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MARKET THICKNESS AND THE IMPACT OF UNEMPLOYMENT ON HOUSING MARKET OUTCOMES

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ABSTRACT

This paper develops a search-matching model to study the impact of the unemployment rate on the housing market in the presence of the thick market effect. We estimate the structural model using Texas city-level data that covers three years, 1990, 2000 and 2010. Our structural estimation helps identify the channel through which the thick market effect amplifies the impact of the unemployment rate on housing market outcomes. Specifically, we show that an increase in the unemployment generates a thinner market, which leads to poorer matching quality on average. As a consequence, prices and the transaction volume both decline more than in the absence of the thick market effect. Simulations based on our estimates predict that a three percentage-point increase in the unemployment rate lowers the price by 7.74% and reduces the transaction volume by 9.98%. In addition, larger cities with more population experience milder changes in prices in response to changes in the unemployment rate compared to smaller cities.

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1. Introduction

This paper develops a search-matching model to study the impact of the unemployment rate on the residential housing market when the thick market effect is present. We conduct a structural estimation using the city-level data of Texas. Simulations based on the structural estimates show that arket thickness plays an important role in determining the housing market outcomes. Specifically, an increase in the unemployment rate generates a thinner market and leads to poorer matching quality. As a result, both the price and the transaction volume decline more than in the absence of the thick market effect. In addition, smaller cities with less population would experience a bigger change in prices than larger cities when facing similar changes in unemployment rates.

There has been substantial interest in understanding how housing markets interact with the aggregate economy. Liu, Miao and Zha (2013) observe a prominent negative co-movement between land price and unemployment at the national level over time since 1975 in the U.S. We show a similar relationship between housing price and unemployment rate in Figure 1-a using Texas city-level data over the three census years of 1990, 2000 and 2010. In addition, Figure 2-b shows a negative relationship between the sales volume and the unemployment rate. Since both the housing market and the labor market are two important markets in the economy, it is essential to understand the interaction between them. Some literature studies the effect of housing market shocks on the labor market. Liu, Miao and Zha demonstrate how a negative housing demand shock can lead to an increase in the unemployment rate by building a model that incorporates a housing market, collateral constrains and a labor market with search friction. Head and Lloyd-Ellis (forthcoming) and Rupert and Wasmer (2012) study how housing market friction causes differences in geographical mobility and unemployment rate. Our paper complements the aforementioned works by examining the causal relationship in the opposite direction; that is, how unemployment influences housing market outcomes.

Intuitively, when the unemployment rate increases (or decreases), the equilibrium price and transaction volume will both decrease (or increase). However, because housing has some distinctive features (e.g., down-payment requirement, search friction and heterogeneity) from other goods markets, the impact of unemployment may be amplified. Some literature studies how search friction amplifies the effect of aggregate shocks on housing markets, without specifically investigating the impact of unemployment. Examples include Diaz and Jerez (2012), Novy-Marx (2009) and Piazzesi and Schneider (2009). Their papers adopt an aggregate matching function (as in Pissarides 2000) in which search friction may cause trading delay. Aggregate shocks change the market tightness and affect the matching probability and the length of delay, which in turn leads to amplified effect on prices. However, none of these papers pay attention to the thick market effect in facilitating the matching process through improving the matching quality. As Diamond (1982) suggests, the thick market effect may be an important factor that compounds the impact of aggregate shocks. Our paper focuses on understanding this distinctive amplifying channel.

This paper also provides a complementary explanation to the well-documented positive correlations between housing prices and transaction volumes. 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 that of Poterba (1984), has difficulty in explaining this strong and positive relationship. The down-payment hypothesis [2] (Stein 1995, Genesove and Mayer 1997, and Ortalo-Magné and Rady 2006) emphasizes the liquidity constraint of individual households. When the house price is down, households may not be able to afford the down-payment of the new house by selling their current house. Therefore, prospective sellers intend to hold their current houses longer, leading to an even smaller transaction volume. According to the loss-aversion hypothesis[3] (Genesove and Mayer 2001, and Engelhardt 2003), 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 a further reduced transaction volume. We study how the thick market effect amplifies the impact of unemployment on both housing prices and transaction volumes in the same direction, which in turn generates a strong positive correlation between them.

In our model, the number of houses is fixed in the short run but is endogenously determined in the long-run. Each house is heterogeneous in its characteristics and each household has heterogeneous preferences on houses. Households are either homeowners or renters. Each period homeowners are assumed to have a probability of changing houses. If a homeowner decides to change house, she will move out of the current house, put the house for sale on the market and meanwhile search for a new house to move in. Renters also search for suitable houses to move in.

[2] The down-payment hypothesis of Stein (1995) is empirically supported by Genesove and Mayer (1997). In Ortalo-Magné and Rady (2006), houses are divided into "starter" homes and "trade-up" homes. An increase in the household income as a positive demand shock 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 raise both the transaction volume and the price of "trade-up" homes.

[3] The prospect theory of Kahneman and Tversky (1979) argues that the marginal disutility from a loss is larger than the marginal utility from a gain. Genesove and Mayer (2001) and Engelhardt (2003) provide supportive evidence to the loss aversion hypothesis in the housing markets.

On the market, buyers and sellers both search for trading partners. If a buyer cannot find a good match this period, she will rent an apartment to live in for this period and continue to search next period. Similarly, if a seller cannot find a good matched buyer, she will hold the house until next period. The market size is characterized by the endogenously determined numbers of buyers and sellers. 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 sales volume. Like Ngai and Tenreyro (2013),[4] we refer to this phenomenon as the thick market effect in our paper.

The unemployment rate has both a direct effect and an indirect effect on the size of the housing market. Directly, from the demand side, it serves as a financial constraint and reduces the number of buyers because being unemployed practically prevents a household from entering the housing market as a buyer since she cannot get a mortgage. From the supply side, an increase in the unemployment rate lowers people's expectations of job security and makes homeowners less willing to change houses since they may not be able to buy new ones because of higher chances of being unemployed the next period. Thus the number of sellers decreases as well. As for the indirect effect, a higher unemployment rate would lower a household's expected income which in turn would make the household less likely to own a house. Also, a higher unemployment rate raises the difficulty to sell houses and thus weakens the homeowners' tendency to change houses. The idea is similar to that of Head and Lloyd-Ellis (forthcoming) where the willingness of a worker to move to other cities depends on how quickly she can sell her current house. As a result, the numbers of buyers and sellers both decrease further. The market becomes thinner. The average matching quality becomes poorer, which lowers the buyers' willingness to pay for houses. Both sellers and buyers find it more difficult to trade. Therefore, in the equilibrium, both the average housing price and sales volume decline more than in the absence of the thick market effect. In solving the model, we focus on the stationary equilibrium, following the tradition of the search-matching literature. We investigate different housing market outcomes in the stationary equilibrium under different unemployment rates, rather than the transitory dynamics.

A structural estimation of our model is conducted using the Texas city-level data that covers the three years of 1990, 2000 and 2010. We explore variation in the unemployment rate across different city-year's. The set of parameters is obtained by matching the predicted values from the model with the corresponding observed values in average housing prices, average rental price, sales volume and time-to-sale at the city level. We find a positive and significant marginal

[4] Ngai and Tenreyro (2013) examines how the thick market effect amplifies seasonal fluctuations in the housing market.

disutility from mismatch for households. This indicates a household's utility flow from the housing services would decrease when the matching quality is poor, which would in turn lower her willingness to pay for the house.

Our simulations using the estimated parameters demonstrate that a decrease (or increase) in unemployment rates would lead to a higher (lower) housing price and a larger (smaller) sales volume, creating a positive relationship between the housing price and transaction volume. Furthermore, changes in either prices or transactions in response to changes in unemployment are amplified by the thick market effect. In particular, we find that in the presence of the thick market effect, when the unemployment rate increases from 5 to 8%, the housing price will fall by 7.74% and the sales volume will fall by 9.98%. An OLS estimate without an amplifying effect would suggest lower percentage changes. At the unemployment rate of 7%, the price elasticity with respect to the unemployment rate is -0.17 while the sales volume elasticity is -0.23. The ratio of the sales volume elasticity to the price elasticity is 1.34.

In addition, our simulation shows that in a larger market with more buyers and sellers, when the unemployment rate goes up (or down), sale prices decrease (or increase) by a smaller percentage than in a thinner market. This result is consistent with Smith and Tesarek (1991) and Mayer (1993). Smith and Tesarek's empirical study of the Houston market shows that prices of more expensive houses rose by larger percentages during the housing market boom and dropped by larger percentages during the bust. Our model helps explain this phenomenon since high-price range houses are typically in a thinner market with smaller numbers of buyers and sellers.

Previous studies have applied a search-matching framework to study housing markets, including Wheaton (1990), Arnott (1989), Mayer (1995),Williams (1995) and Krainer (2001). Our paper is closely related to the literature that studies the thick market effect in facilitating the matching process through improving the matching quality.[5] Zhang (2007) investigates how the thick market effect speeds up the relocation of the used capital. The paper finds that the thick market effect can lead to cyclical behaviors in the used capital market given entry cost even though there are only idiosyncratic shocks at the firm level. Gan and Zhang (2006) apply a

[5] The thick market effect may also influence the *probability* of matching between buyers and sellers. However, the direction is ambiguous and depends on different matching mechanisms. 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). Gan and Li (2004) 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 the market becomes thicker.

similar idea to the labor market matching and find that the thick market effect can lead to unemployment cycles in the local economy given search cost. Moreover, larger cities have shorter and milder cycles on average. Among the earlier works that examine the relationship between market size and housing market outcomes, Arnott (1989) finds that because of the heterogeneity of both households and houses, when the rental market size is larger, the degree of mismatch is smaller in general and 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's. The simulations of Mayer's model show that a larger market has a lower vacancy rate, a shorter time-to-sale and a lower sale price.

A recent study by Ngai and Tenreyro (2013) applies the idea that a thicker market increases the matching quality of the housing market and develops a model to show that smaller deterministic seasonal shocks of the housing markets can be amplified through the thick market effect into greater deterministic seasonal fluctuations in both prices and transaction volumes. Our paper complements Ngai and Tenreyro's work in two perspectives. First, we study the interaction of the thick market effect with unemployment rate changes which is low frequency shock instead of deterministic seasonal shocks. Second, Ngai and Tenreyro assume that the distribution of a match-specific quality in a thicker market first-order stochastically dominates that in a thinner market—a phenomena which they refer to as the thick market effect. To support this assumption, they use individual household data from the American Housing Survey and run OLS regressions to check if the matching quality is related to the seasonal dummy. Because there is no direct data on the quality of matches, they use three proxies: (1) duration of the match, (2) number of repairs and additions made to a house during the first two years after its purchase and (3) cost of repairs and additions. Our paper shows that the discount in households' willingness-to-pay due to mismatch depends on how easily households can adjust their preferences and thus provides a micro-foundation of the channel through which the thick market effect improves the matching quality.

This paper makes two contributions to the literature. First, it incorporates the unemployment rate into a search-matching model. Our model provides a framework to study how the thick market effect amplifies the impact of unemployment on housing markets and how communities with different population size experience demand shocks differently. Second, this paper provides a micro-foundation of the thick market effect. Our structural estimation sheds light into the channel through which the thick market effect influences the housing market outcomes. To our knowledge, few works in the literature have done so.

The rest of the paper is organized as follows. Section 2 presents the model in detail. Section 3 first describes the estimation strategy, and 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 outcomes, 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) through (f). In the last part, part (g), we extend our model to the long run framework by allowing the total number of houses in the market to be endogenously determined.

(a) The Basic Setup

In our model, the number of households in a city, denoted by 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 that any house located at the buyer's location would be a perfect match.

