The Market Thickness and the Impact of Unemployment on Housing Market Outcomes

Li Gan and Qinghua Zhang

Abstract

The housing market exhibits a puzzling phenomenon that transaction volume and prices are strongly positively correlated. This paper develops and estimates a dynamic search-matching model to study the impact of the unemployment rate on the housing market in the presence of the thick market effect. Our analysis shows that an increase in the unemployment reduces the number of buyers, weakens the homeowners’ tendency to change houses and generates poorer matching quality. As a consequence, prices and the transaction volume both decline more than in the absence of the thick market effect. In particular, at 7.0% unemployment rate, the price-unemployment elasticity is -0.0508 in the short run and -0.0588 in the long run, and the volume-unemployment elasticity is -0.260 in the short run and -0.198 in the long run, corresponding to a volume-price elasticity 5.118 in the short run and 3.367 in the long run, comparable with the observed aggregate elasticity of 4. In addition, a larger city with typically more buyers and sellers experiences a smaller change in prices in response to the same change in the unemployment rate.

Key Words: housing market transactions, unemployment rate, the thick market effect, price-transaction volume, search-matching

JEL Classifications: L1, R2

---

1 Gan: Department of Economics, Texas A&M University, College Station, TX 77843-4228, and NBER. gan@econmail.tamu.edu; Zhang: Guanghua School of Management, Peking University, Beijing, China 100871. zhangq@gsm.pku.edu.cn. An earlier version of this paper was circulated as NBER Working Paper #12134 under the title “The Thick Market Effect on Housing Market Transaction.”
1. Introduction

This paper develops a search-matching model of the residential housing market to study the effects of changes in market size driven by changes in economic environment such as the unemployment rate. Through structural estimation using the city-level data in Texas, we identify the marginal disutility of mismatch. Simulations based on the structural estimates show that the market thickness plays an important role in the housing market outcomes. Specifically, an increase in the unemployment rate reduces the numbers of buyers and leads to poorer matching quality. As a result, both prices and transactions decline more than in the absence of the thick market effect. In addition, larger cities with more buyers and sellers would experience a smaller change in prices than smaller cities when facing a similar change in unemployment rates.

The positive correlation between housing prices and transaction volumes is well documented in the literature. Using aggregate data, Stein (1995) finds that the elasticity of transaction volume with respect to price is 4, i.e., a decrease of 10 percent in price is related to a 40 percent decrease in transaction volumes. The standard model such as Poterba (1984) has difficulty in explaining this strong and positive relationship.

So far, literature has offered two alternative explanations on this positive correlation. The down-payment hypothesis of Stein (1995) is empirically supported by Genesove and Mayer (1997). This hypothesis concentrates on the liquidity constraint of individual households. A household who wants to sell her house often needs the equity from the house to pay the down-payment of the new house. When the house price is down, households may not be able to afford the down-payment of the new house. Therefore, prospective sellers intend to hold their current houses longer. In Ortalo-Magné and Rady (2006), houses are divided into “starter” homes and “trade-up” homes. An increase in the household income will drive the price of “starter” homes up. Thus more owners of “starter” homes may be able to afford the down payment of new “trade-up” homes and thus get ready to move up, which may in turn raise the price of “trade-up” homes. The loss-aversion hypothesis, on the other hand, is based on the prospect theory of Kahneman and Tversky (1979) who argue that the marginal disutility from a loss is larger than the marginal utility from a gain. Due to the loss aversion, sellers tend to hold their houses in hope of offers higher than the original purchasing prices when facing a down market, even though they would encounter additional financial loss by doing so. Thus a decline in price leads to reduced transaction volumes. Genesove and Mayer (2001) and Engelhardt (2003) provide supportive evidence to the loss aversion hypothesis.
This paper offers a complementary explanation to the positive correlation between prices and transactions. In the model, houses are heterogeneous in their characteristics and people have heterogeneous preferences on houses. When there are fewer buyers and sellers, the market is thinner and the quality of matching between a buyer and a seller is poorer on average. A poorer matching quality leads to a lower price and a lower probability of selling, and a longer time to sale. This phenomenon is referred as the thick market effect in this paper.

The unemployment rate has both a direct effect and an indirect effect on the housing market. Directly, it serves as a financial constraint and reduces the number of buyers since being unemployed practically prevents a household from entering the housing market as a buyer. As to the indirect effect, an increase in unemployment would raise the difficulty to sell and consequently weaken the homeowners’ tendency to change houses. The average matching quality is thus lowered and the matching process between buyers and sellers slows down. As a consequence, both the transaction volume and the house price decline simultaneously, producing a positive correlation between these two variables.

The key feature in our model is the market size, characterized by the number of buyers and the number of sellers in the market. It is a common belief that market size should matter in matching buyers and sellers, and a market with more buyers and sellers should facilitate the matching process. It is less clear that how precisely that the market size affects the outcomes. Diamond (1982) suggests that market size may generate a positive feedback: more people in the market to produce and to trade could lead to increased willingness to produce and to trade. However, among relatively few papers that have studied the thickness effect on the market outcomes, there is no consensus regarding this intuition. For example, a thicker market has adverse effect in Burdett, Shi and Wright (2002), has no effect in Lagos (2001), and has a positive effect in Coles and Smith (1999). More recently, Gan and Li (2005) provide a model using the matching mechanism of Roth (1984) and show that the average matching probability increases while the variance of the matching probabilities decreases as market becomes thicker. They also test their model using job markets for fresh PhDs in economics.

In a dynamic setting, Zhang (2002) develops a model to show how the thick market effect speeds up the relocation of used capital goods. Gan and Zhang (2006) propose a model to study how market size affects local labor markets, and show in empirical data that a thicker market (characterized by the number of labor force) has a lower average unemployment rate, shorter unemployment cycles, and a lower peak unemployment rate. Lying in the heart of the above models is the thick market effect improving the matching quality in a search-
matching framework. The model in this paper is similar to the above models. While Zhang and Gan (2006) and Zhang (2002) concentrate on the timing of matching and the corresponding cyclical fluctuations, the current paper emphasizes the average selling probabilities.

However, none of the above matching papers provide direct evidence on the role of market thickness in the matching process. Our paper contributes to the literature by directly identifying the marginal disutility from mismatch through a structural estimation. Therefore, our paper is able to look into how the market thickness facilitates matching process through improving matching quality.

It is not new in the literature to apply search-matching models to study housing markets. For example, Wheaton (1990) develops a search model to show how the price and time to sale adjust to the vacancy rate in the short run; and how in the long run the structural vacancy rate is determined through free entry. In his model, there are two types of households and two types of houses correspondingly. Households change types randomly, which generates mismatch and creates turnover. Arnott (1989) investigates rental housing vacancies. Because of the heterogeneity of both households and houses, mismatch incurs, which confers monopoly power on landlords who set rents above costs. His model predicts that when the rental market size is larger, landlords possess weaker monopoly power and thus set a lower rent, which leads to lower vacancy rate. Mayer (1995) presents a negotiated-sale model in the housing market following the setting of Arnott (1989). The simulations of his model show that a larger market has a lower vacancy rate, a shorter time-to-sale and a lower sale price.

However, none of the above housing papers focus on the impact of changes in economic environment on the search-matching outcomes. This paper incorporates the unemployment rate into the model as a financial constraint to buyers. The model thus provides a framework to study how demand shocks affect housing market transactions; how the thick market effect strengthens the impact of demand shocks; and how communities of different sizes experience demand shocks differently because of the marginally diminishing thickness effect. Following the tradition of the search-matching literature, we focus on the stationary equilibrium. We investigate the change in the steady state caused by changes in the unemployment rate rather than the transitory dynamics.

Our matching model is estimated using the Texas city-level data for the years of 1990 and 2000. The set of parameters are obtained by matching the predicted values from the model with the observed values in time-to-sale, average housing prices and average rental
price at the city level. Both a short run model and a long run model are estimated and the results are qualitatively similar. More specifically, the estimated parameter value that measures the marginal disutility from mismatch indicates a thicker market would generate a higher price and a larger transaction volume. Our simulations using the estimated parameters suggest that a decrease (increase) in unemployment rates would lead to a higher (lower) housing price and a larger (smaller) transaction volume, creating a positive relationship between the housing price and transaction volume. In addition, changes in either prices or transactions in response to changes in unemployment are much smaller in the absence of the thick market effect. In the short run, we find that in the presence of the thick market effect, a two percentage points increase in unemployment rate would result in an increase of the housing price by 1.59% and an increase of the transaction volume by 6.74%. In the long run, a two percentage increase in unemployment rate increase the housing prices by 2.07% and transaction volume by 6.22%. The price-unemployment elasticities are -0.0508 in the short run and -0.0588 in the long run, and the volume-unemployment elasticities are -0.260 in the short and -0.198 in the long run, corresponding to a volume-price elasticity at 5.118 in the short run and 3.367 in the long run, comparable with the value of 4.0 in Stein (1990).

Moreover, our simulation indicates that in a larger market with more buyers and sellers, when the unemployment rate goes up (or down), the sale price decreases (or increases) by a smaller percentage than in a smaller market. This result is consistent with an empirical study of the Houston market by Smith and Tesarek (1991) and Mayer (1993). Smith and Tesarek show that prices of more expensive houses rose by larger percentages during the housing market boom while drop by larger percentages during the bust. For example, high-quality houses (with a market value above $150,000 in 1970) increased in value at an annual rate of 9.0% during the period of 1970-1985, while lost 30% of the value during 1985-1987. In the meantime, low-quality houses (with a market value below $50,000 in 1970) increased in value by 8.3% per year over 1970-1985 while lost in value by 18% during 1985-1987. Our model would predict this phenomenon since high-price range houses are typically in a thinner market with smaller numbers of buyers and sellers.

