frac{R_s}{s}\right]^{1-\alpha} \\
\frac{r}{\theta}e^{(1-\alpha)\ln\left[\frac{R_s}{s}\right]} &= e^{[-(\lambda^q+\lambda^s)+(1-\alpha)]\ln\left[\frac{P_s}{s}\right]}-e^{-(\lambda^q+\lambda^s)\ln\left[\frac{P_s}{s}\right]+(1-\alpha)\ln\left[\frac{R_s}{s}\right]} \\
\frac{r}{\theta}e^{(1-\alpha)\ln\left[\frac{R_s}{s}\right]+[(\lambda^q+\lambda^s)-(1-\alpha)]\ln\left[\frac{P_s}{s}\right]} &= 1-e^{(1-\alpha)\ln\left[\frac{R_s}{s}\right]-(1-\alpha)\ln\left[\frac{P_s}{s}\right]} \\
\frac{r}{\theta}e^{-(1-\alpha)\ln\left[\frac{P_s}{R_s}\right]+(\lambda^q+\lambda^s)\ln\left[\frac{P_s}{s}\right]} &= 1-e^{-(1-\alpha)\ln\left[\frac{P_s}{R_s}\right]}.
\end{aligned}
$$

We substitute (27) in the previous expression and obtain that

$$\frac{r}{\theta}\left[1-\frac{1-\alpha}{\lambda^q+\lambda^s}\right]e^{(\lambda^q+\lambda^s)\ln\left[\frac{P_s}{s}\right]}=\frac{1-\alpha}{\lambda^q+\lambda^s}.$$

Then, we solve for

$$\begin{aligned}\ln\left[\frac{P_s}{s}\right] &= \frac{1}{\lambda^q+\lambda^s}\ln\left\{\frac{\theta}{r}\frac{\alpha}{(\lambda^q+\lambda^s-\alpha)}\right\} \\ P_s &= s\left\{\frac{\theta}{r}\frac{\alpha}{(\lambda^q+\lambda^s-\alpha)}\right\}^{\frac{1}{\lambda^q+\lambda^s}}.\end{aligned}$$

Finally, equation (28) is used to find R_s.

Appendix 2

Let $\hat{\kappa}^{p_s}$, $\hat{\kappa}^{p_m}$, $\hat{\kappa}^d$, and $\hat{\kappa}^T$ be the constant terms of the (reduced-form) moment conditions 1, 2, 3 and 4, respectively. From equations (18) and (19), it is clear that

$$\hat{\kappa}^{p_s}=\hat{\delta}^0+\frac{1}{\lambda^q+\hat{\lambda}^s}\ln\left\{\frac{\hat{\theta}}{r}\frac{1-\hat{\alpha}}{(\lambda^q+\hat{\lambda}^s-(1-\hat{\alpha}))}\right\}$$

and

$$\begin{aligned}\hat{\kappa}^{p_m} &= \hat{\delta}^0+\frac{1}{\lambda^q+\hat{\lambda}^s}\ln\left\{\frac{\hat{\theta}}{r}\frac{1-\hat{\alpha}}{(\lambda^q+\hat{\lambda}^s-(1-\hat{\alpha}))}\right\} \\ &\quad -\frac{1-\tilde{\theta}}{1-\hat{\alpha}}\ln\left\{\frac{\lambda^q+\hat{\lambda}^s}{\lambda^q+\hat{\lambda}^s-(1-\hat{\alpha})}\right\}.\end{aligned}$$