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 each make an initial offer and then chooses to negotiate with the one who makes the highest initial offer. 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 holds the house and continues to search for buyers during the 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 city 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:

$$M = N_t^R + N_t^H \tag{1}$$

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

$$U_t = N_t^S - N_t^{sales} \tag{2}$$

During each time period, every household who lives in her own house has μ probability of deciding to change her current house. Note that μ can also be understood as the probability of having her current house listed for sale. In order to change her house, she will need to sell her current house and buy a new one. We assume that she will move out and rent a place to live during the transition if she cannot buy a new house to move in immediately. This simplifying assumption allows us not to consider the situation that a household still lives in her current house that is for sale. 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 μ. For simplicity, we do not explicitly model homeowners' decisions on whether to change houses or not; instead, we specify:

$$\mu = \min\left\lfloor 1, \delta_0 + \delta_1 urate + \delta_2 income + \delta_3 q^S + \delta_4 size \right\rfloor \tag{3}$$

where q^S is the expected selling probability. A positive δ_3 means that the expected selling probability increases the probability of changing houses.[6] The unemployment rate, denoted as *urate*, also influences the probability of changing houses. On the one hand, a higher

[6] Notice that here the probability of changing houses 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). This allows us to focus on the amplifying channel of the impact of unemployment rate through the thick market effect only.

unemployment rate raises job insecurity. A household would worry if she changes her current house; she may not be able to get a mortgage to buy a new house once unemployed. This concern lowers the household's probability of changing houses. On the other hand, as Ngai and Tenreyro (2013) argued, when the matching quality is poor, the probability of changing houses is higher. When the unemployment rate is higher, the average matching quality is poorer; thus the probability of changing houses is higher in such an aggregate environment[7]. This may attenuate the negative impact of unemployment on the probability of changing houses due to job insecurity and financial constraints as discussed earlier. In addition, some household characteristics such as household income and household size may also affect μ .

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, μN_t^H . Namely,

$$N_t^S = U_{t-1} + \mu N_t^H \tag{4}$$

The total number of houses in the city is equal to the sum of the number of owner occupied houses at the beginning of this period, N_t^H , and the number of unsold houses for sale from last period, U_{t-1}. Namely,

$$T^H = U_{t-1} + N_t^H \tag{5}$$

Now we introduce the unemployment rate into the model as demand shocks. Both renters and home occupiers are 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 obtain mortgages. Therefore, for a household who is potential buyer (either a homeowner who changes house or a renter), her probability of actually entering into the market as a buyer, denoted as γ, cannot exceed the employment rate (i.e., $\gamma \leq 1\text{-}urate$). Alternatively, γ 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. In particular, we let:

$$\gamma = (1 - urate) \cdot \frac{\exp(\eta_0 + \eta_1 urate + \eta_2 income + \eta_3 hsize)}{1 + \exp(\eta_0 + \eta_1 urate + \eta_2 income + \eta_3 hsize)}, \tag{6}$$

[7] In our model, for tractability, we do not incorporate the individual-wise matching quality when a household purchases a house into the household's probability of changing houses in the future. Note the relationship between the initial matching quality and the probability of changing houses will be attenuated by the fact that, after purchasing a house, the household typically will do some repairs, alterations and additions to make it more suitable for herself to live in.

The logit-type functional form in the second part of (6) has the advantages that it is bounded between 0 and 1, and that the continuity in *urate* may facilitate the estimation process. The unemployment rate may have an additional discouraging effect on the probability of entering the market because under a higher unemployment rate, a household would worry more about her job security and the possibility of default in the future if unemployed. A negative η_1 would mean that the probability of entering into the market to buy is lower when the unemployment rate gets higher, even if the household is employed this time. γ also depends on other exogenous factors that capture the household characteristics, such as household income and household size, that are typical demand driver of the housing market.

The total number of buyers in the market during time *t*, therefore, is γ times the sum of those homeowners who change their houses, μN_t^H, and those people who are currently renters, N_t^R:

$$N_t^B = \gamma \mu N_t^H + \gamma N_t^R \tag{7}$$

To summarize, in equations (1) through (5) and (7) (a total of six equations), we introduce nine endogenous variables, including the number of renters N_t^R, the number of owner-occupied houses N_t^H, the number of unsold houses at the end of last period U_{t-1} and at the end of the current period U_t, the number of sellers in the market N_t^S, the number of sales N_t^{sales}, the expected probability of selling a house q_t^S, the probability of changing houses μ_t, and finally the number of buyers N_t^B. The exogenous variables so far include the number of households, *M*, the unemployment rate, *urate* the probability of entering into the market as a buyer, γ, and the total number of houses $T^{H.}$. The unknown parameters that need to be estimated include the coefficients $\delta_0 - \delta_4$ in equation (3), and $\eta_0 - \eta_3$ in equation (6). Next, we will introduce more endogenous variables and more equations when we study the search and matching 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 will 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 the next time period. She has incentive to wait if the match between her house and the buyer is poor. Her value function is as follows:

$$J_{it}^S(\pi_{ijt}^S; a_{-it}^S(\cdot), a_t^B(\cdot)) = \max_{a_{it}^S \in (0,1)} \pi_{ijt}^S a_{it}^S + \beta E(J_{it+1}^S; a_{-it+1}^S(\cdot), a_{t+1}^B(\cdot))(1 - a_{it}^S) \qquad (8)$$

where $a_{-it}^S(\cdot)$ represents other sellers' decisions in the market at time *t*, $a_t^B(\cdot)$ are buyers' decisions and a_{it}^S is seller *i*'s decision. If seller *i* decides to sell her house ($a_{it}^S = 1$), her payoff is π_{ijt}^S, defined in detail in part (d) of this section. If the seller decides to wait until next period ($a_{it}^S = 0$), her (discounted) payoff is $\beta E(J_{it+1}^S; a_{-it+1}^S(\cdot), a_{t+1}^B(\cdot))$. The time discount rate is denoted as β.

The optimal decision rule of the seller is rather simple: seller *i* will sell her house if and only if her payoff from selling is higher than the payoff of waiting. Namely,:,

$$a_{it}^S = 1\left[\pi_{ijt}^S \geq \beta E\left(J_{it+1}^S; a_{-it+1}^S(\cdot), a_{it+1}^B(\cdot)\right)\right] \qquad (9)$$

Let $\overline{\pi}_{it}^S$ denote the minimum payoff for which the seller will be willing to sell her house at time *t*, with

$$\overline{\pi}_{it}^S = \beta E(J_{it+1}^S; a_{-it+1}^S(\cdot), a_{t+1}^B(\cdot)) . \qquad (10)$$

Following the search literature, we call $\overline{\pi}_{it}^S$ the seller's reservation payoff. If the seller's payoff from a transaction is at least as large as $\overline{\pi}_{it}^S$, the seller will choose to sell her house. Otherwise, the seller will choose to wait until the 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 willingness-to-pay (*wtp*) per time period for any buyer to live in a perfectly matched-house be u_0^H . Further, we let the utility flow per time period of buyer *j* from living in house *i* be:

$$u_{ij}^H = u_0^H \exp(-c_1 d_{ij}^\alpha) . \qquad (11)$$

We assume $c_1 > 0$ 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 α here to capture the possible multi-dimensionality.[8] When $d_{ij} = 0$, house i is the perfect match for buyer j. Let us define the utility discount ratio due to mismatch as $discount_{ij} = 1 - u_{ij}^H / u_0^H = 1 - \exp(-c_1 d_{ij}^{\alpha})$. This discount ratio measures the matching quality.

Later in part (f) we will demonstrate how the average distance is determined by the number of buyers and the number of sellers in the market. In one word, a thicker market with more buyers and sellers in the market has a shorter distance on average, which leads to better matching quality reflected by smaller discount of utility flow and higher willingness to pay for the house. This is referred to in the paper as the thick market effect. In our empirical part, we will estimate c_1 and α and check if they are indeed positive and significant. Another feature about equation (11) is that the utility is bounded from above, which means that the thick market effect through improving matching quality diminishes as the market gets thicker.

The parameter c_1 defines the marginal disutility from mismatch in a logarithm sense. Or it reflects how easily a household can adjust her preference. This is the key parameter in the model. When c_1 is larger, the utility discount would be greater at any positive d_{ij}. When c_1 gets very small, the discount tends to be negligible. This means if households care little about mismatch, or if households can easily adjust their housing preferences, then the mutual distance between buyers and sellers determined by market size would have negligible effect on the utility flow of housing services—hence households' willingness to pay. In such a case, the thick market effect would not have much influence on housing prices. Therefore, a positive and substantial c_1 is crucial for the thick market effect to play an important role in the market.

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 time period. She has an incentive to wait if the current match is not good enough for her. Buyer j' s value function is as follows:

$$J_{jt}^B(\pi_{ijt}^B; a_{-jt}^B(\cdot), a_t^S(\cdot)) = \max_{a_{jt}^B \in (0,1)} \pi_{ij}^B a_{jt}^B + \left[u_t^R + \beta\left(\gamma E(J_{jt+1}^B; a_{-jt+1}^B(\cdot), a_{t+1}^S(\cdot)) + (1-\gamma) E(J_{jt+1}^{BO}; a_{-jt+1}^B(\cdot), a_{t+1}^S(\cdot))\right)\right](1 - a_{jt}^B), \quad (12)$$

where $a_{-jt}^B(\cdot)$ represents other buyers' decisions in the market at time t, $a_t^S(\cdot)$ represent all sellers' decisions at time t, and a_{jt}^B is the decision made by buyer j at time t. If the buyer purchases the house $\left(a_{jt}^B = 1\right)$, her payoff is π_{ijt}^B. If the buyer decides to wait until next period

[8] See Arnott (1989) and Zhang (2007) for more discussions.

$\left(a_{jt}^{B}=0\right)$, her payoff from waiting would consist of two parts, the net utility flow from renting this time period and the discounted expected payoff next time. Next, we shall define these two parts of payoffs.

The first part is the net utility flow from renting, denoted as u_t^R. We let the net utility be the difference between the gross utility flow from renting, u_0^R, and the paid rent R_t:

$$u_t^R = u_0^R - R_t = u_0^R \exp\left(-{c_2 N_t^R}\big/{M}\right). \tag{13}$$

In (13), we let the net utility depend on the number of renters in the market N_t^R relative to the total number of households. N_t^R is endogenous, first introduced in equation (1). By rearranging (13), we can obtain the equation for R_t:

$$R_t = u_0^R\left(1-\exp\left(-{c_2 N_t^R}\big/{M}\right)\right) \tag{14}$$

Note that equation 14 shows that the rent is determined by two things. One is the gross utility flow u_0^R from renting, which can be estimated through a hedonic regression as discussed in detail later. The other is the relative rental demand to supply at time *t*. The demand side is measured by N_t^R, the total number of renters, while the supply side is approximated by M, the total population, assuming that the total number of available rental apartments is proportional to the total population. The parameter c_2 measures the crowding effect of the number of renters in the rental market. We assume $c_2 > 0$. Then equation (14) suggests that a higher rental demand relative to supply would lead to a higher rent. The rent R_t is an important endogenous variable. Both u_0^R and c_2 will be estimated in our empirical part. We will check if c2 is indeed positive.