The rest of the paper is organized as follows. Section 2 describes the model in detail. Section 3 first describes the estimation strategy. It then proceeds to discuss the data and the estimation results. The estimated parameters are applied to simulate the effect of changing unemployment rates on housing market transactions, suggesting a significant thick market effect. Section 4 concludes the paper.
2. The Model

In this section, we develop a search-matching model of the housing market. The model demonstrates how changes in the unemployment rate change both the numbers of buyers and sellers in the market, which in turn affects the matching quality and market outcomes such as prices, transaction volumes and time-to-sale. We describe the model in seven parts, denoted as part (a) to (g). We first present the short run model where the number of total houses in a market is fixed, in part (a)-(f). In the last part (g), we extend our model to the long run framework by allowing total number of houses in the market to be endogenously determined.

(a) The basic setup

We first describe the basic setup. The number of households in a city, denoted \( M \), is given. A household either lives in her own house or rents an apartment. To simplify our discussions, we assume that a house cannot become an apartment, and vice versa. In the short run, the total number of houses \( T^H \) in a market is fixed. All houses are different in terms of their hedonic characteristics. All the households are different in their preferences in the characteristics of houses. We use a unit circle to model the characteristic space of houses. Each point on the circle represents a unique characteristic. To simplify the analysis, we let all the houses for sale be evenly spaced around the circle. And all the buyers are uniformly distributed around the circle. A buyer’s location on the circle means that she prefers the characteristic represented by this point the most, or, any house located at the buyer’s location would be a perfect match to her.

The matching mechanism between sellers and buyers is as follows. At the beginning of each time period, sellers post advertisements and announce the characteristics of their houses to the public. In order to buy a house, a buyer has to visit the house. We assume each buyer can visit at most one house in one time period. Each buyer then chooses to visit the house that best matches her. A seller may have multiple visitors. We assume each seller can negotiate with at most one buyer in one time period. The seller asks her visitors to make an initial offer each and chooses the one who makes the highest initial offer to negotiate with. We assume that the buyers’ initial offers preserve the ordering of their preferences towards the seller’s house, although the sellers cannot observe the preferences of buyers directly. If a deal is reached finally, the sale price is determined through bargaining between the seller and the buyer. Otherwise, the seller continues to search next time period.
Next, let us introduce some important identity equations. Let $N_t^H$ be the total number of owner-occupied houses in the local area at the beginning of time $t$, and $N_t^R$ be the total number of renters at the beginning of time $t$. The sum of renters and owner-occupied houses is equal to the total number of households in the city:

$$M = N_t^R + N_t^H$$  \hspace{1cm} (1)

Let $N_t^S$ be the total number of houses for sale on the market at time $t$ and let $N_{t}^{BS}$ be the number of sales made during time period $t$. The number of unsold houses $U_t$ at the end of this period equals the difference between the total houses on the market during this period and the total number of houses sold:

$$U_t = N_t^S - N_t^{BS}$$  \hspace{1cm} (2)

During each time period, every household who lives in her own house is assumed to have a probability $\mu$ of changing her current house, either triggered by a change of her preference, a change in her family composition, or a job change. Note that $\mu$ can also be understood as the probability of having her house to be listed for sale. She will need to sell their current houses and buy a new house. We assume that she will move out and rent a place to live during the transition. This assumption simplifies the analysis considerably by allowing us not to explicitly consider the situation that she still lives her current house but being a seller. Unlike Wheaton (1990), the probability of changing houses in this paper is endogenously determined. Since holding vacant houses and putting houses for sale are both costly and time-consuming, a lower expected selling probability would reduce the people’s tendency to change houses. Therefore, we let the probability of people changing their houses, $\mu$, depend on the expected selling probability. For simplicity, we do not explicitly model homeowners’ decision on whether to change houses or not; instead, we specify:

$$\mu = \min\left(\delta_0 + \delta_1 q^S, 1\right)$$  \hspace{1cm} (3)

where $q^S$ is the expected selling probability and $\delta_1 > 0$, meaning that the expected selling probability increases the probability of changing houses; $\delta_0 > 0$ captures the exogenous factors that influence the probability of changing houses. Notice that here the probability does not depend on the expected sale prices. Therefore, our setup does not incorporate the possible effect of loss aversion as in Genesove and Mayer (2001) and the effect of liquidity constraint as in Genesove and Mayer (1997).
The houses on the market for sale this period is equal to those unsold houses from last period, \( U_{t-1} \), plus those from homeowners who would like to change houses and move out of their houses this period, \( \mu N_i^H \). Namely,
\[
N_i^S = U_{t-1} + \mu N_i^H \tag{4}
\]

The total number of houses in the city is equal to the sum of the total number of owner occupied houses at the beginning of this period, \( N_i^H \), and the total number of unsold houses for sale from last period, \( U_{t-1} \); namely,
\[
T^H = U_{t-1} + N_i^H \tag{5}
\]

Now we introduce the unemployment rate into the model as demand shocks. Everybody in the economy (renters and home occupiers) is assumed to have the same probability of being unemployed in each time period. We assume that unemployed people are not in the market to buy houses because it is difficult for them to get mortgages. Therefore, the probability of entering into the market as a buyer, denoted as \( \gamma \), cannot exceed the employment rate, i.e., \( \gamma \leq 1 - urate \), where \( urate \) is the unemployment rate. Alternatively, \( \gamma \) can be considered as the probability of signing on a buying agent who would have to check if the potential buyer is eligible for financing before signing on. Further, we let the unemployment rate have an additional effect on the probability of entering the market. In particular, we let:
\[
\gamma = (1 - urate) \cdot \frac{\exp(\eta \cdot urate)}{1 + \exp(\eta \cdot urate)}, \tag{6}
\]

where \( \eta \) is the parameter that defines the further relationship between \( \gamma \) and the \( urate \). A negative \( \eta \) means that the probability of entering into the market is lower when the unemployment rate gets higher. A higher unemployment rate may affect people’s willingness to buy houses, for worrying about the prospects of their own and/or of the housing market. The logit-type functional form in the second part of (6) has the advantages that is bounded between 0 and 1, and that the continuity in \( urate \) may facilitate the estimation process. Note that \( \gamma \) is assumed to be determined by the exogenous unemployment rate. It is worth noting here that \( \gamma \) can also be modeled as a function of other exogenous factors such as the mortgage rate or some other socio-economic variables that may affect the demand side of the housing market.

The total number of buyers in the market, therefore, is \( \gamma \) times the sum of those people who enter the market to sell their houses, \( \mu N_i^H \), and those people who are currently renters, \( N_i^R \):
To summarize, in equations (1)-(5) and (7) (total six equations), we introduce nine endogenous variables, including the total number of renters $N^R_t$, the number of owner-occupied houses $N^H_t$, the number of unsold houses at the end of the last period $U_{t-1}$, and at the end of the current period $U_t$, the number of sellers in the market $N^S_t$, the number of sales $N^{BS}_t$, the expected probability of selling a house $q^S$, the probability of moving out of current houses $\mu$, and finally the number of buyers $N^B_t$. The exogenous variables so far include the number of households $M$, the unemployment rate $urate$ and the probability of entering into the market as a buyer, $\gamma$, and the total number of houses $T^H$. The unknown parameters that need to be estimated include the coefficients $\delta_0$ and $\delta_1$ in equation (3), and $\eta$ in equation (6). Next, we will introduce more endogenous variables and more equations when we study the matching behavior between sellers and buyers.

(b) The Seller’s Problem:

During each time period, seller $i$ posts an advertisement to sell her house in the local housing market. The advertisement describes the characteristics (and therefore the location of the house on the unit circle). Buyers in the market make independent offers simultaneously to the seller. It is assumed that the buyer who evaluates the house the most shall make the best offer to the seller. We denote this buyer as buyer $j$. Seller $i$ then negotiates with buyer $j$ for the sale price. The outcomes of the negotiations between seller $i$ and buyer $j$ will be described in part (d). The seller’s action set consists of two choices: “1” if she sells the house and “0” if she decides to wait until next time period. She has incentive to wait if the match between her house and the buyer is poor. Her objective function is as follows:

\[
J^S_i (\pi_{j,i}^S, a_{ij}^S, a_i^B) = \max_{a_{ij}^S \in (0,1)} \pi_{j,i}^S a_{ij}^S + \beta E(J^S_{i+1}; a_{ij}^S, a_i^B) (1 - a_i^B) \tag{8}
\]

where $a_{ij}^S$ represents other sellers’ decisions in the market, $a_i^B$ are buyers’ decisions, and $a_i^S$ is seller $i$’s decision at $t$. If seller $i$ decides to sell her house ($a_i^S = 1$), her utility surplus is $\pi_{j,i}^S$, discussed in detailed in part (f) of this section. If the seller decides to wait until next period ($a_i^S = 0$), her (discounted) payoff is $\beta E(J^S_{i+1}; a_{ij}^S, a_i^B)$. The time discount rate is denoted as $\beta$.

The optimal decision rule of the seller is rather simple: Seller $i$ will sell her house if and only if the utility surplus from selling is higher than the payoff of waiting, i.e.,
\[ a_{it}^{S} = \left\lfloor \pi_{it}^{S} \geq \beta E\left(J_{it+1}^{S}, a_{it+1}^{S}(\cdot), a_{it+1}^{B}(\cdot)\right) \right\rfloor \] (9)

Let \( \pi_{it}^{S} \) denote the smallest surplus for which the seller will be willing to sell her house, i.e.,

\[ \pi_{it}^{S} = \beta E(J_{it+1}^{S}, a_{it+1}^{S}(\cdot), a_{it+1}^{B}(\cdot)) \] (10)

Following the search literature, we call \( \pi_{it}^{S} \) the seller’s reservation surplus. When the seller’s surplus from a transaction is at least as large as \( \pi_{it}^{S} \), the seller will choose to sell her house. Otherwise, the seller will choose to wait until next period.