Substracting these two equations it is found that

$$\frac{\hat{\kappa}^{p_s}-\hat{\kappa}^{p_m}}{\hat{\kappa}^d}=\frac{1}{1-\hat{\alpha}}\ln\left\{\frac{\lambda^q+\hat{\lambda}^s}{\lambda^q+\hat{\lambda}^s-(1-\hat{\alpha})}\right\}, \tag{29}$$

where $\hat{\kappa}^d$ has been used to estimate $1-\tilde{\theta}$. Notice that one can use the definition of $\tilde{\theta}$ to find that

$$
\begin{aligned}
1-\hat{\lambda}^{d} &= \tilde{\theta} \\
&= \frac{\hat{\theta}\,\Pr\{trade|P=P_s^*\}}{\Pr\{trade\}} \\
&= \frac{\hat{\theta}\frac{r}{\hat{\theta}}\frac{(\lambda^q+\hat{\lambda}^s-(1-\hat{\alpha}))}{1-\hat{\alpha}}}{\Pr\{trade\}} \\
&= \frac{r\frac{(\lambda^q+\hat{\lambda}^s-(1-\hat{\alpha}))}{1-\hat{\alpha}}}{1/\hat{\kappa}^T},
\end{aligned} \tag{30}
$$

where we have used equation (15) to compute $\Pr\{trade|P=P_s^*\}$ and the properties of the geometric distribution to estimate the unconditional probability that trades occurs. After some manipulation, we obtain that

$$
\lambda^q+\hat{\lambda}^s=(1-\hat{\alpha})\left(1+\frac{1-\hat{\kappa}^d}{\hat{\kappa}^T r}\right). \tag{31}
$$

After replacing (31) into (29) it is found that

$$
\begin{aligned}
1-\hat{\alpha} &= \frac{\hat{\kappa}^d}{\hat{\kappa}^{p_s}-\hat{\kappa}^{p_m}}\ln\left\{\frac{\hat{\kappa}^T r+(1-\hat{\kappa}^d)}{1-\hat{\kappa}^d}\right\} \\
\hat{\alpha} &= 1-\frac{\hat{\kappa}^d}{\hat{\kappa}^{p_s}-\hat{\kappa}^{p_m}}\ln\left\{1+\frac{\hat{\kappa}^T r}{1-\hat{\kappa}^d}\right\}.
\end{aligned}
$$

This result can be plugged back into (31) to obtain

$$
\lambda^q+\hat{\lambda}^s=(1-\hat{\alpha})\left(1+\frac{1-\hat{\kappa}^d}{\hat{\kappa}^T r}\right).
$$

Let us now use the fourth moment condition

$$
\hat{\kappa}^T=\frac{1}{\hat{\theta}\,\Pr\{trade|P=P_s^*\}+(1-\hat{\theta})\,\Pr\{trade|P=R_s^*\}}. \tag{32}
$$

Notice from (30) that $\hat{\theta}\Pr\{trade|P = P_s^*\} = (1-\hat{\kappa}^d)/\hat{\kappa}^T$. Also note that

$$
\begin{aligned}
\Pr\{trade|P &= R_s^*\} = \left[\frac{r}{\hat{\theta}}\frac{(\lambda^q + \hat{\lambda}^s - (1-\hat{\alpha}))}{1-\hat{\alpha}} . \left(\frac{\lambda^q + \hat{\lambda}^s}{\lambda^q + \hat{\lambda}^s - (1-\hat{\alpha})}\right)^{\frac{\hat{\lambda}^s}{1-\hat{\alpha}}}\right] \\
&= \left[\frac{1}{\hat{\theta}}\left\{r\frac{(\lambda^q + \hat{\lambda}^s - (1-\hat{\alpha}))}{1-\hat{\alpha}}\right\} . \exp\left\{\frac{\hat{\lambda}^s}{1-\hat{\alpha}}\ln\left(\frac{\lambda^q + \hat{\lambda}^s}{\lambda^q + \hat{\lambda}^s - (1-\hat{\alpha})}\right)\right\}\right] \\
&= \left[\frac{1}{\hat{\theta}}\left\{\frac{1-\hat{\kappa}^d}{\hat{\kappa}^T}\right\} . \exp\left\{\hat{\lambda}^s \frac{\hat{\kappa}^{p_s} - \hat{\kappa}^{p_m}}{\hat{\kappa}^d}\right\}\right].
\end{aligned}
$$