The second part of the payoff from waiting is the buyer's discounted expected payoff next time period. Its calculation is slightly more complicated. We have to consider that if not buying this time, the current buyer would have a probability (1-γ) of leaving the market and a probability γ of remaining in the market as a buyer next time period, where γ is determined by equation (6). If she remains to be a buyer next period, her expected payoff is $E(J_{jt+1}^{B}; a_{-jt+1}^{B}(\cdot), a_{t+1}^{S}(\cdot))$. If she leaves the market next period, we denote her expected payoff as $E\left(J_{jt+1}^{BO}\right)$. 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 γ again of entering the market as a buyer. Therefore, $E\left(J_{jt+1}^{BO}\right)$ consists of the net utility from renting at *t* +1, and the discounted expected payoff at *t* +2, which is:

$$E\left(J^{BO}_{jt+1}\right) = u^R_{t+1} + \beta\left[\gamma E\left(J^B_{jt+2}\right) + (1-\gamma)E\left(J^{BO}_{jt+2}\right)\right] \quad (15)$$

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

$$a^B_{jt} = 1\left\lfloor \pi^B_{ij} \ge u^R_t + \beta\left(\gamma E\left(J^B_{jt+1}; a^B_{-jt}(\cdot), a^S_t(\cdot)\right) + (1-\gamma)E\left(J^{BO}_{jt+1}\right)\right)\right\rfloor. \quad (16)$$

Similar to the discussion in the seller's case in part (b), the reservation payoff $\bar{\pi}^B_{jt}$ is the minimum payoff at which a buyer will be willing to purchase a house. From equation (16),

$$\bar{\pi}^B_{jt} = u^R_t + \beta\left\lfloor \gamma E\left(J^B_{jt+1}; a^B_{-j}(\cdot), a^S(\cdot)\right) + (1-\gamma)E\left(J^{BO}_{jt+1}\right)\right\rfloor. \quad (17)$$

Note in this subsection, we introduce three additional endogenous variables in three equations. They are the utility flow per time period from living in a house u^H_{ijt} in equation (11), the net utility flow from renting an apartment u^R_t in equation (13), and the rent R_t in equation (14). The newly introduced exogenous variables are the utility flow per time period from living in a perfectly matched house u^H_0 and the utility flow from renting, u^R_0 .

(d) Payoffs of Buyers and Sellers

When a trade takes place between buyer *i* and seller *j* at time *t*, the buyer's payoff from buying a house is:

$$\pi^B_{ijt} = A_{ijt} - P_{ijt},$$

where A_{ijt} is the valuation of buyer *i* of house *j*, and P_{ijt} is the sale price. The seller's payoff from selling a house is simply the sale price:

$$\pi^S_{ijt} = P_{ijt}. \quad (18)$$

Thus the total value~~surplus~~ generated by the sale, which is the sum of the buyer's payoff and the seller's payoff, is equal to the valuation of buyer *i* of house *j*, A_{ijt}:

$$A_{ijt} = \pi^B_{ijt} + \pi^S_{ijt} \quad (19)$$

The buyer's valuation of the house is written in equation

$$A_{ijt} = u^H_0 \exp\left(-c_1 d^{\alpha}_{ijt}\right) + \beta(1-\mu)E\left(A_{ijt+1}\right) + \beta\mu\left(E\left(J^S_{it+1}; a^S_{-it+1}(\cdot), a^B_{it+1}(\cdot)\right) + \gamma E\left(J^B_{t+1}\right) + (1-\gamma)E\left(J^{BO}_{t+1}\right)\right)$$
(20)

The first item in (20) is the utility flow from living in the house this time. The second item is the (discounted) expected valuation of the house next time if the owner continues to live in the same house, which has a probability (1-μ). The third item is for the scenario when the owner moves out of the house next time, which has a probability μ . It consists of three parts because the owner can be a seller and a buyer at the same time after moving out. The first part is $E(J_{jt+1}^{S})$, which is the expected value of being a seller at t+1. The second is $\gamma E\left(J_{t+1}^{B}\right)$, which is the probability of being a buyer at *t+1* times the expected value of being a buyer. The third is $(1-\gamma)E\left(J_{t+1}^{BO}\right)$, which is the probability of not being a buyer at *t+1* times the expected value of potentially being a buyer at some later time.

The total value from the trade has to be larger than the sum of the reservation payoffs of both the buyer $\bar{\pi}_{jt}^{B}$ and the seller $\bar{\pi}_{it}^{S}$. The surpluses will be shared through bargaining. Thus, the buyer's payoff from the transaction is equal to:

$$\pi_{ijt}^{B} = \bar{\pi}_{it}^{B} + \theta(A_{ijt} - \bar{\pi}_{it}^{B} - \bar{\pi}_{jt}^{S}), \quad (21)$$

The seller's payoff, which is also the sale price P_{ijt} according to equation (18), is equal to:

$$P_{ijt} = \pi_{ijt}^{S} = \bar{\pi}_{it}^{S} + (1-\theta)(A_{ijt} - \bar{\pi}_{it}^{B} - \bar{\pi}_{jt}^{S}), \quad (22)$$

where θ is the bargaining power of the buyer (correspondingly, 1-θ is the bargaining power of the seller) which is exogenously given.

(e) The Market Equilibrium

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

From equation (10), the seller's reservation payoff in the equilibrium is:

$$\bar{\pi}^{S} = \beta E\left(J^{S}\right) \quad (23)$$

Similarly, according to equation (17), the buyer's reservation payoff in the equilibrium is:

$$\bar{\pi}^{B} = u^{R} + \beta\left(\gamma E\left(J^{B}\right) + (1-\gamma)E\left(J^{BO}\right)\right). \quad (24)$$

According to equations (11) and (20), the shorter the distance between the buyer and the seller, the better the match between them and thus the higher the total value generated if they reach a deal. By adding the seller's reservation payoff $\bar{\pi}^{S}$ and the buyer's reservation payoff $\bar{\pi}^{B}$, we can see that a sale will be made if and only if the total value is above $\bar{\pi}_{S} + \bar{\pi}_{B}$, which is equivalent to say that a deal will be reached if and only if the mutual distance between the buyer and the seller is short enough. Let us denote $\bar{d}$ as the maximum distance corresponding to the minimum total value, denoted as $\bar{A}$. According to equation (20), we have:

$$\bar{A} = \bar{\pi}^B + \bar{\pi}^S = \frac{u_0^H}{1-(1-\mu)\beta}\exp\left(-c_1\bar{d}^{\alpha}\right) + \frac{\mu\beta E\left(J^S\right)}{1-(1-\mu)\beta} + \frac{\mu\beta\left(\gamma E\left(J^B\right)+(1-\gamma)E\left(J^{BO}\right)\right)}{1-(1-\mu)\beta}$$

(25)

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

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

Finally, note in the stationary equilibrium, the number of unsold houses at the end of each time period is the same over time. Namely,,

$$U_t = U_{t-1}. \quad (27)$$

In equations (23) through (27), we introduce six new endogenous variables in addition to part (a) in six equations: the seller's reservation payoff, $\bar{\pi}^S$, the buyer's reservation payoff, $\bar{\pi}^B$, the maximum mutual distance, $\bar{d}$, to reach a deal, and the values $E(J^S)$, $E(J^B)$, and $E(J^{BO})$. None of these endogenous variables are likely to be observable in the data.

(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 $\left[s_0 - \bar{d}, s_0 + \bar{d}\right)$ 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 sellers, the distance between any two adjacent sellers are $1/2N^S$. 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 $[s_0-1/2N^S, s_0+1/2N^S)$ are 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 equilibrium where $2\bar{d} \le 1/N^S$. For those buyers located in the interval $\left[s_0 - \bar{d}, s_0 + \bar{d}\right)$, the seller picks one who is the closest to him to negotiate with.

While 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 during 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[9]. Finally, if the closest buyer turns out to be within the seller's acceptable interval of $\left[s_0-\bar{d}, s_0+\bar{d}\right)$, 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:

$$q^S = 1-\left(1-2\bar{d}\right)^{N^B}. \tag{28}$$

The expected number of sales each time period is:

$$N^{sales} = N^S q^S \tag{29}$$

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

$$E\left(J^S\right) = E\left(\pi^S \mid \pi^S \geq \bar{\pi}^S\right)q^S + \beta E\left(J^S\right)\left(1-q^S\right) \tag{30}$$

Equation (30) is obtained by taking expectation of (8), and considering $E\left(J_t^S\right) = E\left(J_{t+1}^S\right) \equiv E\left(J^S\right)$ in the stationary equilibrium. Re-arranging equation (30), we get:

$$E\left(J^S\right) = \frac{E\left(\pi^S \mid \pi^S \geq \bar{\pi}^S\right)q^S}{1-\beta+\beta q^S} \tag{31}$$

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 j and the house located at s_0 be D_j, $j=1,2,\ldots,N^B$. The shorter arc distance between the closest buyer and the house, denoted D, is: $D = \min\left\{D_1,\ldots,D_{N^B}\right\}$.

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

$$f\left(D\right) = 2N^B\left(1-2D\right)^{N^B-1}.$$

As $N^B \to \infty$, D converges in distribution to an extreme value distribution, so that,

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

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

[9] This is a coordination failure as noted by Burnet, Shi and Wright (2001).

density function of D conditional on the closest buyer falling in the seller's acceptable interval $[s_0 - \bar{d}, s_0 + \bar{d})$ is:

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

Therefore, according to equation (20), the expected total surplus conditional on the house being sold, is calculated:

$$E\left(A \mid \pi^S \geq \bar{\pi}^S\right) = \frac{\int_0^{\bar{d}} u^H(x) f(x) dx}{\left(1-\beta(1-\mu)\right) q^S} + \frac{\mu\beta E\left(J^S\right)}{\left(1-\beta(1-\mu)\right)} + \frac{\mu\beta\left(\gamma E\left(J^B\right) + (1-\gamma) E\left(J^{BO}\right)\right)}{\left(1-\beta(1-\mu)\right)}$$

$$= \frac{\int_0^{\bar{d}} u_0^H \exp\left(-c_1 x^\alpha\right) 2N^B \exp\left(-2N^B d\right) dx}{\left(1-\beta(1-\mu)\right) q^S} + \frac{\mu\beta E\left(J^S\right)}{\left(1-\beta(1-\mu)\right)} + \frac{\mu\beta\left(\gamma E\left(J^B\right) + (1-\gamma) E\left(J^{BO}\right)\right)}{\left(1-\beta(1-\mu)\right)}$$

(32)

Note the first term in the above equation is divided by the probability of the house being sold, which is q^S. Taking expectation of the seller's surplus, π^S, defined in (22), conditional on the seller's house being sold, we have:

$$E\left(\pi^S \mid \pi^S \geq \bar{\pi}^S\right) = \bar{\pi}^S + (1-\theta)\left(E\left(A \mid \pi^S \geq \bar{\pi}^S\right) - \bar{\pi}^S - \bar{\pi}^B\right) \quad (33)$$

where $E\left(A \mid \pi^S \geq \bar{\pi}^S\right)$ 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 the number of houses sold and number of buyers in the market:

$$q^B = \frac{N^{sales}}{N^B} \quad (34)$$

The buyer's expected value of searching for a house is obtained by taking expectation of (12) and considering $E\left(J_t^B\right) = E\left(J_{t+1}^B\right) \equiv E\left(J^B\right)$ in the stationary equilibrium:

$$E\left(J^B\right) = E\left(\pi^B \mid \pi^B \geq \bar{\pi}^B\right) q^B + \left(\frac{u^R + \beta\gamma E(J^B)}{1-\beta(1-\gamma)}\right)(1-q^B) . \quad (35)$$

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

$$E\left(J^B\right) = \frac{E\left(\pi^B \mid \pi^B \geq \bar{\pi}^B\right) q^B (1-\beta(1-\gamma)) + u^R (1-q^B)}{1-\beta+\beta\gamma q^B} \quad (36)$$

Taking the expectation of the buyer's surplus π^B defined in equation (21), conditional on the buyer purchasing a house, we have:

$$E\left(\pi^B \mid \pi^B \geq \bar{\pi}^B\right) = \bar{\pi}^B + \theta\left(E\left(A \mid \pi^S \geq \bar{\pi}^S\right) - \bar{\pi}^S - \bar{\pi}^B\right) \quad (37)$$

In equations (28)-(29), (31)-(34) and (36)-(37) (total eight equations), we introduce four new endogenous variables: the conditional expected payoff of selling the house $E\left(\pi^S \mid \pi^S \geq \bar{\pi}^S\right)$ (which is also the equilibrium price), the expected payoff of purchasing a house, $E\left(\pi^B \mid \pi^B \geq \bar{\pi}^B\right)$, the expected total surplus $E\left(A \mid \pi^S \geq \bar{\pi}^S\right)$, and the probability of buying a house (q^B). Note the probability of selling a house (q^S) was first introduced in equation (3). Only the probability of selling a house, q^S, may be observable in the data.

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 in the short rum equilibrium.