(c) The Buyer’s Problem:

Buyers are heterogeneous in their preferences. Each time period, a buyer, denoted as buyer \( j \), searches for houses in the market. Let the shorter arc distance between buyer \( j \) and house \( i \) be \( d_{ij} \). We let the utility flow or the willingness-to-pay (wtp) per time period for any buyer to live in a perfect matched-house be \( u_{0i}^{H} \). Further, we let the one-period net utility flow or wtp of buyer \( j \) from living in house \( i \) be:

\[ u_{ij}^{H} = u_{0i}^{H} \exp(-c_{i}d_{ij}^{a}) \] (11)

where \( c_{i}>0 \) and \( \alpha>0 \). Although we use a unit circle to characterize the preference space of households for simplicity, the preference space could be multi-dimensional in reality. Therefore, we use a curvature coefficient \( \alpha \) here to capture the possible multi-dimensionality.\(^2\) That is, \( d_{ij}^{a} \) measures the degree of mismatch. A smaller \( d_{ij}^{a} \) means a better matching quality. When \( d_{ij}^{a} = 0 \), house \( i \) is the perfect match for buyer \( j \).

More importantly, the parameter \( c_{i} \) defines the marginal disutility from mismatch in a logarithm sense. Later in part (f) we will discuss how the distance \( d_{ij} \) is determined by numbers of buyers and sellers in the market. If \( c_{i} > 0 \) and \( \alpha > 0 \), more buyers and sellers in the market would result in a higher matching quality, and therefore a higher wtp for the house. This is referred in the paper as the thick market effect. Another feature about the equation (11) is that it is bounded from above, which means that the thick market effect through improving matching quality diminishes as the market gets thicker.

Buyer \( j \)’s action set consists of two choices: “1” if she purchases the house during this time period and “0” if she does not purchase the house but rents an apartment for this

\(^2\) See Arnott (1989) and Zhang (2007) for more discussions.
time period. She has an incentive to wait if the current match is not good enough. Buyer $j$’s objective function is as follows:

$$ J_{jt}^B(\pi_{jt}^B; a_{jt}^B(\cdot), a_{jt}^S(\cdot)) = \max_{a^S_t \in (0,1)} \pi_{jt}^B a_{jt}^B + \left[ t^R_t + \beta \left( \varphi E(J_{jt+1}^B; a_{jt+1}^B(\cdot), a_{jt+1}^S(\cdot)) + (1-\gamma)E(J_{jt+1}^B; a_{jt+1}^B(\cdot), a_{jt+1}^S(\cdot)) \right) \right] 1 - a_{jt}^B, $$

(12)

where $a_{jt}^B(\cdot)$ represents other buyers’ decisions in the market at $t$, $a_{jt}^S(\cdot)$ represents all sellers’ decisions at $t$, and $a_{jt}^B$ is the decision made by buyer $j$ at $t$. If the buyer purchases the house ($a_{jt}^B = 1$), her utility surplus is $\pi_{jt}^B$. If the buyer decides to wait until next period ($a_{jt}^B = 0$), her payoff from waiting consists of two parts, the net utility flows from renting this time period, and the discounted expected future payoff at the next time period. These two parts of payoffs are discussed next.

The first part of payoff from waiting is the net utility flow from renting, denoted as $u_{jt}^R$. We let the net utility be the difference between the utility flow from renting, $u_{jt}^R$, and the paid rent $R_t$:

$$ u_{jt}^R = u_{jt}^R - R_t = u_{jt}^R \exp \left( -c_2 N_{jt}^R / M \right). $$

(13)

In (13), we let the net utility depend on the number of renters in the market $N_{jt}^R$ relative to the total number of households. $N_{jt}^R$ is endogenous, first introduced in equation (1). Rearrange (13), we can obtain the equation for $R_t$:

$$ R_t = u_{jt}^R \left( 1 - \exp \left( -c_2 N_{jt}^R / M \right) \right). $$

(14)

Note the ratio $N_{jt}^R$ is the occupancy rate in the rental market. If $c_2 > 0$, equation (14) suggests that a higher occupancy rate of apartments because of more renters would lead to a higher rent. The rent $R_t$ is an important endogenous variable. The parameter $c_2$ measures the crowding effect of the number of renters in the rental market. Both $u_{jt}^R$ and $c_2$ will be estimated.

The second part of the payoff from waiting is the buyer’s expected future payoff at the next time period. Its calculation is slightly more complicated. We have to consider that the current buyer has a probability $(1-\gamma)$ to leave the market, and a probability $\gamma$ to remain in the market. $\gamma$ is determined by equation (6). If she is a buyer again next period, her expected payoff is $E(J_{jt+1}^B; a_{jt+1}^B(\cdot), a_{jt+1}^S(\cdot))$. If she is not a buyer next period, we denote her expected
payoff as $E(J_{j,t+1}^{BO})$. Note that in the latter case, she will have to rent a place to live at $t+1$ and wait until $t+2$ when she has a probability $\gamma$ again of remaining as a buyer. Therefore, 

$E(J_{j,t+1}^{BO})$ consists of the net utility from renting at $t+1$, and the discounted future expected payoff at $t+2$, which is:

$$E(J_{j,t+1}^{BO}) = u_t^B + \beta [\gamma E(J_{j,t+2}^{BO}) + (1-\gamma)E(J_{j,t+2}^{BO})].$$

(15)

Thus, the optimal decision rule of buyer $j$ at $t$ is:

$$a_{j,t}^B = \left\{ \begin{array}{ll}
u_t^B + \beta [\gamma E(J_{j,t+1}^{BO}, a_{j,t+1}^B(\cdot), a_{j,t+1}^S(\cdot)) + (1-\gamma)E(J_{j,t+1}^{BO}, a_{j,t+1}^B(\cdot), a_{j,t+1}^S(\cdot))].
\end{array} \right.$$

(16)

Similar to the discussion in the seller’s case in part (b), the reservation surplus $\pi_{j,t}^B$ is the minimum surplus for which a buyer will be willing to purchase a house. Apparently, from equation (16),

$$\pi_{j,t}^B = u_t^B + \beta [\gamma E(J_{j,t+1}^{BO}, a_{j,t+1}^B(\cdot), a_{j,t+1}^S(\cdot)) + (1-\gamma)E(J_{j,t+1}^{BO}, a_{j,t+1}^B(\cdot), a_{j,t+1}^S(\cdot))].$$

(17)

Again, a buyer will purchase a house if and only if her surplus from the purchase is at least as large as $\pi_{j,t}^B$.

Note in this subsection, we introduce three endogenous variables in three equations. They include the one-period utility flow from owning a house $u_{ij,t}^H$ in equation (11), the utility flow from renting an apartment $u_{ij,t}^R$ in equation (13), and the rent $R_t$ in equation (14). The newly introduced exogenous variables are the utility from a perfectly matched house $u_{ij,t}^H$, and the utility flow from renting, $u_{ij,t}^R$.

(d) Surpluses of buyers and sellers

When a trade occurs between buyer $i$ and seller $j$ at time $t$, the buyer’s surplus from buying a house is:

$$\pi_{ij,t}^B = A_{ij,t} - P_{ij,t},$$

where $A_{ij,t}$ is the valuation of buyer $i$ of house $j$, and $P_{ij,t}$ is the sale price. The seller’s surplus from selling a house is simply the sale price:

$$\pi_{ij,t}^S = P_{ij,t}.$$  

(18)

Thus the total surplus generated by the sale, denoted as $\Sigma_{ij,t}$, which is the sum of the buyer’s surplus and the seller’s surplus, is equal to the valuation of buyer $i$ of house $j$, $A_{ij,t}$:

$$\Sigma_{ij,t} = A_{ij,t} = \pi_{ij,t}^B + \pi_{ij,t}^S.$$  

(19)
We let the buyer’s valuation of the house be consisted of two parts, as in equation (20):

\[ \Sigma_{ij} = \frac{u_0^H \exp(-c_id^H_{ij})}{1-(1-\mu)\beta} + \frac{\mu \beta E(J^S_{ij};a^S_{ij+1}(),a^B_{ij+1}())}{1-(1-\mu)\beta} \]

The first part in (20) is the present value of the sum of utility flows from owning the house over time. This is obtained by assuming that the probability of remaining in the same house is \((1-\mu)\). The second part in (20) is the expected resale value of the house when the buyer enters into the market to sell the house in the future, where \(E(J^S_{ij})\) is the value of searching for a buyer to sell the house in the market.

The total surplus from the trade has to be larger than the sum of the reservation surplus of both the buyer \(\bar{\pi}^B\) and the seller \(\bar{\pi}^S\). The remaining surpluses will be shared through bargaining. Thus, the buyer’s surplus from the transaction is equal to:

\[ \pi^B_{ij} = \pi^B_{it} + \theta(\Sigma_{ij} - \pi^B_{it} - \pi^S_{ij}) \]  

and the seller’s surplus, which is also the sale price \(P_{ij}\) according to equation (18), is equal to:

\[ P_{ij} = \pi^S_{ij} = \pi^S_{it} + (1-\theta)(\Sigma_{ij} - \pi^B_{it} - \pi^S_{ij}) \]

where \(\theta\) is the bargaining power between the seller and the buyer.

(e) The Market Equilibrium:

We only consider the symmetric and stationary equilibrium that all buyers adopt the same decision rule over time and all sellers adopt the same decision rule over time. Thus from now on, for expositional simplicity, we will omit the subscript of each variable as long as it does not cause any confusion.