We replace this into (32)

$$
\hat{\kappa}^T = \frac{1}{(1-\hat{\kappa}^d)/\hat{\kappa}^T + \frac{(1-\hat{\theta})}{\hat{\theta}}\left\{\frac{1-\hat{\kappa}^d}{\hat{\kappa}^T}\right\} . \exp\left\{\hat{\lambda}^s \frac{\hat{\kappa}^{p_s} - \hat{\kappa}^{p_m}}{\hat{\kappa}^d}\right\}}
$$

and solve for $\hat{\theta}$

$$
\hat{\theta} = \frac{1}{1 + \left(\frac{\hat{\kappa}^d}{1-\hat{\kappa}^d}\exp\left\{-\hat{\lambda}^s \frac{\hat{\kappa}^{p_s} - \hat{\kappa}^{p_m}}{\hat{\kappa}^d}\right\}\right)}.
$$

We now have enough information to derive

$$
\hat{\delta}^0 = \hat{\kappa}^{p_s} - \frac{1}{\lambda^q + \hat{\lambda}^s}\ln\left\{\frac{\hat{\theta}}{r}\frac{1-\hat{\alpha}}{(\lambda^q + \hat{\lambda}^s - (1-\hat{\alpha}))}\right\}.
$$

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Table 1: Description of Variables

Variable	Description
	Transaction
Ps	Listing price in thousands $
Pm	Transaction price in thousands $
DOM	Days on the market
Ps>Pm	Equals one if listing price is greater that the transaction price
	Housing unit
Sqft	Living area square feet
Acreage	Lot acreage
Bedrooms	Number of bedrooms
Full Bathrooms	Number of full bathrooms
Half Bathrooms	Number of half bathrooms
Basement	Equals one if unit has a basement and zero otherwise
Central	Equals one if unit has central heating and zero otherwise
Fireplace	Number of fireplaces
New	Equals one if unit is new and zero otherwise
Age	Age of the unit (in years)
HOA	Equals one if property has a home ownership association and zero otherwise
Detached [a]	Equals one if unit is a detached single family home
Townhome [a]	Equals one if unit is a townhome
	Neighborhood
Density	Population density in Census Block Group (CBG)
Black	Proportion of Blacks in CBG
Hispanic	Proportion of Hispanics in CBG
Greater than 65	Proportion of population older than 65 in CBG
HS dropouts	Proportion of high school dropouts in CBG
Unemployment	Unemployment rate in CBG
Income	Median household income in CBG (in 1999 thousands $)

[a] For definitions see text.

Table 2: Descriptive Statistics

Variable	Mean	St. Dev.	Min	Max
Transaction				
Posting price	555.8	266.2	125.0	2,650.0
Transaction price	528.4	244.5	125.0	1,995.0
Days on the market	54.9	53.2	1.0	391.0
Equals one if Ps > Pm	0.73	0.44	0.0	1.0
Unit				
Sqft	1,709.3	834.4	426.0	9,590.0
Acreage	0.21	0.46	0.0	8.6
Bedrooms	3.30	1.07	0.0	13.0
Full Bathrooms	2.29	0.83	1.0	8.0
Half Bathrooms	0.77	0.64	0.0	11.0
Basement	0.69	0.46	0.0	1.0
Central	0.94	0.24	0.0	1.0
Fireplace	0.90	0.71	0.0	5.0
New	0.02	0.15	0.0	1.0
Age	25.8	15.3	0.0	136.0
HOA	0.61	0.49	0.0	1.0
Detached	0.45	0.50	0.0	1.0
Townhome	0.38	0.49	0.0	1.0
Neighborhood				
Density	20.9	21.5	0.2	237.5
Black	0.08	0.09	0.0	0.9
Hispanic	0.10	0.09	0.0	0.7
Greater than 65	0.08	0.06	0.0	0.5
HS dropouts	0.08	0.08	0.0	0.7
Unemployment	0.02	0.02	0.0	0.2
Income	85.9	28.2	14.5	200.0
Observations	14,182			

Table 3a. Structural Parameters

α	0.522
$\lambda^q + \lambda^s$	15.971
θ	0.486
σ^u	0.108

Note: We normalize the annual discount rate r=0.04 and λ^q=1. All coefficients are significant at the 1% level.