(g) Long-run equilibrium

Notice that so far our model assumes the total number of houses 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. More specifically, assume that it takes just one period to build house. A builder has to invest a fixed amount F to build a house, but he also incurs an additional cost if he cannot immediately sell the house he has just built. Given the real interest per period r, and the probability of selling this house q^S, the long run equilibrium requires one more condition to be satisfied; that is, the expected sale price of a house equal the expected cost of building this house:

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

where E(P) is the expected sale price with P defined by equation (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 are likely to be built in the long run.

3. Estimation and Simulations

3.1 Estimation Strategy

Since the model outlined in Section 2 is unlikely to have 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 numerical simulations 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 on which we do have data. They are the rents R, the price of a house P, the number of sales transactions and the time-to-sale, which is the inverse of the probability of selling a house q^S. Therefore, we have four equations:

$$E(R_k) = R(\Theta, X_k), \tag{39.1}$$

$$E(P_k) = P(\Theta, X_k), \tag{39.2}$$

$$E\left(N^{sales}{}_k\right) = N^{sales}\left(\Theta, X_k\right) \tag{39.3}$$

$$E\left(TS_k\right) = 1/\left\lfloor q^S\left(\Theta, X_k\right)\right\rfloor, \tag{39.4}$$

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 equilibrium rent R, based on the information on city k, denoted as X_k, and a given set of parameters Θ. Obtaining $R(\Theta, X_k)$ requires solving all twenty-two equations of the model, which we do numerically.

Similarly, P_k in (39.2) is the observed housing price in city k, and $P(\Theta, X_k)$ is the implicit function that describes the equilibrium expected sale price of a house from the model conditional on Θ and X_k. Note $P(\Theta, X_k)$ and $E\left(\pi^S \mid \pi^S \geq \bar{\pi}^S\right)$ in equation (33) are equivalent. N_k^{sales} is the observed transaction volume each month in city k, and $N^{sales}\left(\Theta, X_k\right)$ is the equilibrium number of sales from the model that appears in equation (29). Finally, TS_k in (39.4) is the observed time-to-sale of city k. Because we do not have the individual time-to-sale data averaged at the city-level, we use inventory as proxy which measures the number of months it would take to sell all unsold housing stock on the market[10]. $q^S(\Theta, X_k)$ is the equilibrium probability of selling a house

[10] Diaz and Jerez (2012) and Piazzesi and Schneider (2009) use the average time-to-sale data at the national level. For each city in Texas, we use inventory as proxy to time-to-sale. This proxy captures the expected selling probability of a typical house during a month in a city. The implicit assumption is that *ex-ante* each house in a city has the same expected selling probability, which is consistent with our model. We understand the limitation of this proxy if there are heterogeneous housing markets within the same city.

from the model based on Θ and X_k. Remember $q^S(\Theta, X_k)$ appears in equations (28) and (29). Like $R(\Theta, X_k)$, solving for $P(\Theta, X_k)$, $N^{sales}(\Theta, X_k)$ and $q^S(\Theta, X_k)$ requires solving all twenty-two endogenous variables using the twenty-two equations described in the previous section.

One can use the expectations in (39.1) through (39.4) to construct the moment conditions and apply the GMM. However, the standard way of constructing the moment conditions requires a rather difficult first derivatives of the implicit functions of $R(\Theta, X_k)$, $P(\Theta, X_k)$, $N^{sales}(\Theta, X_k)$ 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) through (39.4) into the following form:

$$R_k = R(\Theta, X_k) + \varepsilon_1, \tag{40.1}$$

$$P_k = P(\Theta, X_k) + \varepsilon_2, \tag{40.2}$$

$$N^{sales}{}_k = N^{sales}(\Theta, X_k) + \varepsilon_3 \tag{40.3}$$

$$TS_k = 1/\left\lfloor q^S(\Theta, X_k)\right\rfloor + \varepsilon_4. \tag{40.4}$$

where we assume $E(\varepsilon_i|X_k) = 0$ for $i = 1, 2, 3, 4$ and covariance matrix of the error term $(\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4)$ is $\Sigma = Var\ (\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4)$. Here we allow Σ to be flexible to capture the possible heteroscedasticity $\mathrm{Var}(\varepsilon_i) \neq \mathrm{Var}(\varepsilon_j)$ and the correlation $\mathrm{Cov}(\varepsilon_i, \varepsilon_j) \neq 0$. A weighted nonlinear least square estimator is given by:

$$\min_{\Theta} \quad \frac{1}{K}\sum_{k=1}^{K}\begin{pmatrix} R_k - R(\Theta, X_k) \\ P_k - P(\Theta, X_k) \\ N^{sales}{}_k - N^{sales}(\Theta, X_k) \\ TS_k - \left[1/q^S(\Theta, X_k)\right] \end{pmatrix}' \Sigma^{-1} \begin{pmatrix} R_k - R(\Theta, X_k) \\ P_k - P(\Theta, X_k) \\ N^{sales}{}_k - N^{sales}(\Theta, X_k) \\ TS_k - \left[1/q^S(\Theta, X_k)\right] \end{pmatrix}, \tag{41}$$

where K is the total number of cities. Note the usual identification condition for the non-linear least square applies here. This estimator is consistent and has an asymptotical normal distribution. To implement this estimator, we first estimate equation (41) with Σ 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 Θ includes δ_i for i=0, 1, …, 4, in equation (3), η_i for i=0,1,2 and 3, in equation (6), u_0^H, c_1 and α in equation (11), and u_0^R and c_2 in equation (14). It also includes the time discount rate β and the bargaining power parameter θ in equations (33) and (37). We let monthly time discount rate β = 0.997, which corresponds to a yearly time discount factor of

0.965. We also let θ=.50 for simplicity, assuming the buyers and sellers equally share the surplus. These two parameters are not our focus, 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 living in perfectly matched houses u_0^H and the gross rental utility u_0^R to be dependent on these housing and neighborhood characteristics. To determine what characteristics to use, we first conduct auxiliary hedonic price regressions of average housing prices and average rental prices on characteristics of house and apartments[11]. In order to reduce the number of parameters to be estimated, only those regressors that are statistically significant in the auxiliary regressions are kept in the structural estimation. In particular, we let u_0^H in (11) and u_0^R in (13) be:

$$\ln u_0^H = a_0 + a_1 HouseRooms + a_2 HouseAge + a_3 WhitePct + a_4 D_{2000} + a_5 D_{2010} + a_6 income \tag{42}$$

$$\ln u_0^R = b_0 + b_1 AptRooms + b_2 Crime + b_3 WhitePct + b_4 D_{2000} + b_5 D_{2010} + b_6 income \tag{43}$$

In equations (42) and (43), *WhitePct* is the percentage of white population. *HouseRooms* in (42) is the city average number of house rooms and *HouseAge* in (42) is the city average number of years since construction of houses. *AptRooms* in (43) is the city average number of rooms in rental apartments and *Crime* in (43) the city crime rate. D_{2000} is the dummy for the year 2000 and D_{2010} is the dummy for the year 2010. The coefficients for this two dummy variables in both equations capture changes in the aggregate environment that affect the markets of all cities in this two years, such as changes in mortgage markets and in demographics.

Notice that we also include city average income in both equations (42) and (43) for two reasons. First, the hedonic housing price and rental price regressions aim to estimate people's willingness to pay. A standard bid-rent model that incorporates internal urban structure and commuting cost would suggest that urban income influences people's willingness to pay for living within the city because opportunity cost for commuting is higher for higher income people (see

[11] In the simple linear hedonic regressions, we regress log(housing prices) and log(rental prices) on characteristics such as crime rates, average number of rooms in a house or in an apartment (rental property), average age of houses, the percentage of population who is white, etc.

Duranton and Puga (2004)). Thus higher urban income would make people willing to pay higher housing or rental price. The search-matching model developed in this paper basically seeks to capture the variations that are not captured in the hedonic price regressions.

In sum, the total parameters to be estimated are: the hedonic parameters include a_i for i = 0, 1, …,6 in equation (42) and b_i, i = 0, 1, .., 6 in equation (43), δ_i for i=0, 1, …, 4 in equation (3), η_i for i=0,1,2 and 3 in equation (6), c_1 and α in equation (11), and c_2 in equation (14). The total number of parameters to be estimated is twenty-four. 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 that covers 28 cities in 1990, 38 cities in 2000, and 37 cities in 2010 in Texas for which we can find complete information. City-level total number of houses sold, average prices and inventory are produced from various multiple-listing service markets by Texas Real Estate Center[12]. Other information is obtained from censuses. All cities of 1990 show up again in 2000 and 2010 except for the city of Texarkana, which has information in 1990 but not in later years. Four cities that appeared in the year 2000 do not appear in 2010, while three cities appear in 2010 but not in 2000. It is also noted that the definitions of a city may vary across these three years due to changes from the multiple-listing service markets. Other variables are constructed based on information from censuses. It is important to point out that this paper does not utilize the panel aspect of the data. Instead, it treats a city in 1990, in 2000 and in 2010 as three different cities. The construction cost of a city is the average cost of new houses in the city.

Table 1 lists the summary statistics of the variables used in estimation. Several observations are noted here. First, there are substantial differences across cities. The ratio of the number of households between the biggest city and the smallest city is 35.0 in 1990, 120.3 in 2000 and 128.3 in 2010. The difference between the first ratio and the other two ratios is mostly because the smallest city in the sample of 2000, San Marcos, is not included in the sample year 1990.[13] The ratios of the unemployment rates between the highest city and the lowest city are 5.89 in 1990, 8.07 in 2000, and 3.11 in 2010. 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

[12] http://recenter.tamu.edu/

[13] The dataset includes San Marcos as part of Austin in 1990.

households and the unemployment rates. These factors may also affect transaction volumes, rental prices, time-to-sale and other housing market outcomes simultaneously.

Second, there is substantial difference across three 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. In 2010, similar to the national economy, Texas economy had barely come out from the worst recession since World War II. The variable in this paper used to describe the overall economy is the unemployment rate. The average unemployment rate dropped from 7.08% in 1990 to 5.04% in 2000, but rose to 8.06% in 2010. The housing market improved between 1990 and 2000. For example, although the samples in 1990 and 2000 are not directly comparable, the average housing price increased by 28.5%, from $70,648 (in 1990 dollar) for the 28 cities in 1990, to $89,316 (in 1990 dollar) for the 37 cities in 2000. The average housing price increased by just 6.7%, from $89,316 in 2000 to $95,303 in 2010. The time-to-sale was 14.3 months in 1990, 6.48 months in 2000, and 9.15 months in 2010. The average rent also went up by 15.5% from $375 per month in 1990 to $433.3 per month in 2000. Similar to the average housing price, average rent only has a slight increase between 2000 and 2010. Note a significant part of the differences in housing prices and in rental prices among the three years would be captured by the coefficients for the dummy variable D_{2000} and D_{2010} in equations (42) and (43).

It is important to point out that this paper assumes all houses and households in each city to be a single market because of data constraint or each city has the same number of housing markets. Both assumptions are obviously not accurate. Cities such as Houston, Dallas, San Antonio and Austin will probably have more locality-based markets than a small city such as Bryan-College Station. Houses of different types or at different price ranges may 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 will 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 issue 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 the 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. Let M be the total number of household of a city; the imputed number of houses of the city is thus calculated as $M*64\%/(100\%-2\%)$.

Table 2 reports the estimates of the parameters of the short run model. The first panel of table 2 lists two constants: β, the monthly time discount rate and θ, the bargaining power of buyers. As discussed before, the time discount rate is not a focus of this paper. Thus we let β equal 0.997, which is a commonly used value in the literature and corresponds to a yearly time discount rate of 0.965. The real interest rate is derived consistently with the time discount rate, namely, $r = 1/\beta - 1 = 0.003$. The bargaining power of buyers 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 of the short-run model. Part A lists the estimates of the parameters in a household's probability equation of entering the market to buy, as in equation (6). In addition to the direct financial constraint effect as discussed earlier, the unemployment rate has an additional negative effect on a household's probability of entering the market to buy, which may reflect concerns about the household's future employment uncertainty. This additional effect is captured by η_1 in equation (6) and is estimated at -9.997 (0.3359)[14] , which is statistically significant. Furthermore, a household's income level has a positive and significant effect on the household's probability of entering the market to buy; specifically, η_2 in equation (6) is estimated at 0.47 (0.1258). If we take all the other variables of equation (6) at the 2010 sample mean income level, when the unemployment rate increases from 5% to 7%, the probability of entering the market to buy would drop from 0.439 to 0.384[15]. When the unemployment rate decreases from 9% to 7%, the probability would rise from 0.332 to 0.384. So an increase in the unemployment rate would reduce the number of buyers.