According to (9), the seller’s equilibrium decision rule is to sell her house if and only if the surplus from trade is at least as high as \(\beta E(J^S)\). Thus, based on equation (10), the seller’s reservation surplus at equilibrium is:

\[ \bar{\pi}^S = \beta E(J^S) \]  

Similarly, according to (17), the buyer’s reservation surplus is:

\[ \bar{\pi}^B = u^B + \beta(\gamma E(J^B) + (1-\gamma)E(J^{BO})) \]

According to equations (11), when \(c_1 > 0\) and \(\alpha > 0\), the shorter the distance between the buyer and the seller, the better the match between them and thus the higher the total

---

\(^3\) Most search literature, including Arnott (1989) and Wheaton (1990), only discusses symmetric equilibrium.
surplus generated if they reach a deal. Thus, by adding the seller’s reservation surplus \( \bar{\pi}^S \) and the buyer’s reservation surplus \( \bar{\pi}^B \), we can see that a sale will be made if and only if the total surplus is above a certain level, which is equivalent to say that a deal will be reached if and only if the match between the buyer and the seller is good enough, namely, if and only if the mutual distance between them is short enough. Let us denote \( \bar{d} \) as the maximum distance corresponding to the minimum total surplus, according to equation (20), we have:

\[
\bar{\pi}^B + \bar{\pi}^S = \frac{u_0^R}{1-(1-\mu)\beta} \exp\left(-c_i \bar{d}^a\right) + \frac{\mu \beta E(J^S)}{1-(1-\mu)\beta}
\] (25)

From (15), the \( E(J^{BO}) \) in (24) can be written as a function of \( E(J^B) \):

\[
E(J^{BO}) = \frac{u^R + \beta y E(J^B)}{1 - \beta(1 - \gamma)}.
\] (26)

Note in the stationary equilibrium, the total number of unsold houses are equal over time, i.e.,

\[
U_t = U_{t-1}
\] (27)

In equations (23)-(27), we have six endogenous variables in five equations: the seller’s reservation surplus, \( \bar{\pi}^S \), the buyer’s reservation surpluses, \( \bar{\pi}^B \), the maximum mutual distance \( \bar{d} \), the payoffs \( E(J^S) \), \( E(J^B) \), and \( E(J^{BO}) \). None of these six endogenous variables are likely to be observable.

(f) The Solution of the Model:

The market equilibrium condition indicates that a buyer and a seller will trade if and only if they are located close enough to each other on the circle. This means that each seller will only accept offers from buyers who fall within her adjacent interval on the circle, which is \( 2\bar{d} \) in length. Consider a house that is located at point \( s_0 \), only the buyers located in the interval \( [s_0 - \bar{d}, s_0 + \bar{d}] \) are matches good enough to the seller of the house.

Remember we assume that all the houses for sale are evenly spaced around the circle. Among the \( N_S \) buyers, the distance between any two adjacent buyers are \( 1/N_S \). In addition, according to our matching mechanism, every buyer visits only the house that she prefers most during each time period. Thus, a house located at \( s_0 \) will be visited only by those buyers who are located in the interval \( [s_0 - 1/2N_S, s_0 + 1/2N_S] \). If \( 2\bar{d} > 1/N_S \), every buyer located in the interval \( [s_0 - 1/2N_S, s_0 + 1/2N_S] \) is acceptable to the seller at \( s_0 \) and every buyer outside this interval will visit other sellers. Thus this case is equivalent to \( \bar{d} = 1/2N_S \). Therefore we...
only need to focus on the equilibria where $2\bar{d} \leq 1/N^S$. For those buyers located in the interval $[s_0 - \bar{d}, s_0 + \bar{d}]$, the seller picks one who is the closest to him to negotiate with. Note that our setup excludes the possibility that two different sellers compete for the same buyer.

Although sellers are evenly spaced around a circle, buyers are assumed to be uniformly distributed on the circle. For a seller at $s_0$, it is possible that no buyers are located in the interval $[s_0 - 1/2N^S, s_0 + 1/2N^S]$ at all. In this case, no buyers visit the seller’s house and the house is not sold at this time period. If multiple buyers fall in the interval, the seller has multiple visitors and she will choose the one closest to herself to negotiate with during this period, and the rest of the buyers will have to wait until next period. Finally, if the closest buyer turns out to be within the seller’s acceptable interval of $[s_0 - \bar{d}, s_0 + \bar{d}]$, a sale will occur this time. Otherwise, the seller will wait until next time. Therefore, given the minimum distance $\bar{d}$ and the $N^B$ buyers, the probability of which the seller sells her house during this time period is:

$$q^S = 1 - (1 - 2\bar{d})^{N^S}. \quad (28)$$

The expected number of sales each time period is:

$$N^B q^S = N^S \cdot q^S. \quad (29)$$

For any seller, the value of searching for a buyer to sell her house is:

$$E(J^S) = E(\pi^S | \pi^S \geq \bar{\pi}^S)q^S + \beta E(J^S)(1 - q^S) \quad (30)$$

Equation (30) is obtained by taking expectation of (8), and by recognizing $E(J^S_t) = E(J^S_{t+1}) \equiv E(J^S)$. Re-arranging equation (30), we get:

$$E(J^S) = \frac{E(\pi^S | \pi^S \geq \bar{\pi}^S)q^S}{1 - \beta + \beta q^S}. \quad (31)$$

When there are more than one buyers interested in the seller’s house, the seller selects the closest one to herself to negotiate with. Let the shorter arc distance between any buyer $i$ and the house located at $s_0$ be $D_i$, $i=1,2,...,N^B$. The shortest arc distance between the closest buyer and the house, denoted $D$, is: $D = \min\{D_1,...,D_{N^S}\}$.

Because $D$ is uniformly distributed at the unit circle, $D$ is the first ordered statistic of a random variable uniformly distributed on $[0, 1/2]$. Thus the density function of $D$ is given by:

$$f(D) = 2N^B \left(1 - 2D\right)^{N^B - 1}.$$
As $N^B \to \infty$, $D$ converges in distribution to an extreme value distribution, i.e.,

$$f\left( D \right) \sim N^B \exp\left( { - 2N^B D} \right).$$

Since $D$ converges to the extreme value distribution very fast (the rate of convergence is $N$), we use the extreme value distribution to approximate the distribution of $D$. Furthermore, the density function of $D$ conditional on the closest buyer falling in the seller’s acceptable interval $[s_0 - d, s_0 + d]$ is:

$$f\left( d \mid \pi^S \geq \pi^S \right) = 2N^B \exp\left( { - 2N^B d} \right)/q^S.$$

Therefore, the expected total surplus in (20) is given by:

$$E\{\Sigma \mid \pi^S \geq \pi^S\} = \int_0^d u^B(x)f(x)dx \cdot \left( \frac{\mu_BE(J^S)}{(1 - \beta(1 - \mu))q^S} + \left( \frac{\mu_BE(J^S)}{(1 - \beta(1 - \mu))q^S} \right) \right)$$

The first term in the previous equation is divided by the probability of the house being sold, which is $q^S$. Taking expectation of the seller’s surplus, $\pi^S$, defined in (22), conditioning on sellers selling her house, i.e., $\pi^S \geq \pi^S$, we have:

$$E\left( \pi^S \mid \pi^S \geq \pi^S \right) = \pi^S + \left( 1 - \theta \right)\left( E\left( \Sigma \mid \pi^S \geq \pi^S \right) - \pi^S - \pi^B \right)$$

where $E\left( \Sigma \mid \pi^S \geq \pi^S \right)$ is given by equation (32). Note equation (33) also gives the equilibrium transaction price. For a buyer, the equilibrium probability of successfully buying a house, denoted as $q^B$, equals to the number of houses sold and number of buyers in the market:

$$q^B = N^B / N^B.$$

The buyer’s expected value of searching for a house is given by weighted average of the surplus from successfully purchasing a house and the expected future payoff of continuously looking:

$$E\left( J^B \right) = E\left( \pi^B \mid \pi^B \geq \pi^B \right)q^B + \left( \frac{u^R + \beta yE(J^B)}{1 - \beta(1 - \gamma)} \right)\left( 1 - q^B \right).$$

The second part of (35) comes from (26). Re-arranging the previous equation, we get:

$$E\left( J^B \right) = \frac{E\left( \pi^B \mid \pi^B \geq \pi^B \right)q^B (1 - \beta(1 - \gamma)) + u^R(1 - q^B)}{1 - \beta + \beta yq^B}$$

Taking the expectation of the buyer’s surplus $\pi^B$ defined in equation (21), conditional on the buyer purchasing a house, we have:
In equations (28)-(29), (31)-(34) and (36)-(37) (total eight equations), we introduce four new endogenous variables: the conditional expected surpluses of selling the house \( E(\pi^S | \pi^S \geq \pi^B) \) (which is also the equilibrium price), the expected surplus of purchasing a house, \( E(\pi^B | \pi^B \geq \pi^B) \), the expected total surplus \( E(\Sigma | \pi^S \geq \pi^S) \), and the probability of buying a house \( (q^B) \). The probability of selling a house \( (q^S) \) was first introduced in equation (3). Only the probability of selling a housing \( q^S \) may be observable if the multiple listing service (MLS) data are available.

In summary, part (a) introduces nine endogenous variables in six equations. Part (c) introduces three endogenous variables and three equations, Part (e) introduces six endogenous variables in five equations. Part (f) has four endogenous variables in eight equations. Therefore, by solving this equation system of twenty-two endogenous variables and twenty-two equations, we can solve for the endogenous variables as functions of the exogenous variables and parameters of the model.