Table 3b. Structural Coefficients of ln*(s)* and OLS

	(1) Structural estimates of ln*(s)*		(2) OLS Dependent variable is the log of transaction prices	
δ^0	2.038	(0.080) ***		
Constant			2.368	(0.079) ***
Log square footage	0.340	(0.004) ***	0.334	(0.006) ***
Acreage	0.080	(0.004) ***	0.075	(0.005) ***
Bedrooms	0.029	(0.002) ***	0.030	(0.002) ***
Full Bathrooms	0.045	(0.002) ***	0.044	(0.002) ***
Half Bathrooms	0.013	(0.002) ***	0.012	(0.003) ***
Basement	0.062	(0.002) ***	0.063	(0.003) ***
Central	-0.001	(0.003)	0.000	(0.004)
One fireplace	0.028	(0.002) ***	0.027	(0.002) ***
More than one fireplace	0.074	(0.003) ***	0.074	(0.004) ***
New	0.006	(0.008)	0.027	(0.012) **
Age	-0.010	(0.000) ***	-0.010	(0.001) ***
Age ^{2}	0.0001	(0.000) ***	0.0001	(0.000) ***
HOA	0.006	(0.002) **	0.004	(0.003)
Detached	0.357	(0.005) ***	0.357	(0.007) ***
Townhome	0.148	(0.003) ***	0.153	(0.005) ***
Density	-0.006	(0.002) ***	-0.006	(0.002) ***
Black	-0.159	(0.015) ***	-0.152	(0.021) ***
Hispanic	0.054	(0.016) ***	0.064	(0.023) ***
Greater than 65	0.292	(0.019) ***	0.290	(0.026) ***
HS dropouts	0.006	(0.019)	0.005	(0.027)
Unemployment	0.088	(0.050) *	0.075	(0.070)
Log median household income	0.082	(0.005) ***	0.082	(0.006) ***
Dummies for Month/Year (11)	Yes		Yes	
Dummies for Zip Codes (51)	Yes		Yes	
R square			0.931	
Number of observations	14,182		14,182	

Notes: Robust standard errors in parenthesis.
*, **, ***, denote significance at the 10, 5, and 1 percent level, respectively.

Table 4a. Within Sample Fit: Means

Variable	Mean Actual	Mean Predicted
Posting price ($ thousands)	555.81	551.21
Transaction price ($ thousands)	528.36	526.33
Days on market	54.93	54.71

Table 4b. Within Sample Fit: Marketing Time C.D.F.

Percentile	Actual	Predicted
5th	1	3
10th	6	6
25th	15	16
50th	38	38
75th	78	76
90th	127	124
95th	164	161

Note: To simulate time on the market, we first use the structural parameters of the model to construct ω, the unconditional per-period probability of trade. Then, for each property and every period t we draw an independent realization of a standard uniform random variable, u. If u is less than ω, then trade occurs at period t; otherwise, the seller stays on the market for another period. We repeat this procedure until every unit in our sample has been sold.