Part B reports the estimates of the parameters in equation (3), which determines a household's probability of changing house per month. The effect of the unemployment rate,

[14] Standard errors are in parentheses.

[15] Note in doing calculations here, we do not consider the possible income change caused by the change in the unemployment rate. If we do, the calculated changes in the probability of entering the market to buy will be even larger.

denoted δ_1, is estimated at -0.0081 (0.0024), which is negative and significant. The effect of household income, denoted δ_2, is estimated at 0.013 (0.0005), which is positive and significant. The parameter δ_3 that measures the effect of the expected selling probability per month is estimated at 0.0026 (0.0016). This suggests that there would be fewer homeowners who would like to change houses (and thus move out of their current houses) when the expected probability of selling[16] their current houses is lower. However, it is just marginally significant. Finally, the household size has a positive and significant effect on the probability of changing house, and δ_4 is estimated at 0.0004 (0.0001). If we take all the other variables at the 2010 sample mean income level[17], when the unemployment rate increases from 5% to 7%, the probability of changing houses drops from 0.0114 to 0.0113. When the unemployment rate decreases from 9% to 7%, the probability rises from 0.0111 to 0.0113[18]. So an increase in the unemployment rate would reduce the number of sellers as well as the number of buyers and lead to a thinner market.

Part C reports the estimates of the parameters in the housing utility equations (11) and (42). The key parameters in this paper are the coefficients in equation (11): the coefficient for utility discount from mismatch c_1 and the curvature coefficient α that reflects the multi-dimensionality of housing characteristics. While c_1 defines the marginal disutility due to mismatch in a logarithm sense, d^{α} measures the degree of mismatch. The estimate is 98.59 (9.5540) for c_1 and 0.4212 (0.0092) for α; both are at more than 1% significance level. As discussed earlier, since both c_1 and α are 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 more in the simulation section.

For the hedonic parameters in the housing utility equation (42), the coefficient for the number of rooms in a house is positive and significant as expected. The coefficient for the age of a house is negative but insignificant. The coefficient for the percentage of whites in the city is negative but insignificant.[19] The dummy variables for year 2000 and year 2010 are both positive and significant. The household income coefficient is also positive and significant, which indicates that higher income generates higher willingness to pay for houses as discussed earlier.

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[16] The probability of selling per month is equal to the inverse of time-to-sale in months.

[17] Note the only exception is the selling probability, which is endogenously determined. For this, we use the equilibrium selling probability 0.1724 corresponding to the unemployment rate of 0.07, calculated based on our estimations and simulations discussed later in this paper.

[18] Note in doing calculations here, we do not consider the possible changes in either income or expected selling probability caused by the change in the unemployment rate. If we do, the calculated changes in the probability of changing houses will be even larger.

[19] The hedonic regression of log(housing price) on housing characteristics also shows a negative coefficient for the percentage of whites.

The crowding out of parameter c_2 in the rental price equation (14) is estimated at a positive value of 6.906 and is statistically significant. This suggests that more renters would increase the rental price given the number of apartments. For the hedonic parameters in the rental utility 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 an apartment may negatively affect the prices. The coefficient for the percentage of whites in a city is positive and significant while the coefficient for the crime rate in a city is negative and significant as expected. The dummy variables for years 2000 and 2010 are both positive and significant. The household income coefficient is also positive and significant.

To check the goodness of fit, we calculate the R^2 for the three matched endogenous variables. They are 0.34, 0.74, 0.77 and 0.09 for housing price, transaction volume, rental price and time-to-sale, respectively. For comparison, we also run OLS regressions of the three outcome variables on all the exogenous variables in our short-run model. The R^2 is 0.839, 0.762, 0.886 and 0.537 for housing price, transaction volume, rental price and time-to-sale, respectively.

b. Estimation results from the long run model

There is one extra equilibrium condition in the long run, as discussed in part (g) of section 2, where the total number of houses is endogenously determined. We introduce one more exogenous variable in the estimation; 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 the marginal disutility from mismatch is c_1 = 90.27 (7.54) and the curvature parameter that defines the mismatch magnitude is α = 0.4499 (0.0092). Both are statistically significant. Note the estimated utility discount is a bit smaller than that in the short run. This may reflect that in the long-run households can adjust their preferences. Moreover, the estimated coefficient for expected selling probability in the equation that determines the probability of changing houses is $\delta_3 = 0.0024\,(0.0006)$ in the long run model and becomes significant. Again, the economic significance of these parameters will be discussed in the following simulation subsection.

To check the goodness of fit of the long-run model, we calculate the R^2 for the three matched endogenous variables. They are 0.27, 0.29, 0.76, and 0.09 for housing price, transaction volume, rental price and time-to-sale, respectively. For comparison, we also run OLS regressions of the three outcome variables on all the exogenous variables in our long-run model. The R^2 is 0.841, 0.789, 0.891 and 0.540 for housing price, transaction volume, rental price and time-to-sale, respectively.

3.3 Simulations

In this subsection, we conduct simulations utilizing the above estimated parameters to fully understand how changes in unemployment rates influence housing market outcomes in the presence of the thick market effect. Unless specifically noted, our simulations are conducted at the 2010 sample mean level for all exogenous variables except the household income.

Because at the aggregate level, the unemployment rate would affect the income level, we use the simple Okun's law to capture their relationship; that is, growth rate of income=-2.86*(urate-0.05). Here we assume the growth rate of income is zero at the natural unemployment rate of 0.05. Let the income level corresponding to the natural unemployment rate be y_0. A one-percentage point increase in the unemployment rate above the natural rate would lower the income level by 2.86%. In our simulations, we set the 2010 sample mean income of $73,000 per household as the income level at the natural unemployment rate.

At any given unemployment rate, we numerically solve for the equilibrium set of housing market outcomes such as average sale price, sales volume, and time-to-sale from the model. At different unemployment rates, we obtain different sets of outcomes. Next, we 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 2 shows housing 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 increases by 5.14%, from $159,700 to $151,700; the sales volume increases by 6.51%, from 1932 houses to 2062 houses; and the time-to-sale decreases by 7.64%, from 5.8 months to 5.37 months.

We also did the case of opposite movement where the unemployment rate increases from 5% to 8%, corresponding to the average unemployment rate change in Texas between 2000 and 2010. The average sale price decreases by 7.74%; the sales volume decreases by 9.98%; and the time-to-sale increases by 11.69%.

For comparison, we use the OLS estimates to predict the percentage changes in the housing price, sales volume and time-to-sale. When the unemployment rate decreases from 7% to 5%[20], the housing price would go up by 2.7%, the sales volume would go up by 2.6% and the time-to-sale would decrease by 3.2%. When the unemployment rate increases from 5% to 8%, the housing price would go down by 4.1%, the sales volume would go down by 3.8% and the time-to-sale would increase by 4.7%. In either case, the predicted percentage changes by OLS are much smaller than those by the structural model. This suggests the OLS estimation may not fully account for the amplifying effect of the thick market effect on the impact of the unemployment change while the structural estimation does.

Note 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 elasticity with weights being the number of households in each city, divided by the total number of households of all cities. The weighted average price elasticity is -0.1680 while the weighted average transaction volume elasticity is -0.2249. Therefore, the ratio of the transaction volume elasticity to the price elasticity is 1.34. This is smaller than the 4 roughly estimated by Stein (1995).

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,[21] which is also smaller than the Stein estimate.

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[20] We also let the income change with the unemployment rate according to Okun'law in the OLS prediction.

[21] We calculate the elasticity using Tables VI and VII from 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 (i.e., 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%*0.10 = 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 point. This leads to an increase of 0.07 percentage points 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 0.50*0.50 = 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

One may concern our measurement of the potential market size (not the actual market size, which is endogenously determined). Due to the data limitation, we assume that each metropolitan area consists of one single market or that 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 896,000. 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: $M_i^n = a\sqrt{M_i}$, where M_i is the city size for the *i*-th metropolitan area, and M_i^n is the new potential market size for the *i*-th city we use in this robustness check. The scale *a* is determined such that $\overline{M} = a\sqrt{\overline{M}}$, where $\overline{M}$ 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[22]. All the key results remain qualitatively the same. The key coefficient is c_1=100.011. The weighted average price elasticity is -0.1787 while the weighted average transaction volume elasticity is -0.2499. Therefore, the ratio of the transaction volume elasticity to the price elasticity is 1.40, a bit higher than the previous 1.34. It is likely that using city size as a proxy of the potential market size probably underestimates the elasticity of transactions with respect to prices. More importantly, the basic qualitative conclusions of our paper remain valid.

Figure 3 illustrates how market thickness and the matching quality vary with the unemployment rate. Market thickness is measured by the average mutual distance between a

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the number of transactions would be reduced by 0.33 percentage points. Therefore, the elasticity of transactions with respect to prices is 0.375.

[22] In this estimation, we only match three variables: housing price, rental price and time-to-sale while dropping the sales volume because the total number of households has been arbitrarily changed.

seller and a buyer, which is determined by the number of buyers and sellers. The thicker the market, the shorter is the mutual distance 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,

$$ave\_dist = E\left(D \mid D \leq \frac{1}{2N^S} \right) \qquad (44)$$

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 by both the number of buyers and the number of sellers.

When the housing market gets thicker, what would happen to the matching quality reflected by the discount in the utility flow of housing services? We calculate the average discount ratio of utility flow due to mismatch as follows:

$$ave\_discount = 1 - E\left(\exp(-c_1 D^{\alpha}) \mid D \leq \frac{1}{2N^S} \right) \qquad (45)$$

At the 2010 sample mean level of total number of households (i.e., 276,460) we obtain the equilibrium number of buyers and sellers and then calculate the average mutual distance between sellers and buyers as well as the average discount ratio under different unemployment rates. Figure 3 shows that both the average mutual distance and the average discount ratio increase as the unemployment rate rises, which suggests when the market is getting thinner with the unemployment rate, the average matching quality is worsening at the same time. According to panel 2 of Figure 3, when the unemployment rate increases from 5% to 8%, the average discount ratio in the utility flow increases from 0.48 to 0.51.

As discussed in our model in Section 2, when the marginal disutility from mismatch is smaller, there would be less room for the market thickness to play through improving the matching quality in the housing market. In order to understand how different values of c_1 affect market outcome, we arbitrarily use $c_1 = 5$ as a comparison. Figure 4 illustrates the elasticity of outcome variables (i.e., average sales prices, transaction volumes, and time-to-sale)with respect to the unemployment rate at two different values of c_1. The dotted curve in the first panel of Figure 3 is drawn at the estimated value of $c_1 = 98.5891$, while the starred curve is drawn assuming $c_1 =$

5. Other parameters used are the same as our structural estimates of the short-run model. Panel 2 of Figure 3 shows that at a small marginal disutility value of c_1 = 5, the average utility discount ratio is 0.0037 at 5% unemployment rate—very small compared to the discount ratio 0.48 when c_1 = 98.5891—and it changes little with the unemployment rate. Specifically, when the unemployment rate increases from 5% to 8%, the average discount ratio in utility flow increases from 0.0037 to 0.0041.