(g) Long-run equilibrium

Notice that so far our model assumes the total number of house is fixed in the short run. By introducing the construction cost and assuming free entry, we can easily extend our model to the long-run framework by letting the expected sale price of a house equal the expected cost of building this house in the equilibrium. More specifically, assume that it takes one period to build house. A builder has to invest a fixed amount \( F \) to build a house, but he also incurs additional cost if he is not able to sell the house he just built. Given the real interest per period \( r \), and the probability of selling this house in the period \( q^S \), the long run equilibrium requires one more condition to be satisfied:

\[
E(P) = \left( 1 + \frac{r}{q^S} \right) \times F, \quad (38)
\]

where \( E(P) \) is the expected sale price with \( P \) defined by Eq. (22). The right hand side is the expected cost of building the house, with the explicit consideration on the probability of selling this house. With this additional equation, we can pin down the total number of houses \( T^H \) which is endogenously determined in the long run.
The key insight of the model remains unchanged. Intuitively, the thick market effect would be stronger in the long run. This is because the total number of houses would adjust to demand shocks in the long run. For example, when there is a positive demand shock, the seller side of the market would become thicker because new houses would be likely to be built in the long run.

3. Estimation and Simulations

3.1 Estimation Strategy

Since the model outlined in Section 2 has no closed form solutions, it is difficult to characterize its properties. An alternative way to find the solutions and properties of the model is to conduct simulation after the parameter values of the model are estimated.

The estimation strategy is to find a set of parameters that minimizes the difference between some of the observed endogenous variables and the corresponding outcomes generated from the model. In principle, we can use any subset of the twenty-two endogenous variables and the corresponding observed outcomes. However, in reality, most of the endogenous variables are not observable. Here we match the endogenous variables that we do have data. They are the rents $R_k$, the price of a house $P_k$, and the time-to-sale, which is the inverse of the probability of selling a house $q^S$. Therefore, we have three expectations:

$$E(R_k) = R(\Theta, X_k),$$
$$E(P_k) = P(\Theta, X_k),$$
$$E(T_{S_k}) = 1/[q^S(\Theta, X_k)],$$

where $R_k$ in (39.1) is the observed monthly rent of city $k$, while $R(\Theta, X_k)$ is an implicit function that can be used to obtain the rent $R$, based on the information on city $k$, denoted as $X_k$, and a given set of parameters $\Theta$. Obviously, obtaining $R(\Theta, X_k)$ requires solving all twenty-two equations of the model.

Similarly, $P_k$ in (39.2) is the observed housing price at city $k$, and $P(\Theta, X_k)$ is the implicit function that describes the expected sale price of a house from the model conditional on $\Theta$ and $X_k$. Note $P(\Theta, X_k)$ and $E(\pi^S | \pi^S \geq \pi^S)$ in equation (33) are equivalent. Finally, $T_{S_k}$ in (39.3) is the observed time-to-sale of city $k$, and $q^S(\Theta, X_k)$ is the probability of selling a house from the model based $\Theta$ and $X_k$. Remember $q^S(\Theta, X_k)$ appears in equations (28) and (29). Similarly, solving for $P(\Theta, X_k)$ and $q^S(\Theta, X_k)$ requiring solving all twenty-two endogenous variables using the twenty-two equations described in the previous section.
One can use the expectations in (39.1)-(39.3) to construct the moment conditions and apply the GMM. However, the standard way of constructing the moment conditions require a rather difficult first derivatives of the implicit functions of \( R(\Theta, X_k) \), \( P(\Theta, X_k) \), and \( q^S(\Theta, X_k) \) with respect to the parameter set. Instead, a consistent albeit less efficient weighted nonlinear estimator will be used here.

We write equations (39.1)-(39.3) into the following form:

\[
R_k = R(\Theta, X_k) + \epsilon_1, \quad \text{(40.1)}
\]
\[
P_k = P(\Theta, X_k) + \epsilon_2, \quad \text{(40.2)}
\]
\[
TS_k = \frac{1}{q^S(\Theta, X_k)} + \epsilon_3. \quad \text{(40.3)}
\]

where we assume \( E(\epsilon_i | X_k) = 0 \) for \( i = 1, 2, 3 \) and covariance matrix of the error term \( (\epsilon_1, \epsilon_2, \epsilon_3) \) is \( \Sigma = \text{Var}(\epsilon_1, \epsilon_2, \epsilon_3) \). Here we allow \( \Sigma \) to be flexible to capture the possible heteroscedasticity \( \text{Var}(\epsilon_i) \neq \text{Var}(\epsilon_j) \) and the correlation \( \text{Cov}(\epsilon_i, \epsilon_j) \neq 0 \). A weighted nonlinear least square estimator is given by:

\[
\min_{\Theta} \frac{1}{K} \sum_{k=1}^{K} \left( \begin{array}{l}
R_k - R(\Theta, X_k) \\
P_k - P(\Theta, X_k) \\
TS_k - \frac{1}{q^S(\Theta, X_k)}
\end{array} \right)^\top \Sigma^{-1} \left( \begin{array}{l}
R_k - R(\Theta, X_k) \\
P_k - P(\Theta, X_k) \\
TS_k - \frac{1}{q^S(\Theta, X_k)}
\end{array} \right),
\]

where \( K \) is the total number of cities. Note the usual identification condition for the nonlinear least square applies here. This estimator is consistent and has an asymptotical normal distribution. To implement this estimator, we first estimate equation (41) with \( \Sigma \) being the identity matrix and use the residuals to construct an estimate of \( \hat{\Sigma} \). The final estimate of (41) is conducted using the estimated \( \hat{\Sigma} \).

The set of parameters \( \Theta \) includes the time discount rate \( \beta \), the bargaining power parameter \( \theta \) in equations (33) and (37), parameters \( u^H_0 \), \( c_1 \) and \( \alpha \) in equation (11), and \( u^R_0 \) and \( c_2 \) in equations (13) and (14). We let monthly time discount rate \( \beta = 0.997 \), which corresponding to a yearly time discount factor of 0.96. We also let \( \theta = .50 \) for simplicity, assuming the buyers and sellers share equally the surplus. These two parameters are not critical, so we choose to set them to be constants. The rest of the parameters will be estimated in the paper.

Before we discuss the data to be used in the estimation, we consider a slight complication of the model. So far the model ignores the quality aspects of the houses or apartments, and suggests that the difference in housing prices across different cities may only be due to the market size and unemployment rates. We are able to collect some information
on the housing and neighborhood characteristics for different cities. Empirically we allow the utility from a perfectly matched houses $u_0^H$ and the overall rental utility $u_0^R$ to be dependent on these housing and neighborhood characteristics. To determine what characteristics to use, we conduct auxiliary hedonic price regressions of average housing prices and average rental prices on characteristics of house and apartments. Those regressors that are statistically significant in auxiliary regressions are kept here. In particular, we let $u_0^H$ in (11) and $u_0^R$ in (13) be:

$$u_0^H = a_0 + a_1 \text{HouseRooms} + a_2 \text{HouseAge} + a_3 \text{WhitePct} + a_4 D_{2000}$$  \hspace{1cm} (42)

$$u_0^R = b_0 + b_1 \cdot \text{AptRooms} + b_2 \cdot \text{WhitePct} + b_3 \cdot D_{2000}$$  \hspace{1cm} (43)

In equations (42) and (43), WhitePct is the percentage of white population. HouseRooms and HouseAge in (42) are the city average number of rooms and city average years since construction of houses. AptRooms in (43) is the average number of rooms in an apartment. $D_{2000}$ is the dummy for the year 2000. The coefficients for this dummy variable in both equations capture the differences in aggregate environment that affect all markets between these two years, including differences in mortgage markets, in the economy, and in the demographics. To reduce the number of parameters to be estimated, we choose the characteristics in both equations if they are statistically significant in the corresponding linear hedonic regressions. The search-matching model developed in this paper basically seeks to capture the variations that are not captured in the hedonic price regressions.

Therefore, the hedonic parameters include $a_i$ for $i = 0, 4$ in equation (42) and $b_i, i = 0, 1, 3$, in equation (43). Other parameters to be estimated include $\delta$ in equation (3), $\eta$ in equation (6), $c_1$ and $\alpha$ in equation (11), and $c_2$ in equation (13). The total number of parameters to be estimated is fourteen. The estimation is carried out by the nonlinear least square estimation procedure described in equation (41).

3.2 Data and the Estimation Results

3.2.1. The Data

The data set is the city-level data for 28 cities in 1990 and 37 cities in 2000 in Texas in which we can find complete information. City-level total number of houses sold, average

---

4 In the simple linear hedonic regressions, we use log(housing prices) and log(rental prices) to regress characteristics such as crime rates, average number of rooms in a house or in an apartment (rental property), average age of houses, and the percentage of population who is white.
prices, and total listings are obtained from Texas Real Estate Center.\textsuperscript{5} Other information is obtained from census. All cities of 1990 show up again in 2000 except the city of Texarkana that has information in 1990 but not in 2000. It is also noted that the definitions of a city may vary across these two years. This paper does not utilize the panel aspect of the data. Instead, it treats a city in 1990 and in 2000 as two different cities.

Table 1 lists the summary statistics of the variables used in estimation. Several observations are noted here. First, there are substantially differences across cities. The ratio of the number of households between the biggest city and the smallest city is 35.0 in 1990 and 120.3 in year 2000. The difference in the two ratios is mostly because the smallest city in the sample of 2000, San Marcos, is not included in the sample year 1990.\textsuperscript{6} The ratios of the unemployment rates between the highest city and the lowest city are 5.89 in 1990 and 8.07 in 2000. This paper exploits these variations. It suggests that part of variations in housing prices are due to the variations in factors such as the total number of households and the unemployment rates. These factors may also affect transaction volumes, rental prices, time-to-sell and other housing market outcomes simultaneously.

