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A fundamentalist theory of real estate market outcomes

Stuart J. Fowler[a,*], Jennifer J. Fowler[b], Philip A. Seagraves[a], Charles F. Beauchamp[c]

[a] Economics and Finance Department, MTSU, Box 27, Murfreesboro, TN 37132, USA
[b] Jack C. Massey College of Business, Belmont University, Nashville, TN 37212, USA
[c] College of Business, Mississippi College, USA

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ABSTRACT

This study introduces and estimates a structural model of search and matching in real estate markets. There are benefits of developing such a theory to better understand the structure that determines these processes. First, the estimation method accurately and efficiently models the structural demand and supply functions of buyers and sellers. Second, the model replicates several salient features of real estate markets with respect to how sales price and weeks on the market are correlated across time and sellers. Finally, despite full seller rationality, the model predicts sticky sales prices by fact of the trade-off between price and weeks on the market.

1. Introduction

Two salient and well known empirical findings from real estate research are: (i) there is a positive cross-sectional relationship between sales price and time on the market (*e.g.*, Miller, 1978; and Asabere and Huffman, 1993) and (ii) there is a negative time-series relationship between sales price and time on the market (the positive price-volume correlation anomaly is studied by Stein, 1995 and Genesove and Mayer, 1997). With regards to the cross-sectional fact, it is of interest to understand why some owners delay selling for the opportunity of a higher price while others do not. Similarly, the time-series fact naturally leads one to ask: during times of falling demand, why don't owners lower their sales price to keep time on the market from increasing?

In an earlier paper, Case and Shiller (1988) address the time-series fact and conclude behavioral reasons for the negative time-series correlation. The behavioral explanations given by Case and Shiller (1988) include notions of fairness, intrinsic worth, and irrational exuberance which all result in home owners being unable to recognize the reality of the situation. When sellers do not recognize reality, housing prices are determined, in part, by non-fundamentals. In contrast, a price theory grounded in fundamentals would result when property owners evaluate current and future expected discounted net benefits of their decisions. That is, sellers solve a dynamic program. The main purpose of this research is to develop and evaluate a fundamentalist theory of real estate market outcomes. The benefit of this endeavour is that it provides competition benchmarks for alternative theories such as those proposed by Case and Shiller (1988).

The empirical approach presented in this paper uses a discrete choice dynamic programming (DCDP) model of real estate owners' selling decisions. A key feature of DCDP models is that equilibrium decisions are made on a reservation price basis; an action is undertaken when the offer price exceeds the reservation price.[1] The reservation price is determined by comparing current offers to the expected discounted value of potential future offers. In this case, the dynamic programming problem is of searching for offers until a match is found. As noted by Miller (1978), models of search and matching naturally extend to real estate markets – a prime example is the decision to accept an offer on a real estate property.

Yinger (1981) is credited with first applying a search model to real estate. His study models real estate broker search efforts. In this case, a

* Corresponding author.

E-mail addresses: stuart.fowler@mtsu.edu (S.J. Fowler), jennifer.fowler@belmont.edu (J.J. Fowler), philip.seagraves@mtsu.edu (P.A. Seagraves), cfbeauchamp@mc.edu (C.F. Beauchamp).

[1] See Keane and Wolpin (2009) for a review of applications of DCDP models.

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broker's search effort is weighed against the uncertainty of the arrival and size of offers to the expected discounted costs of brokering an unsold house. Subsequent studies have used search and matching models for the purpose of examining the relationships between, for example, price, vacancies, and the time it takes to sell a home (*e.g.*, Wheaton, 1990; Stein, 1995; Read, 1997; Caplin and Leahy, 2008; Cheng et al., 2008). Though theoretical DCDP models of search and matching are becoming more prominent in the real estate literature, there are few studies[2] on the structural estimation of these models. Structural estimation is desirable as it captures the dynamic, forward-looking behavior of individuals. The dearth of research on structural estimation is due to, as we see it, the nature of the data sets used in real estate research. Real estate researchers often have detailed data sets that make the estimation of structural dynamic programming problems difficult since the "curse of dimensionality"[3] is a significant obstacle. Thus, an ancillary purpose of our study is to introduce an estimable structural model of search and matching in real estate markets.

The model and estimation method we implement has several key features. To start, the model is stylized. By stylized we imply that the model is in the same spirit as Yinger (1981). That is, the demand for property follows a simple hedonic pricing relationship. Second, supply decisions depend on the seller's preferences (utility) and beliefs of the structure of future offers. Third, the model is flexible as it is easy to extend to include idiosyncratic elements to agents' choices not considered by Yinger (1981). One such extension considered relates to differences in how agents discount current and future payoffs. Fourth, the estimation method is derived from a class of Bayesian Markov-Chain-Monte-Carlo (MCMC) methods studied by Geweke and Keane (2000), Imai et al. (2009), and Norets (2009). A key to these methods is that the value function is approximated and thus breaks the "curse of dimensionality" to the dynamic programing problem.[4]

The estimation method is implemented on a unique set of data. This study uses multiple listing service data from the Mt.Tabor-Richmond-Sunnyside neighborhoods of Portland, Oregon. The data extracted cover the weekly time period of March 2008 to August 2015. During this period, a sample of houses on the listing service is followed to completion of sale (last sale closed in October 2015). The resulting data set is an unbalanced panel with an observation length of 1458 weeks. The data-set contains details of the housing attributes (all built within 20 years of the turn of the twentieth century, 1892–1920) and information on when offers are accepted or rejected by the seller. Though rejection is not necessary, the information contained in the rejection of offers improves the efficiency of our reservation price estimates.