From Figure 4, when the thick market effect is negligible at c_1 = 5, the elasticity of sale price, sales volume and time-to-sale at the unemployment rate of 7% are -0.129, -0.1761 and 0.0001, respectively, which is much smaller compared to -0.1738, -0.2257, and 0.2636 when c_1=98.5891 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 5 shows the elasticity of average sales price with respect to the unemployment rate for two different city sizes, measured by the total number of households M. The dotted curve is drawn at M = 276,460, the sample mean level, while the starred curve is drawn at M = 14,976, the sample minimum level. From the figure, a smaller city is 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 -0.2082 when M = 14,976, which is higher than -0.1738 in abstract value when M = 276,460. The reason behind this is that the thick market effect diminishes and its amplifying function gets weaker as the market gets thicker, while a larger city is more likely to generate a thicker housing market in equilibrium. Smith and Tesarek (1984) show that prices of more expensive houses rose by larger percentages during the housing market boom while dropping 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 losing 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 losing 18% in value from 1985-1987. Our model simulation result is consistent with this phenomenon since high-price range houses are typically in a thinner market with a smaller number of buyers and sellers.

b. Simulations of the long run model

Figure 6 through Figure 9, corresponding to Figure 2 through Figure 5, 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 6 shows how market outcomes (sale price, volumes, and time-to-sale) vary with the unemployment rate. Consider the case where the unemployment rate drops from 7% to 5%. From Figure 6, the average sale price increases by 5.25%, from $144,600 to $152,400; the transaction volume increases by 6.87%, from 1883 houses to 2017 houses; and the time-to-sale decreases by 7.74%, from 5.67 months to 5.24 months. In the case of opposite movement where the unemployment rate increases from 5% to 8%,the average sale price decreases by 7.91%; the transaction volume decreases by 10.49%; and the time-to-sale increases by 11.77%. Note that compared to the short run case, the percentage changes in price, sales volume and time to sale are slightly larger in the long run.

As with the short-run model, we also calculate the percentage changes in the housing price, sales volume and time-to-sale predicted by the OLS estimation[23]. When the unemployment rate decreases from 7% to 5%, the housing price would go up by 2.9%, the transaction volume would go up by 2.3% and the time-to-sale would decrease by 2.9%. When the unemployment rate increases from 5% to 8%, the housing price would go down by 4.3%, the transaction volume would go down by 3.5% and the time-to-sale would increase by 4.3%. Again, the percentage changes predicted by OLS estimation are much smaller than those by the structural estimation.

The weighted average price and volume elasticity with respect to unemployment rate at 7.0%, calculated in the similar way as in the short run case, are -0.1744 and -0.2367, respectively—very close to the ones in the short run. The ratio of the transaction volume elasticity to the price elasticity is 1.36, slightly larger than that in the short run case.

Comparing Figure 3 and Figure 7, it remains true in the long run that an increase in the unemployment rate enlarges the average distance between a buyer and a seller and therefore worsens the matching quality on average. Note the average discount ratio in the long run model is smaller than in the short run. This is because the estimated marginal disutility from mismatch is smaller in the long run.

Like Figure 4, the two curves in Figure 8 correspond to two different values of parameter c_1. The dotted curve is drawn at the estimated value of c_1 = 90.2645 based on the long-run model, while the starred curve is drawn assuming c_1 = 5 (note the thick market effect is negligible when c_1 = 5 as shown in the second panel of Figure 7). Other parameters used are the same as our structural estimates of the long-run model. From figure 8, when c_1=5, the elasticity

[23] The long-run OLS regression adds in one more explanatory variable: construction cost.

of sale price, sales volume and time-to-sale at the unemployment rate of 7% are -0.1408, -0.1810, and 0.0001, respectively, which is much smaller compared to -0.1798, -0.2376, and 0.2726 when c_1=90.2645. Therefore, as with the short run model, the long run model demonstrates that the thick market effect strengthens the impact of the unemployment rate significantly.

Finally, the long run price elasticity with respect to the unemployment rate at different city sizes is shown in figure 9. The two curves are drawn at the sample mean and the sample minimum level of city size, respectively. From the figure, a smaller city is much more responsive to changes in the unemployment rate. For example, at the unemployment rate of 7%, the price elasticity is about -0.2061 when the city size is 14,976, higher than -0.1798 when the city size is 276,460. The pattern is the same as in the simulation of the short run model. Again, the idea behind this is the diminishing thick market effect as the market gets thicker.

4. Conclusions

In this paper, we develop a search-matching model to study how changes in the unemployment rate affect housing market transactions in the presence of the thick market effect. According to the model, the average matching quality between buyer and sellers is better in a thicker market. A higher unemployment rate prevents more renters from entering the housing market as buyers. It also reduces current homeowners' probability of of changing houses due to increased job insecurity. Therefore, the housing market becomes thinner with fewer buyers and sellers, which leads to poorer matching quality on average. As a result, both the housing price and sales volume would decline more than in the absence of the thick market effect.

Our structural estimations and simulations based on Texas city-level data show that an increase in the unemployment rate lowers the sales price, reduces the transaction volume, and increases the time-to-sale in the housing market. The thick market effect significantly strengthens the impact of unemployment on housing market outcomes. At our estimated value of the marginal disutility from mismatch, the short run elasticity of housing price, sales volume and time-to-sale at the 7% unemployment rate is -0.1738, -0.2257 and 0.2636, respectively. A three percentage increase in unemployment rate (from 5% to 8%) would lower the sale price by 7.74% in the short run and 7.91% in the long run, reduce the sale volumes by 9.98% in the short run and 10.49% in the long run, and increase the time-to-sale by 11.69% in the short run and 11.77% in the long run. In addition, 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 short run price elasticity is -0.1738 at the sample mean city size (total number of households = 276,460), smaller than -0.2082 at the sample minimum city size (total number of households = 11,578).

In addition, an increase in the unemployment rate reduces both the sales volume and the housing price, generating a positive correlation between them. The ratio of the sales volume elasticity to the price elasticity is 1.34 in the short run and 1.36 in the long run.

Our model helps understand the interaction between housing markets and aggregate demand shocks. Simulations of this paper demonstrate that the thick market effect is an important amplifying channel of the impact of unemployment on housing market outcomes. Moreover, our model provides a micro-foundation of the thick market effect. It sheds light on how the thick market effect facilitates the matching process through improving the average matching quality between buyers and sellers.

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Table 1: Summary Statistics for Texas Cities

Variable descriptions	Year	Mean	Std dev	Min	Max	No of cities
Rents per month ($)	1990	375	38.1	282	453	27
(in 1990 price)	2000	426.0	79.6	308.5	613.8	38
	2010	441.3	60.1	341.6	617.4	37
House prices ($)	1990	70,648	16,426	43,800	111,400	27
(in 1990 price)	2000	89,316	26,154	58,846	153,462	38
	2010	95,303	23,696	67,267	153,354	37
Sales volume per quarter	1990	3577	6958	319	33617	27
	2000	5854	11081	308	52459	38
	2010	5756	11577	317	56804	37
Inventory (in months)	1990	14.3	5.16	6.5	27.1	27
	2000	6.48	4.12	1.9	27.3	38
	2010	9.15	3.96	5.6	26.4	37
Total number of households	1990	205,626	304,605	24,563	1,201,494	27
	2000	235,397	336,421	14,585	1,527,081	38
	2010	276,460	436,875	14,976	1,922,909	37
Unemployment rate	1990	7.08	2.82	2.8	16.5	27
	2000	4.76	2.37	1.5	12.1	38
	2010	8.06	1.92	5.3	16.5	37
Household income ($)	1990	37,166	5,210	24,602	46,641	27
(in 1990 price)	2000	46,666	8,757	27,881	72,453	38
	2010	45,888	6,652	32,043	64,186	37
Household size	1990	3.38	0.34	2.84	4.65	27
	2000	3.35	0.31	2.70	4.48	38
	2010	3.26	0.27	2.69	4.17	37
Rooms in a house	1990	5.840	0.186	5.557	6.288	27
	2000	5.926	0.336	5.3	7.3	38
	2010	5.839	0.389	5.3	7.7	37
Age of a house	1990	21.1	5.451	12	34	27
	2000	27.2	6.675	10	38.7	38
	2010	34.5	7.855	18	47	37
Rooms in an apartment	1990	4.0	0.198	3.695	4.401	27
	2000	3.9	0.242	3.4	4.4	38
	2010	4.0	0.410	3.4	5.8	37
Percentage of white	1990	59.0%	16.3%	21.9%	83.3%	27
	2000	50.4%	17.3%	7.7%	81.4%	38
	2010	47.8%	16.9%	13.7%	80.2%	37
Crime	1990	1062.6	417.3	226.1	1977.8	27
	2000	627.9	262.5	53.3	1193.7	38
	2010	411.6	94.8	246.5	665.3	37
Construction cost ($)	1990	85,963	22,475	41,400	118,300	27
(in 1990 price)	2000	93,070	22,319	41,479	134,475	38
	2010	104,385	28,805	47,423	188,650	37

Table 2: Parameter Estimates of the Short-run Structural Model

Parameters	Value	Standard Errors
<u>Constants</u>		
Monthly Time discount rate β	.997	
Bargaining power of buyers θ	.5	
<u>Estimated Coefficients</u>		
A. Coefficients in a household's probability equation of entering the market to buy a house:		
Effect of the unemployment rate η_1	-9.9970	0.3359.
Effect of household income η_2	0.0470	0.0126
B. Coefficients in a homeowner's probability equation of changing house:		
Intercept δ_0	0.0010	0.0004
Effect of the unemployment rate δ_1	-0.0081	0.0024
Effect of household income δ_2	0.0126	0.0005
Effect of the expected selling probability δ_3	0.0026	0.0016
Effect of household size δ_4	0.0004	0.0001
C. Coefficients in the house utility flow equation:		
Curvature parameter α	0.4216	0.0092
Percentage of utility discount from per unit mismatch c_1	98.5891	9.5540
Hedonic parameters: intercept a_0	1.7172	0.0498
rooms in a house a_1	0.5423	0.0075
Age of the house a_2	-0.0004	0.0004
white percentage a_3	-0.0026	0.0202
dummy for year 2000 a_4	0.8351	0.0154
dummy for year 2010 a_5	1.1022	0.0185
household income a_6	0.9679	0.0341
D. Coefficients in the rental equation:		
Crowding out parameter c_2	6.9065	3.3999
Hedonic parameters: intercept b_0	5.9290	0.0245
rooms in an apartment b_1	-0.0191	0.0052
Crime rate b_2	-0.0001	0.0000
white percentage b_3	0.1492	0.0071
dummy for year 2000 b_4	0.2648	0.0035
dummy for year 2010 b_5	0.4494	0.0049
household income b_6	0.3250	0.0139

Table 3: Parameter Estimates of the Long-run Structural Model

Parameters	Value	Standard Errors
Constants		
Monthly Time discount rate β	.997	
Bargaining power of buyers θ	.5	
Estimated Coefficients		
A. Coefficients in a household's probability equation of entering the market to buy a house:		
Effect of the unemployment rate η_1	-9.9906	0.2992.
Effect of household income η_2	0.0508	0.0153
B. Coefficients in a homeowner's probability equation of changing house:		
Intercept δ_0	0.0021	0.0003
Effect of the unemployment rate δ_1	-0.0083	0.0012
Effect of household income δ_2	0.0102	0.0003
Effect of the expected selling probability δ_3	0.0024	0.0006
Effect of household size δ_4	0.0000	0.0001
C. Coefficients in the house utility flow equation:		
Curvature parameter α	0.4499	0.0092
Percentage of utility discount from per unit mismatch c_1	90.2645	7.5328
Hedonic parameters: intercept a_0	1.3516	0.0515
rooms in a house a_1	0.5635	0.0073
Age of the house a_2	-0.0000	0.0004
white percentage a_3	-0.0000	0.0179
dummy for year 2000 a_4	0.9077	0.0173
dummy for year 2010 a_5	1.1754	0.0217
household income a_6	1.0597	0.0307
D. Coefficients in the rental equation:		
Crowding out parameter c_2	8.4319	1.3654
Hedonic parameters: intercept b_0	5.8869	0.0252
rooms in an apartment b_1	-0.0000	0.0052
Crime rate b_2	-0.0001	0.0000
white percentage b_3	0.1226	0.0075
dummy for year 2000 b_4	0.2545	0.0035
dummy for year 2010 b_5	0.4198	0.0047
household income b_6	0.3151	0.0106

Figure 1-a. Housing price (in 1990 dollars) vs. Unemployment rate across Texas cities (Three years 1990, 2000 and 2010 pooled together).