Second, there is substantial difference across two years. The economy in general and the housing market in particular were not doing well in 1990 in the state of Texas. However, in 2000, both the economy and the housing market have significantly improved. The variable in this paper to describe the overall economy is the unemployment rate. The average unemployment rate drops from 7.08% in 1990 to 5.04% in 2000. The housing market has improved too. For example, although the samples in 1990 and 2000 are not directly comparable, the average house price has increased by 28.5%, from $70,648 (in 1990 dollar) for the 28 cities in 1990, to $90,811 (in 1990 dollar) for the 37 cities in 2000. The time-to-sale was 14.3 months in 1990 and 6.48 months in 2000. The average rent has also gone up by 15.5% from $375 per month in 1990 to $433.3 per month in 2000. Note a significant part of the differences in housing prices and in rental prices between 1990 and 2000 would be captured by the coefficients for the dummy variable $D_{2000}$ in equations (42) and (43).

It is important to point out that this paper assumes that all the houses and households in a city as a single market because of data constraint, or all cities have the same number of housing markets. Both assumptions are obviously not accurate. Cities such as Houston, Dallas, San Antonio and Austin will probably have many locality-based markets than a small city such as Bryan-College Station. Houses of different types or at different price ranges may

\textsuperscript{5} http://recenter.tamu.edu/

\textsuperscript{6} The dataset includes San Marcos as part of Austin in 1990.
belong to different markets. However, without detailed house-level information, defining markets within a city is impossible. In fact, the maintained assumption in this paper is that a local market in a larger city would have more houses than a local market in a smaller city. An alternative definition of market sizes would be discussed later as a robustness check.

3.2.2 Estimation results

We estimate both the short run model and the long run model. They produce qualitatively the same results. Next, we first present the short run results.

a. Estimation results from the short run model

Before we proceed to the results, there is one thing worth noting; that is, in the short run, we assume the total number of houses in each city is exogenously given. However, the total number of existing houses \( T_H \) is not always observed in data. In this case, we use a simple method to impute its value. According to census, 64\% of households are homeowners in Texas. Also, the average housing vacancy rate is 2\% . For each city, we apply the homeowner ratio of 64\% and the housing vacancy rate of 2\% to obtain its \( T_H \) for our short-run model estimation.

Table 2 reported the values of the parameters of the short run model. The first panel lists two constants, the monthly time discount rate \( \beta \) and the bargaining power of the buyer \( \theta \). As discussed before, the time discount rate is not a focus of this paper. Thus we let \( \beta \) be the commonly-used value, 0.997, corresponding to a yearly time discount value of 0.96. The real interest rate is derived consistently with the time discount rate, namely, \( r = \frac{1}{\beta} - 1 = 0.042 \).

The bargaining power of the buyer is also set to be a constant at 0.5.

The second panel in table 2 reports the weighted non-linear least square estimation results. First, in the homeowners’ decisions to change houses i.e., equation (3), \( \delta_0 \) is statistically significant at 0.0013 (0.0004)\(^7\), suggesting that the probability changing houses is at least 0.13\% in a month. More importantly, the parameter \( \delta_1 \) for the expected selling probability is 0.0173 (0.0031) per month. This suggests that there would be more homeowners who would like to change houses (and thus move out of their current houses) when the expected probability of selling their current houses is higher. If the monthly probability of selling a house is at the sample average value of 8.1\% in 1990, the probability of homeowners who would like to change houses, \( \mu \), would be 0.27\%. If the monthly probability of selling a house is at the average value of 21.6\% in 2000, \( \mu \) would be 0.50\%.

\(^7\) Standard errors are in parentheses.
In equation (6), the estimated coefficient for the effect of unemployment rate on the probability of being able to buy a house, $\eta$, is statistically significant at -14.7060 (0.7089). The negative $\eta$ indicates that a higher unemployment rate would impose a financial constraint and lead to a lower probability of entering the market for potential buyers. If the unemployment rate is at the Texas average of 7.08% in 1990, then the probability of being able to buy a house in the market within a month is 24%. If the unemployment rate is at the Texas average of 5.04% in 2000, then the probability of being able to buy a house within a month is 46%.

Most importantly, the key parameters in this paper are the coefficients in equation (11): the coefficient for disutility from mismatching $c_1$ and the curvature coefficient $\alpha$. While $c_1$ determines the marginal disutility from mismatch, $d^\alpha$ measures the magnitude of mismatch. The estimate is 62.3980 for $c_1$ and 0.4717 for $\alpha$; both are at more than 5% significance level. As discussed earlier, since both $c_1$ and $\alpha$ is positive, more buyers and sellers in the market would result in higher matching qualities on average and higher transaction prices. The economic significance of these parameters will be discussed in the simulation section.

For the hedonic parameters in the house utility function in equation (42), the coefficient for the rooms in a house is positive and significant, while the coefficient for the age of houses is negative and significant as expected. The coefficient for the percentage of white in the city is negative. The dummy for year 2000 is positive and significant.

The crowding out parameter $c_2$ in the rental price equations (12) and (13) is estimated at a positive value of 11.6987. This suggests that a higher number of renters would increase the rental price at given the number of apartments. But it is not statistically significant. For the hedonic parameters in the rental equation of (43), it may initially look surprising that the coefficient for the number of rooms is negative. However, from table 1, apartments in 1990 have 4.047 rooms while apartments in 2000 have 3.895 rooms. This shows older apartments have more rooms than newer apartments, and hence the number of rooms in a department may negatively affects the prices. The coefficient for the percentage of whites in a city is positive and marginally significant while the dummy for the year 2000 is positive and significant.

b. Estimation results from the long run model

---

8 The hedonic regression of log(housing price) on characteristics also show a negative coefficient for the percentage of whites.
There is one extra equilibrium condition in the long run as discussed in section 2(g), where the total number of houses is endogenously determined. We introduce one more exogenous variable; that is, the construction cost, of which the data is available.

Table 3 reports the estimates of parameters of the long run model. The long-run estimates are qualitatively the same as the short run ones. In particular, the key parameter of marginal disutility from mismatch is $c_1 = 61.1709 (33.0108)$ and the curvature parameter that defines the mismatch magnitude is $\alpha = 0.4686 (0.0578)$. Both are statistically significant. Moreover, the parameter for crowding out effect in the rental price equation is $c_2 = 14.0186 (2.2306)$ in the long run model, and becomes significant. Again, the economic significance of these parameters will be discussed in the following simulation subsection.

3.3 Simulations

In this subsection, we conduct simulations utilizing the above estimated parameters, in order to fully understand how changes in unemployment rates influence housing market outcomes, and what is the role played by the market thickness. Unless specifically noted, all the simulations are conducted when exogenous variables are taken at the sample mean level. In particular, at any given unemployment rate, we numerically obtain a set of outcomes such as average sale price, sales volume, and time-to-sale from the model. At a different unemployment rate, we can obtain a different set of outcomes. We first discuss the simulations of the short-run model.

a Simulations of the short run model

First, we apply the parameter estimates from the short run model. Figure 1 shows market outcomes (sale price, volumes, and time-to-sale) at various unemployment rates. Consider the case where the unemployment rate drops from 7% to 5%, corresponding to the average unemployment rate change in Texas between 1990 and 2000. From figure 1, the average sale price would increase by 1.59%, from $86,053 to $87,424; the transaction volume would increase by 6.74%, from 459 houses to 430 houses; and the time-to-sale would decrease by 10.68%, from 5.99 months to 5.35 months. In reality between 1990 and 2000, the observed average housing prices in our sample increased by 28.5%, the transaction volume increases by 63.8%, and the time-to-sale declines by 54.7%. Therefore, according to our model, the drop of unemployment rate can explain 5.58% of the percentage change in price, 10.56% of the volume change, and 19.52% of the decrease in time-to-sale.
That the change in unemployment rate can only explain a small portion of the housing price change is likely due to the inclusion of the year 2000 dummy, $D_{2000}$. This dummy, as discussed earlier, captures the changes of the aggregate environment that affects the utility flow from a perfectly matched house, $u^H_0$, for all cities. According to equation (37), a one percentage point increase in $u^H_0$ would raise the equilibrium price by 0.5 percentage point ($\theta = 0.5$) if other variables in the equation remain the same. The dummy variable, $D_{2000}$, however, do not have this type of direct relationship with the transaction volume and the time-to-sale in the model.

It is important to point out that both the transaction volumes and prices are endogenous variables in this model. They change in the same direction in response to a change in unemployment rates or other exogenous shocks. To understand the correlation between transaction volumes and prices, we calculate the price elasticity and the transaction volume elasticity with respect to the unemployment rate for each city at the unemployment rate of 7.0%, and then calculate the weighted average of the two elasticities with weights being the number of households in each city. The weighted average price elasticity is -0.05 while the weighted average transaction volume elasticity is -0.26. Therefore, the ratio of the transaction volume elasticity to the price elasticity is 5.12, larger than the roughly 4 estimated by Stein (1995). Later in the robustness check, we will discuss a possible source for the bias.

To compare our estimated ratio with the ones from Genesove and Mayer (1997, 2001), we consider a scenario where the expected overall housing price index is lowered by 1 percentage point due to some exogenous factors. In this case, the total reduction in the transaction volume for both the loss aversion effect and liquidity constraint effect is 0.375 percentage points, which is much smaller than the Stein estimate. Therefore, our model

---

9 We calculate the elasticity using Tables VI and VII in Genesove and Mayer (2001) who consider both the down-payment hypothesis and the loss-aversion hypothesis. Table VI presents the effect of two hypotheses on prices. Consider the loss-aversion hypothesis first. Assume that half of the houses incur losses, $\Pr(LOSS > 0) = 0.5$. A one percentage drop in expected prices would increase the expected value of $LOSS$ by 0.5 percentage points. Therefore, the loss-aversion effect would increase the price by $0.5\% \times 0.1 = 0.05\%$, where the coefficient 0.10 is the average of the two estimates, as suggested in the paper. Now consider the effect of the down-payment hypothesis. With a one percentage point drop in expected prices, the loan-to-value ($LTV$) ratio would increase by 1 percentage points. This leads to an increase of 0.07 percentage point in prices. Therefore, overall prices would decrease by $1 - 0.05 - 0.07 = 0.88\%$ percentage points. Table VII lists the results on time-to-sell. Similarly, one percentage drop in expected prices would result in a $0.5\% \times 0.5 = 0.25$ percentage point increase in time-to-sell because of the loss aversion hypothesis, and a 0.08 percentage point increase in time-to-sell due to the down-payment hypothesis. If the total number of houses on the market remains the same (a very strong assumption), then the number of transactions would be reduced by 0.33 percentage points. Therefore, the elasticity of transactions with respect to prices is 0.375.