Figure 1
Mean List and Transaction Price

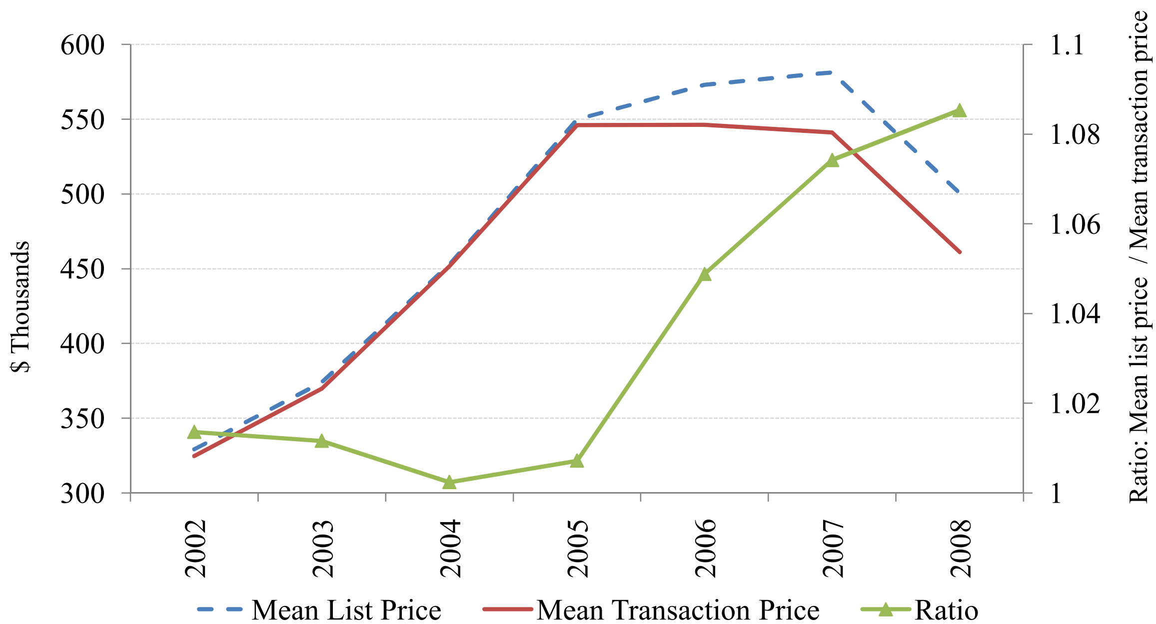


Figure 2
Marketing Time and Price Discounts

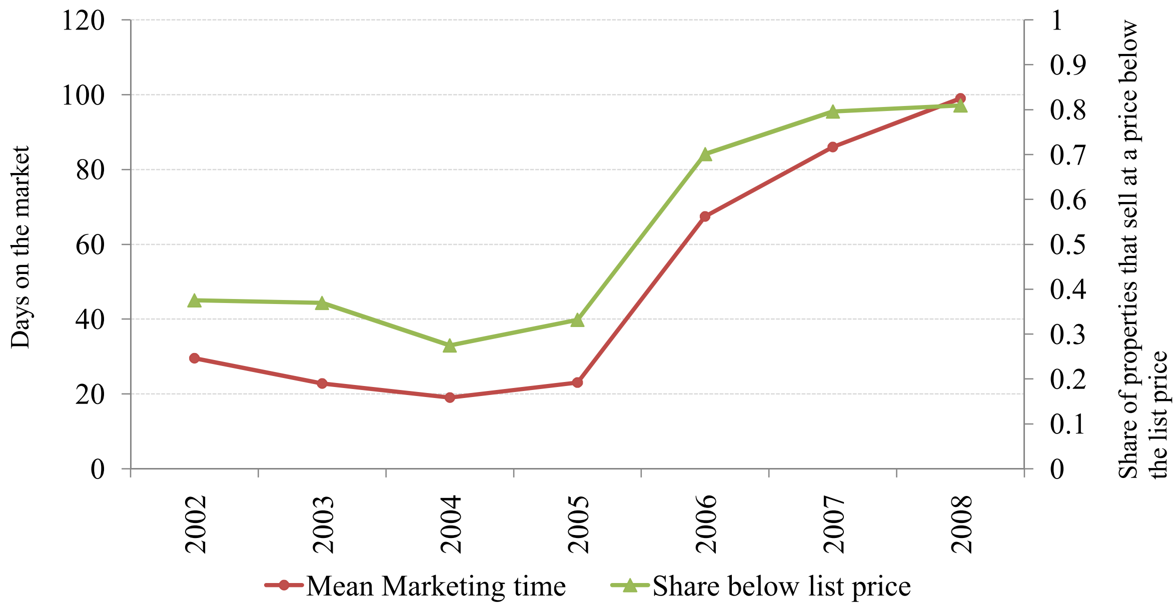


Figure 3
Distribution of Marketing Time
Actual vs. Predicted Empirical C.D.F.