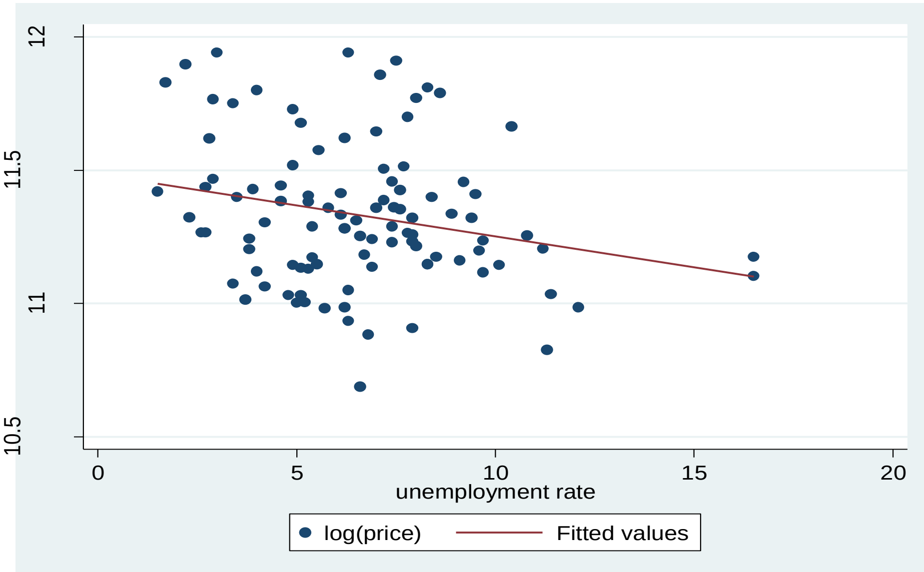

Figure 1-b. Sales volume vs. Unemployment rate across Texas cities (Three years: 1990, 2000 and 2010 pooled together).

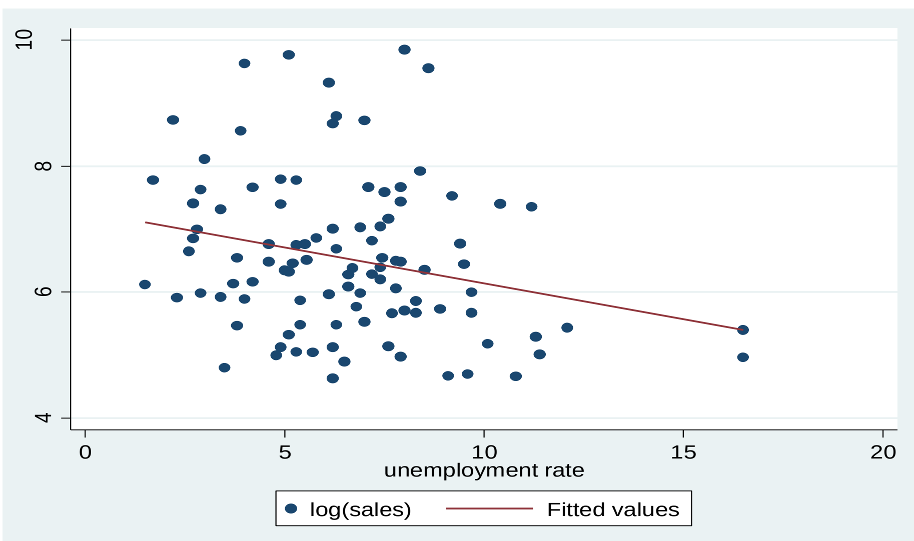

Figure 2. Short run market outcomes as unemployment rate varies

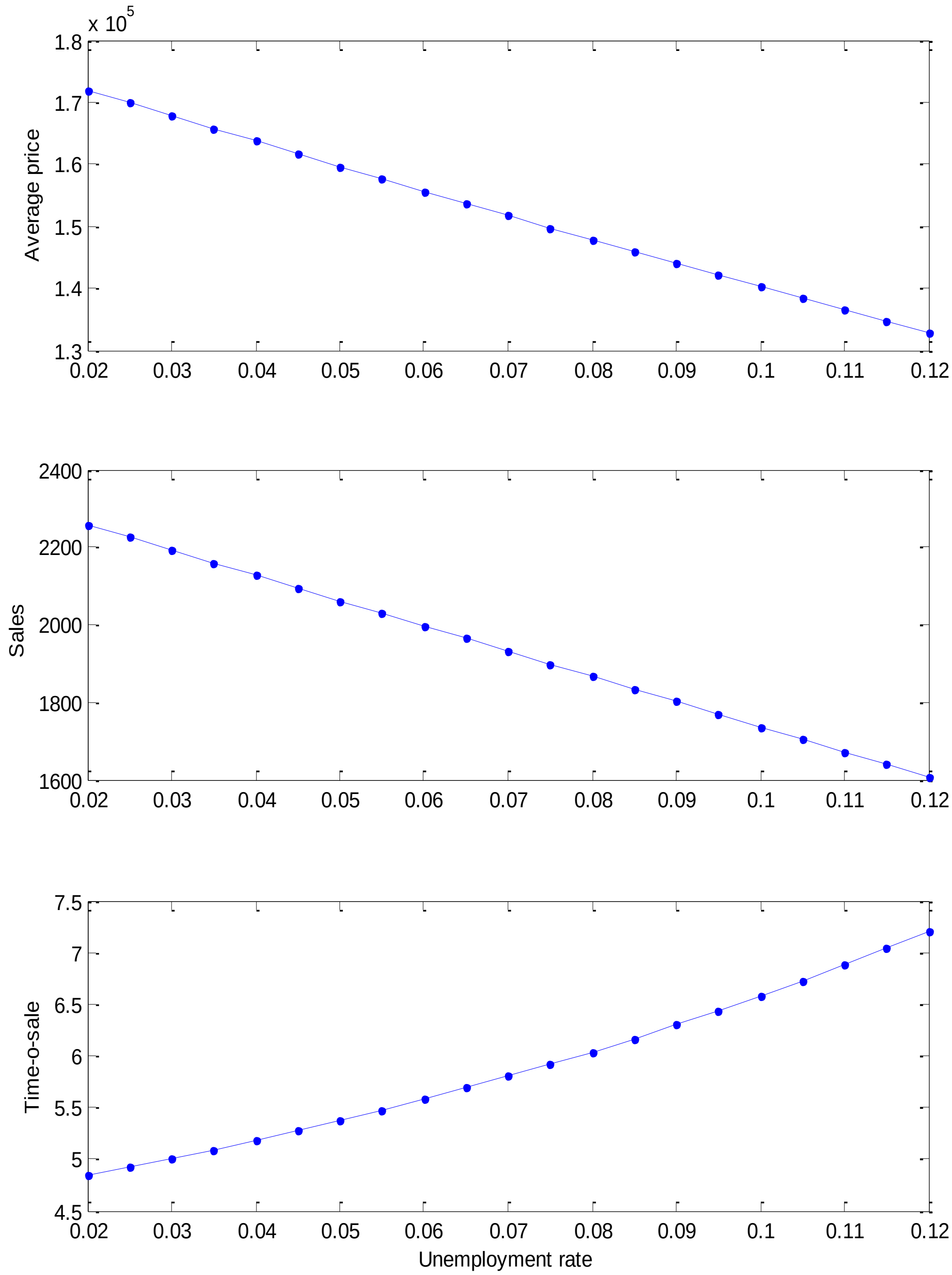

Figure 3. Short run market thickness and matching quality as unemployment rate varies
Dotted curve: c_1=98.59
Starred curve: c_1=5

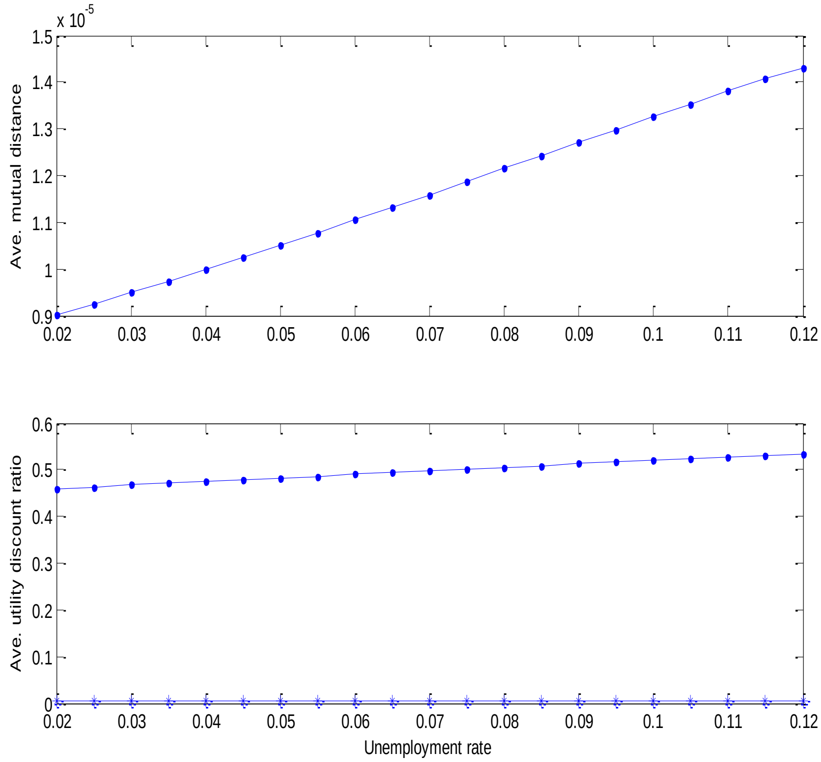

Figure 4. Short run elasticity of market outcomes with respect to unemployment rate
Dotted curve: c_1=98.59
Starred curve: c_1=5