25
implies a larger elasticity of transaction volumes with respect to prices while Genesove and Mayer (1997, 2001) implies a smaller elasticity than the observed elasticity.

One of the main reasons why our elasticity is larger than observed lies in our measurement of the potential market size. Due to the data limitation, we assume that each metropolitan area consists of one single market, or all metropolitan areas consist of exactly the same number of local markets. Therefore, differences in city size are used to map the differences in potential market size. To the extent that our measure of potential market size is biased, it is more likely that using city-level household numbers would overstate the difference in potential market sizes between big cities and small cities. For example, consider two metropolitan areas, Bryan-College Station with total households of roughly 60,000 and total number of houses at 38,400, and the Houston metropolitan area with 1.4 million households and a total number of houses at 0.896 million. The current model assumes that the housing market size in Houston is 23.3 times the one in Bryan-College Station. While this is unlikely to be true, we think that the difference in total households across cities overstates the difference in potential market size, since a large city may consist of a disproportionally larger number of housing markets.

For a robust check, we consider a somewhat arbitrary transformation of city size to potential market size: the square root of city size. In particular, we consider the following transformation: 

$$ M_i^\alpha = a \sqrt{M_i} $$

where $M_i$ is the city size for the ith metropolitan area, and $M_i^\alpha$ is the new potential market size for the ith city we use in this robustness check. The scale $a$ is determined in the way such that 

$$ \bar{M} = a \sqrt{\bar{M}} $$

where $\bar{M}$ is the mean city size across all cities. This transformation ensures that the transformed city size is equal to the original city size at the mean level. Note after the transformation, the market size in Houston is 4.83 times the one in Bryan-College Station.

With this newly constructed potential market size, we re-estimate our model. All key results remain qualitatively the same. The key coefficient is $c_1=66.692$, while the elasticity of volume with respect to price is roughly 3.98. Therefore, it is likely that using city size as a proxy of the potential market size probably overestimate the elasticity of transactions with respect to prices. More importantly, the basic qualitative conclusions of our paper remain valid.

Figure 2 illustrates how market thickness varies with the unemployment rate. Market thickness is measured by the average mutual distance between a seller and a buyer.
The shorter the distance, the better is the matching quality on average. Suppose there are $N_S$ sellers and $N_B$ buyers. Sellers are evenly spaced around a unit circle and buyers are uniformly distributed around the same circle. Each seller has an adjacent interval of length $1/N_S$. According to our matching mechanism, a seller can only be matched with the closest buyer who is located within her adjacent interval. Therefore, we define the average mutual distance between a seller and a buyer as the average distance between a seller and the closest buyer who is located within her adjacent interval. Specifically,

$$\text{ave}_{D\text{dist}} = E\left(D \mid D \leq \frac{1}{2N_S}\right)$$

where $D$ is the distance between the seller and her closest buyer among the total $N_B$ buyers. Its density function is $f(D) = 2N_B(1-2D)^{N_B-1}$. Note that the thickness measure thus defined is determined solely by the number of buyers and the number of sellers.

At the sample mean level of total number of households, 172,305, we obtain the equilibrium numbers of buyers and sellers and then calculate the average mutual distance between sellers and buyers under different unemployment rates. Figure 2 shows that the average mutual distance increases as the unemployment rate rises, which means the market is getting thinner and the average matching quality is worsening.

Figure 3 illustrates how the thick market effect strengthens the impact of the unemployment rate on market outcomes. Specifically, the figure shows the elasticities of outcome variables (average sales prices, transaction volumes, and selling probabilities) with respect to the unemployment rate. The two curves in figure 3 correspond to two different marginal disutility of mismatch; namely, the different values of $c_I$. The squared curve is drawn at the estimated value of $c_I = 62.3980$, while the dimond curve is drawn assuming $c_I = 3.75$. Other parameters used are the same as our structural estimates. For all three outcome variables, the magnitude of the elasticities is smaller when $c_I = 3.75$ than when $c_I = 62.40$. Note that when $c_I$ is smaller, the marginal disutility from mismatch is smaller. Therefore, there would be less room for the market thickness to play through facilitating matching in the housing market. From figure 3, when the thick market effect is negligible (i.e., when $c_I=3.75$), the elasticities of sale price, sales volume and time-to-sale at the unemployment rate of 7% are -0.014, -0.031 and 0.034 respectively, which is much smaller compared to -0.055, -0.2186, and 0.3827 when $c_I=62.3980$ as estimated. Therefore, our simulation demonstrates that the thick market effect significantly strengthens the impact of the unemployment rate.

Notice our setup does not consider the effects of liquidity constraint as in Genesove and Mayer (1997) or loss aversion as in Genesove and Mayer (2001). If those two effects are
incorporated, the thick market effect would be even stronger through interactions with them. This is because those two effects would likely lead to further shrink in the number of sellers in the market when there is a negative demand shock.

Finally, figure 4 shows the elasticities of average sales price with respect to the unemployment rate for two different city sizes, measured by the total number of households $M$. A city with a larger $M$ has typically more buyers and sellers. Therefore, $M$ measures the potential market size. The dotted curve is drawn at $M = 172,305$, the sample mean level, while the starred curve is drawn at $M = 11,578$, the sample minimum level. We can see from the figure that a smaller market is much more responsive to changes in the unemployment rate. For example, at the unemployment rate of 7%, the price elasticity with respect to the unemployment rate is about -0.1200 when $M = 11,578$, and is about -0.055 when $M = 172,305$. The idea behind this is that the thick market effect diminishes as the market gets thicker, while a larger city has in general thicker market; namely, more buyers and sellers.

b. Simulations of the long run model

In the simulations of the long-run model, we let the construction cost be equal to $70,000. The values of other exogenous variables are at their sample mean level respectively. Figure 5 – figure 8, corresponding to figure 1- figure 4, are simulation results using estimates from the long run model. All qualitative results from the short run model remain the same in the long run. Figure 5 shows how market outcomes (sale price, volumes, and time-to-sale) vary with the unemployment rate. From the figure, when unemployment rate drops from 7% to 5%, the average sale price would increase by 2.07%, from $85,251 to $87,013; the transaction volume would increase by 5.22%, from 287 houses to 302 houses; and the time-to-sale would decrease by 10.18%, from 9.63 months to 8.65 months. Therefore, in the long run, the decrease in unemployment rate can explain 7.4% of the percentage change in price from 1990 to 2000, 8.18% of the percentage change in volume, and 18.59% of the percentage decrease in time-to-sale. Note that compared to the short run case, the percentage change in price is larger in the long run.

The weighted average price-unemployment and volume-unemployment elasticities, calculated at 7.0% unemployment rate, are -0.0588 and -0.1983, respectively. The ratio of the transaction volume elasticity to the price elasticity is 3.37, smaller than the one in Stein (1995).

Note that the potential market size is not the same as market size. The latter is characterized by the actual numbers of buyers and sellers, which are endogenously determined.
Comparing figure 2 and figure 6, it remains to be true in the long run that unemployment increases the average distance between a buyer and a seller, and therefore makes the market thinner. The average distance in the long run model is longer than in the short run.

The two curves in figure 7 correspond to two different values of parameter $c_1$. The square curve is drawn at the estimated value of $c_1 = 61.17$, while the diamond curve is drawn assuming $c_1 = 3.75$. From the figure, when $c_1 = 3.75$, the elasticities of sale price, sales volume and time-to-sale at the unemployment rate of 7% are -0.026, -0.063, and 0.071 respectively, which is much smaller compared to -0.073, -0.1654, and 0.3593 when $c_1 = 61.17$. Therefore, just as the simulations of the short run model shows, the simulations based on the long run model also demonstrate that the thick market effect strengthens the impact of the unemployment rate significantly.

Finally, the long run price elasticities with respect to the unemployment rate at different city sizes are shown in figure 8. The two curves drawn at the sample mean and the sample minimum level of city sizes. From the figure, a smaller market is much more responsive to changes in the unemployment rate. For example, at the unemployment rate of 7%, the price elasticity with respect to the unemployment rate is about -0.1457 when the city size is 11,578, almost twice as much as the one -0.073 when the city size is 172,305. The pattern is the same as in the simulation of the short run model. The idea behind this is again, the diminishing thick market effect as the market gets thicker.

IV. Conclusions

In this paper, we develop a search-matching model to study the thick market effect on housing market transactions when interacted with demand shocks. According to the model, it is easier to obtain a good match in a market with more buyers. Being unemployed prevents a household from entering the housing market as a buyer. Therefore, an increase in the unemployment rate reduces demand in the market and leads to a thinner market. A thinner market in turn generates a lower price and a lower transaction volume, in addition to a longer time-to-sale.