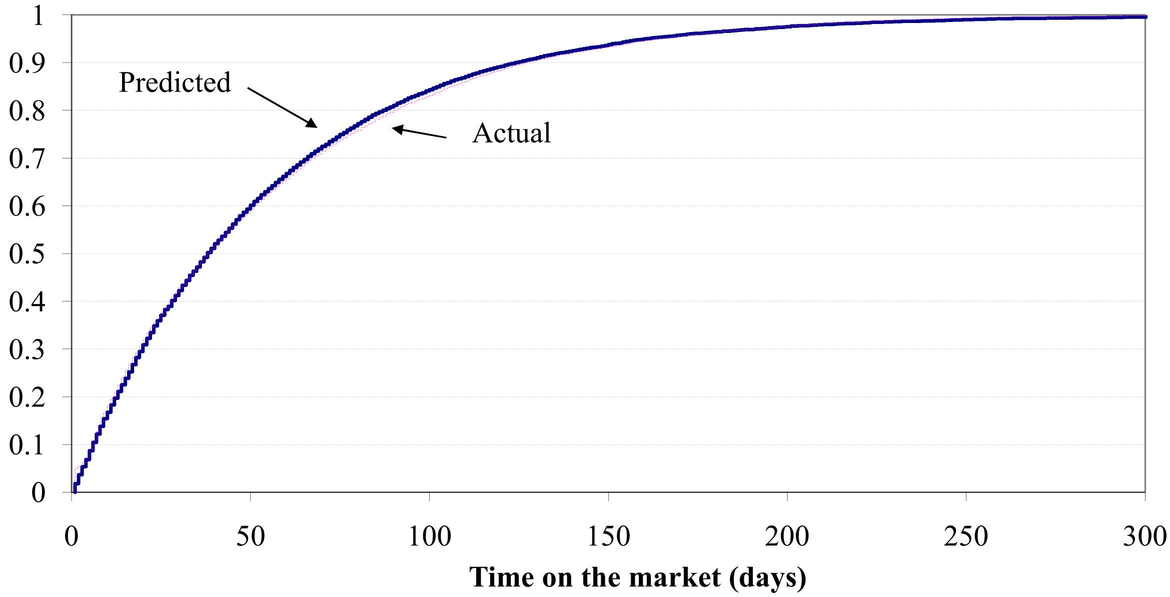


Figure 4
List Price and Time on the Market of Average Unit

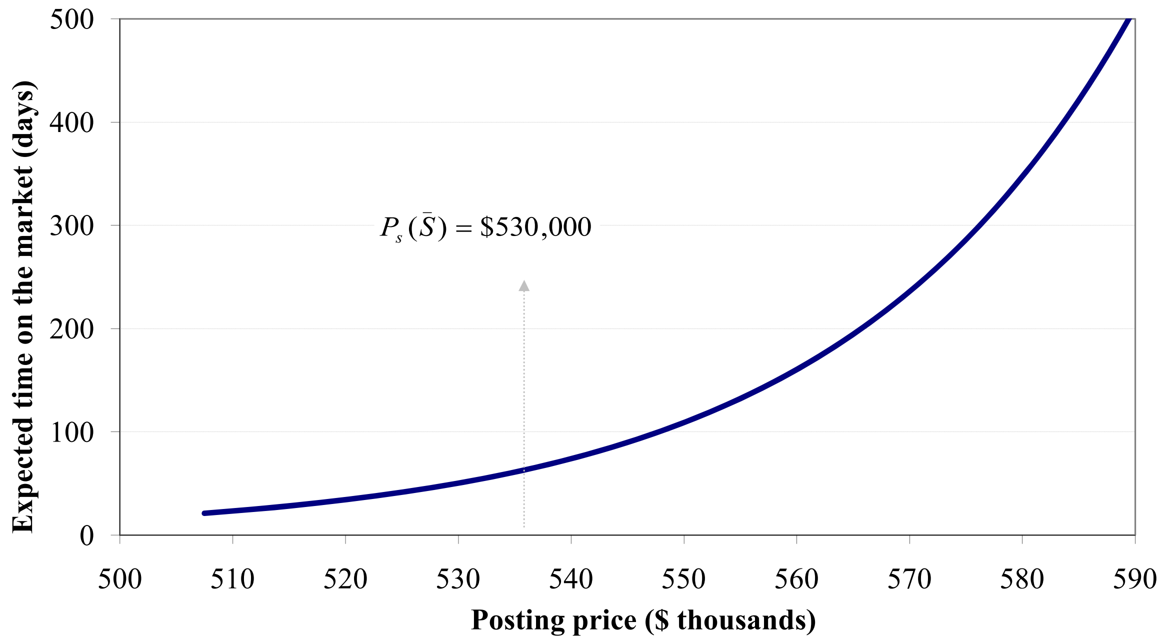
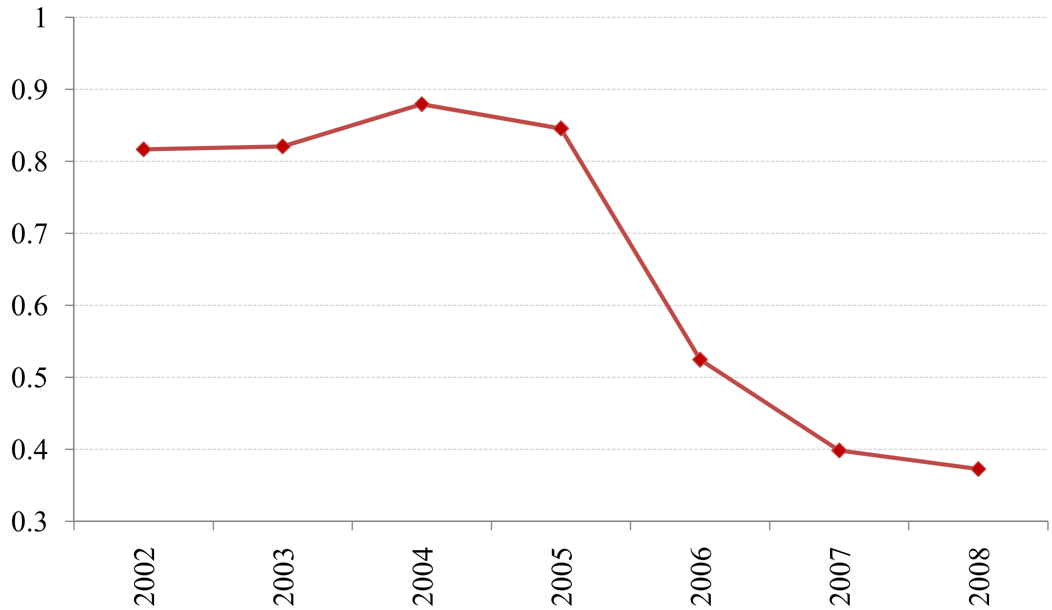


Figure 5
Seller's Bargaining Power



Notes: Seller's bargaining power has been computed using equation (24) and aggregate annual data from Fairfax County, VA.