A main result of the study is that the estimated DCDP model replicates two well known empirical facts. First, patient sellers (due to lower opportunity costs of not selling) receive higher sales prices but take longer to sell. In this case, when preferences are heterogenous with respect to this type of patience, the DCDP model generates a positive cross-sectional relationship between sales price and time on the market (*e.g.*, Miller, 1978; and Asabere and Huffman, 1993). Second, falling demand, represented by falling offer rates, is smoothed over the seller's two margins of choices: maximize selling price while minimizing time on the market. In this case, falling demand leads to a partial lowering of the seller's reservation price. In total, the sales price falls and time on the market increases. This represents the positive price-volume correlation anomaly studied by Stein (1995) and Genesove and Mayer (1997).

The rest of this paper is organized as follows. Section 2 defines the discrete choice model. Section 3 describes the data. The Bayesian estimator is presented in Section 4. Section 5 presents the results. Finally, the paper concludes with Section 6.

2. The model

The model economy is populated by agents who are separated into two categories: sellers and buyers. A seller, who has already exogenously decided to list the property, solves a stochastic dynamic programming problem by choice of a reservation price. The two types of stochastic uncertainty that face the sellers are: (i) uncertainty about the arrival of buyers and (ii) uncertainty about the amount of offer to be made on their property. The ith seller weighs the benefits of accepting the offer against the expected discounted value of future offers given the uncertainty and a set of the current states $\Omega_{i,t}$.

For the model economy, time evolves in discrete units called periods, specified to be one week long in the quantitative results to follow. At the start of the economy ($t = 0$), a seller announces a preset listing price. In the beginning of a period, an offer is made on the house. At the end of the period, the seller makes a decision to sell or hold. An accepted offer means that bidding ends. If an offer is rejected or if an offer doesn't arrive, time evolves one period and the process begins again.

2.1. Housing demand

Housing demand for the ith house follows a Bernoulli process with an offer rate of $1 - \lambda_i$; alternatively, an offer will not be made with probability λ_i. When an offer is made, it is assumed that each buyer values the property by its attributes plus some idiosyncratic part that is specific to their utility. That is, the buyer makes a time t offer on the ith house that follows a hedonic pricing formula (demand) of:

$$\ln P_{i,t} = \mathbf{x}_i \alpha + \varepsilon_{i,t}, \tag{1}$$

where $\varepsilon_{i,t} \sim N(0, \sigma_\varepsilon^2)$ and $\mathbf{x}_i$ is a vector of housing characteristics. The $\mathbf{x}_i \alpha$ term represents the deterministic value of house i fixed across all buyers – a common assumption in the real estate literature (*e.g.*, Yinger, 1981). Due to differences in utility, each buyer has idiosyncratic preferences for each property; $\varepsilon_{i,t}$ are the differences in valuation by the buyers. Because $\varepsilon_{i,t}$ is random from the seller's point of view, it represents part of the seller's uncertainty about the offer process.

The offer rate is determined by a probit link function. More specifically, we define the probability that an offer will not be made as $\lambda_i = 1 - \Phi(\mathbf{z}_i \phi)$ where $\Phi(\cdot)$ is the density of the standard normal distribution function and $\mathbf{z}_i$ is a vector of the demand covariates. One covariate considered is whether the house has an online virtual tour. Increased information from virtual tours can facilitate seller/buying matching thereby decreasing λ_i. On the other hand, virtual tours may discourage bidders if the pictures show the property in a negative light. Recently, Carrillo (2008) found that virtual tours are negatively correlated with time on the market in the Washington D.C. Metropolitan Area.

2.2. The Seller's preferences and the Bellman equation

A property owner (the seller) evaluates current offers to expectations of future offers. Because the seller is comparing payoffs across time, discounting is an important component of the seller's preferences. In the model, there are two types of discounting. The first type of discounting is that all net payoffs are normalized relative to the average sales price in the market (denoted P^s). Therefore, property owners are evaluating real offers. The other type of discounting involves a rate of time preference, β. This rate captures the trade off between consumption today and consumption in the future. It is important to note that β

[2] Carrillo (2012) and Merlo et al. (2015) are examples of structural estimation in the real estate literature.

[3] In solving the dynamic programming problem, the Bellman equation must be solved at each possible point in the state space. The possible number of points in the state space increases exponentially with the increased dimension of the state space. This is commonly referred to as the "curse of dimensionality." See Keane et al. (2011) for details.

[4] Essentially, the dynamic programming problem is only solved once during a single estimation routine.