Our structural estimations based on Texas city-level data show that: (1) an increase in the unemployment rate reduces transaction volumes, sales price, and increase the time-to-sale in the housing market. At the sample mean, a two percentage increase in unemployment rate (from 5% to 7%) would decrease sale price by 1.59% in the short run, and 2.07% in the long run, reduce the sale volumes by 6.74% in the short run, and 5.22% in the long run, and
increase the time-to-sale by 10.68% in the short run, and by 10.18% in the long run. (2) The thick market effect significantly strengthens the decline in both transaction volumes and sales price, generating a strong positive correlation between them. Comparing the elasticities of market outcomes calculated at our estimate which is 62.3980 in the short run model with those calculated at a much smaller value of 3.75, the elasticities of price, sale volume and time-to-sale are -0.055, -0.2186, and 0.3827 at our estimate, respectively, much larger than -0.014, -0.031, and 0.034 when using the dismatch parameter of 3.75. (3) A larger city with typically more buyers and sellers experiences a smaller percentage change of price in response to a change in the unemployment rate. The price elasticity is -0.055 at the sample mean city size (total number of households = 172,305), but it is -0.1200 at the smallest city in the sample (total number of households = 11,578).

Our model provides an alternative explanation to the positive correlations between price change and transaction volume in the housing market. An increase in unemployment rate would reduce both the transaction volume and sale prices. The implying volume elasticity with respect to prices is 5.12 in the short run and 3.37 in the long run, comparable with the value of 4 in Stein (1995).

References:


Table 1: Summary Statistics for Texas Cities

<table>
<thead>
<tr>
<th>Variable descriptions</th>
<th>year</th>
<th>Mean</th>
<th>Std dev</th>
<th>Min</th>
<th>Max</th>
<th>No of cities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rents per month ($) (in 1990 price)</td>
<td>1990</td>
<td>375</td>
<td>38.1</td>
<td>282</td>
<td>453</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>2000</td>
<td>433.3</td>
<td>80.9</td>
<td>313.6</td>
<td>624.1</td>
<td>38</td>
</tr>
<tr>
<td>House prices ($) (in 1990 price)</td>
<td>1990</td>
<td>70,648</td>
<td>16,426</td>
<td>43,800</td>
<td>111,400</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>2000</td>
<td>90,811</td>
<td>26,591</td>
<td>59,830</td>
<td>156,029</td>
<td>38</td>
</tr>
<tr>
<td>Time to Sale (in months)</td>
<td>1990</td>
<td>14.3</td>
<td>5.16</td>
<td>6.5</td>
<td>27.1</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>2000</td>
<td>6.48</td>
<td>4.12</td>
<td>1.9</td>
<td>27.3</td>
<td>38</td>
</tr>
<tr>
<td>Total number of households</td>
<td>1990</td>
<td>171,092</td>
<td>247,093</td>
<td>31,673</td>
<td>1,107,342</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>2000</td>
<td>173,167</td>
<td>273,432</td>
<td>11,578</td>
<td>1,392,549</td>
<td>38</td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>1990</td>
<td>7.08</td>
<td>2.82</td>
<td>2.8</td>
<td>16.5</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>2000</td>
<td>5.043</td>
<td>2.592</td>
<td>1.5</td>
<td>12.1</td>
<td>38</td>
</tr>
<tr>
<td>Rooms in a house</td>
<td>1990</td>
<td>5.840</td>
<td>.186</td>
<td>5.557</td>
<td>6.288</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>2000</td>
<td>5.926</td>
<td>.336</td>
<td>5.3</td>
<td>7.3</td>
<td>38</td>
</tr>
<tr>
<td>Age of a house</td>
<td>1990</td>
<td>21.053</td>
<td>5.451</td>
<td>12</td>
<td>34</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>2000</td>
<td>27.167</td>
<td>6.675</td>
<td>10</td>
<td>38.7</td>
<td>38</td>
</tr>
<tr>
<td>Rooms in an apartment</td>
<td>1990</td>
<td>4.047</td>
<td>.198</td>
<td>3.695</td>
<td>4.401</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>2000</td>
<td>3.895</td>
<td>.242</td>
<td>3.4</td>
<td>4.4</td>
<td>38</td>
</tr>
<tr>
<td>Percentage of white</td>
<td>1990</td>
<td>59.0%</td>
<td>16.3%</td>
<td>21.9%</td>
<td>83.3%</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>2000</td>
<td>50.4%</td>
<td>17.3%</td>
<td>7.7%</td>
<td>81.4%</td>
<td>38</td>
</tr>
<tr>
<td>Construction cost</td>
<td>1990</td>
<td>85,963</td>
<td>22,475</td>
<td>41,400</td>
<td>118,300</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>2000</td>
<td>115,204</td>
<td>135,496</td>
<td>41,686</td>
<td>917,253</td>
<td>38</td>
</tr>
</tbody>
</table>
Table 2: Parameter Estimates of the Short-run Structural Model

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
<th>Standard Errors</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Constants</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monthly Time discount rate $\beta$</td>
<td>.997</td>
<td></td>
</tr>
<tr>
<td>Bargaining power of buyers $\theta$</td>
<td>.5</td>
<td></td>
</tr>
<tr>
<td><strong>Estimated Coefficients</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>A.</strong> Coefficients in a household’s probability equation of being able to buy a house</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Effect of the unemployment rate $\eta$</td>
<td>-14.7060</td>
<td>.7989</td>
</tr>
<tr>
<td><strong>B.</strong> Coefficients in a homeowner’s probability equation of changing house</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept $\delta_0$</td>
<td>0.0013</td>
<td>0.0004</td>
</tr>
<tr>
<td>Effect of the expected selling probability $\delta_1$</td>
<td>0.0173</td>
<td>0.0031</td>
</tr>
<tr>
<td><strong>C.</strong> Coefficients in the house utility equation:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Curvature parameter $\alpha$:</td>
<td>0.4717</td>
<td>0.0480</td>
</tr>
<tr>
<td>Marginal disutility from mismatch $c_1$</td>
<td>62.3980</td>
<td>28.2019</td>
</tr>
<tr>
<td>hedonic parameters: intercept $a_0$</td>
<td>10.0803</td>
<td>.0835</td>
</tr>
<tr>
<td>rooms in a house $a_1$</td>
<td>.1433</td>
<td>.0105</td>
</tr>
<tr>
<td>Age of the house $a_2$</td>
<td>-.0083</td>
<td>.0005</td>
</tr>
<tr>
<td>white percentage $a_3$</td>
<td>-.0469</td>
<td>.0006</td>
</tr>
<tr>
<td>dummy for year 2000 $a_4$</td>
<td>.6631</td>
<td>.0077</td>
</tr>
<tr>
<td><strong>D.</strong> Coefficients in the rental equation:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crowding out parameter $c_2$</td>
<td>11.6987</td>
<td>12.7410</td>
</tr>
<tr>
<td>hedonic parameters: intercept $b_0$</td>
<td>6.1286</td>
<td>.1287</td>
</tr>
<tr>
<td>rooms in an apartment $b_1$</td>
<td>-.0352</td>
<td>.0103</td>
</tr>
<tr>
<td>white percentage $b_2$</td>
<td>.1605</td>
<td>.0978</td>
</tr>
<tr>
<td>Dummy for year 2000 $b_3$</td>
<td>.2939</td>
<td>.0043</td>
</tr>
</tbody>
</table>
Table 3: Parameter Estimates of the Long-run Structural Model

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
<th>Standard Errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly Time discount rate $\beta$</td>
<td>.997</td>
<td></td>
</tr>
<tr>
<td>Bargaining power of buyers $\theta$</td>
<td>.5</td>
<td></td>
</tr>
</tbody>
</table>

Estimated Coefficients

A. Coefficients in a household’s probability equation of being able to buy a house
   - Effect of the unemployment rate $\eta$: $-14.7535$, .9609

B. Coefficients in a homeowner’s probability equation of changing house
   - Intercept $\delta_0$: 0.0009, 0.0004
   - Effect of the expected selling probability $\delta_1$: 0.0111, 0.0048

C. Coefficients in the house utility equation:
   - Curvature parameter $\alpha$: 0.4686, 0.0578
   - Marginal disutility from mismatch $c_1$: 61.1709, 33.0108
   - Hedonic parameters: intercept $a_0$: 9.9767, 0.101
     - rooms in a house $a_1$: .1338, .0036
     - Age of the house $a_2$: -.0063, .0005
     - white percentage $a_3$: -.0514, .0307
     - dummy for year 2000 $a_4$: .8721, .0095

D. Coefficients in the rental equation:
   - Crowding out parameter $c_2$: 14.0186, 2.3206
   - Hedonic parameters: intercept $b_0$: 6.0995, .0414
     - rooms in an apartment $b_1$: -.0326, .0135
     - white percentage $b_2$: .1589, .0315
     - Dummy for year 2000 $b_3$: .3459, .0067
Figure 1: Short run market outcomes as unemployment rate varies

Ave. sale price vs. unemployment rate

Sales volume vs. unemployment rate

Time-to-sale vs. unemployment rate

Figure 2: Short run market thickness as unemployment rate varies

Ave. distance between sellers and buyers vs. unemployment rate
Figure 3  Short run elasticities of market outcomes with respect to unemployment rate
   Square curve: $c_f=62.4$
   Diamond curve: $c_f=3.75$

Figure 4  Short run elasticities of sale prices with respect to unemployment rate
   Diamond curve: $M=172,305$ (sample mean of households)
   Square curve: $M=11,578$ (sample min of households)
Figure 5 Long run market outcomes as unemployment rate varies

Figure 6: Long run market thickness as unemployment rate varies
Figure 7  Long run elasticities of market outcomes with respect to unemployment rate

Square curve: $c_1=61.17$
Diamond curve: $c_1=3.75$

Figure 8  Long run elasticities of sale prices with respect to unemployment rate

Diamond curve: $M=172,305$ (sample mean of households)
Square curve: $M=11,578$ (sample min of households)