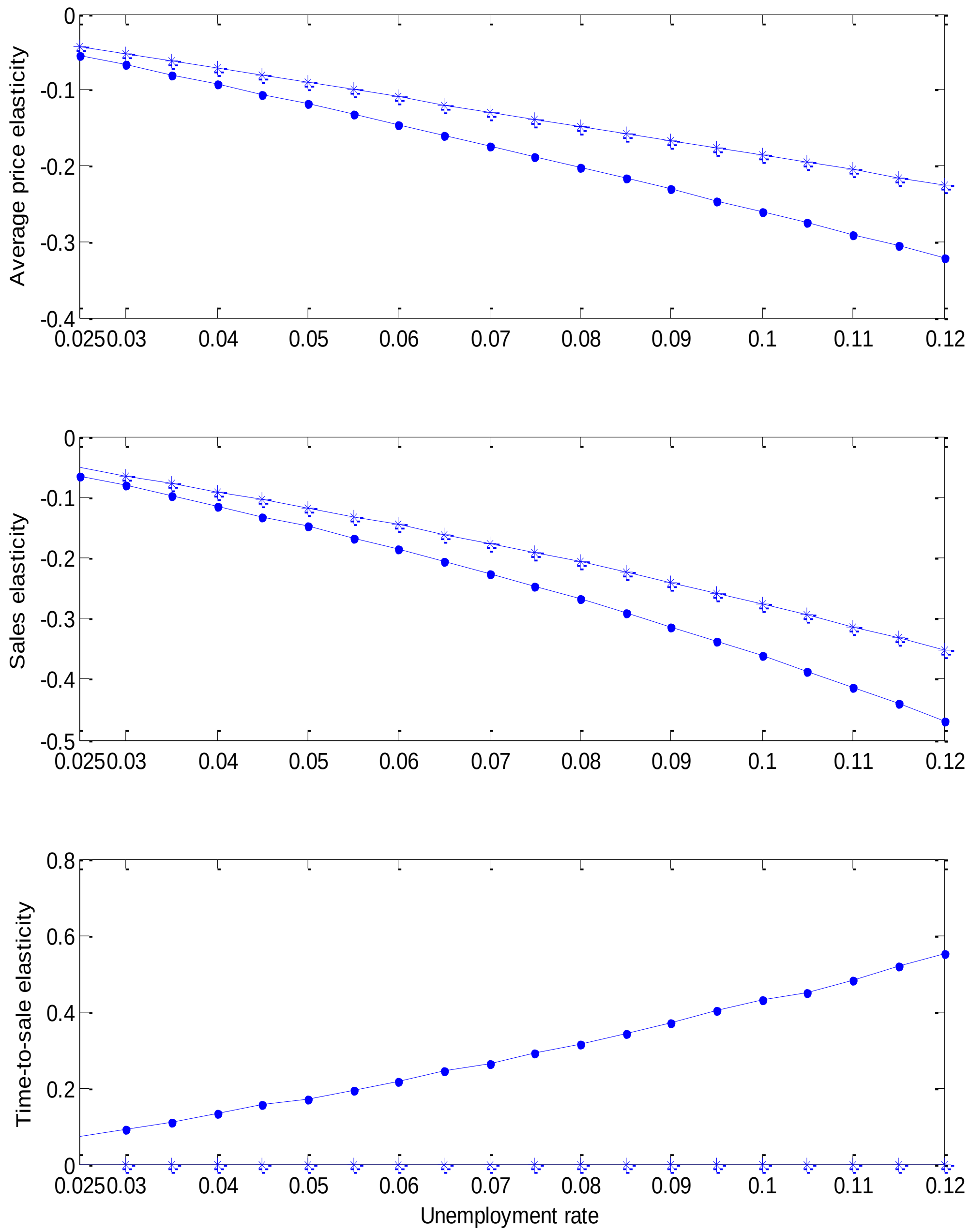

Figure 5 Short run elasticities of sale prices with respect to unemployment rate
Dotted curve: *M*= 276,460 (2010 sample mean of total number of households)
Starred curve: *M*= 14,976 (2010 sample min of total number of households)

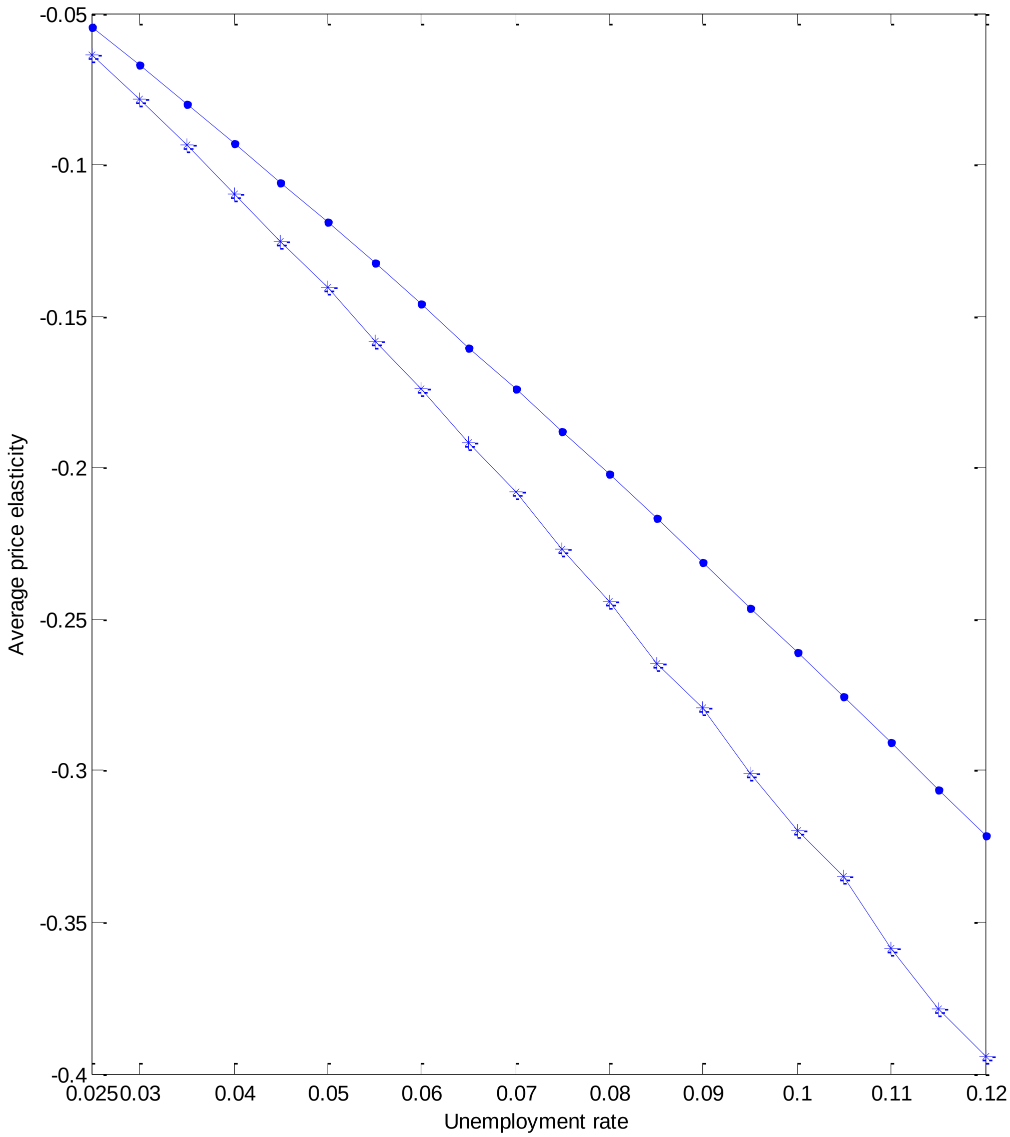

Figure 6 Long run market outcomes as unemployment rate varies

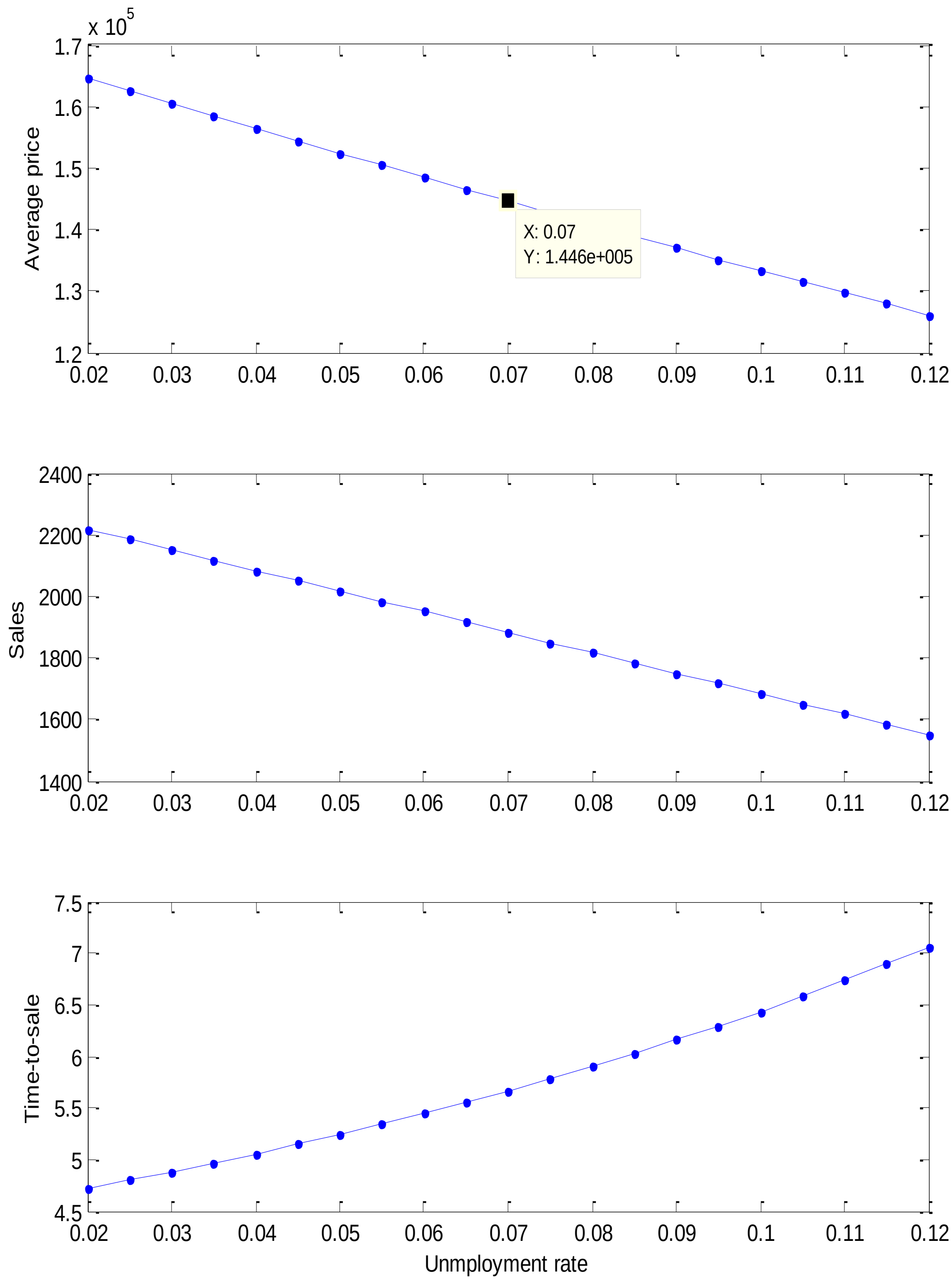

Figure 7: Long run market thickness and matching quality as unemployment rate varies
Dotted curve: c_1=90.26
Starred curve: c_1=5

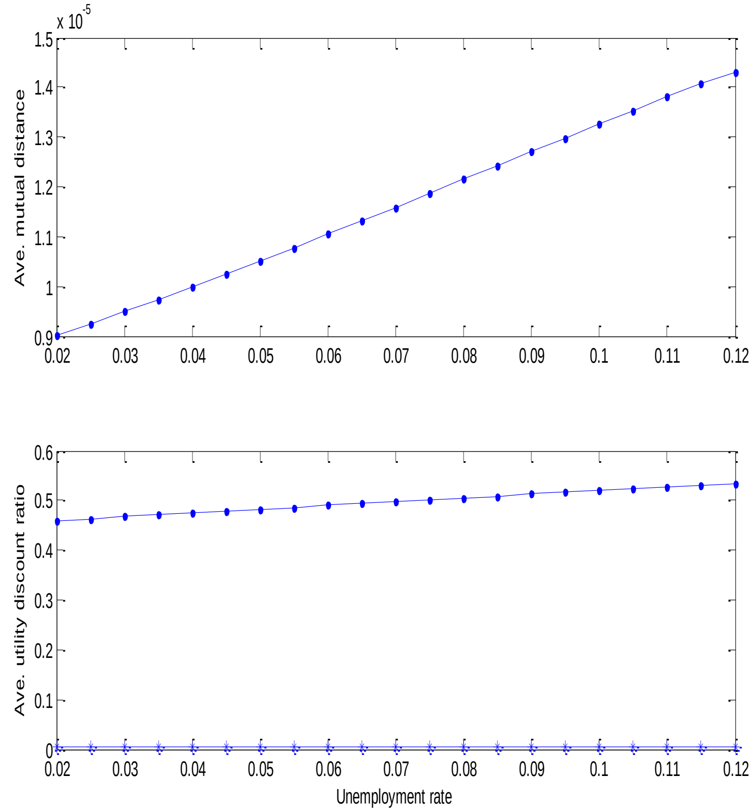

Figure 8 Long run elasticities of market outcomes with respect to unemployment rate
Dotted curve: c_1=90.26
Starred curve: c_1=5

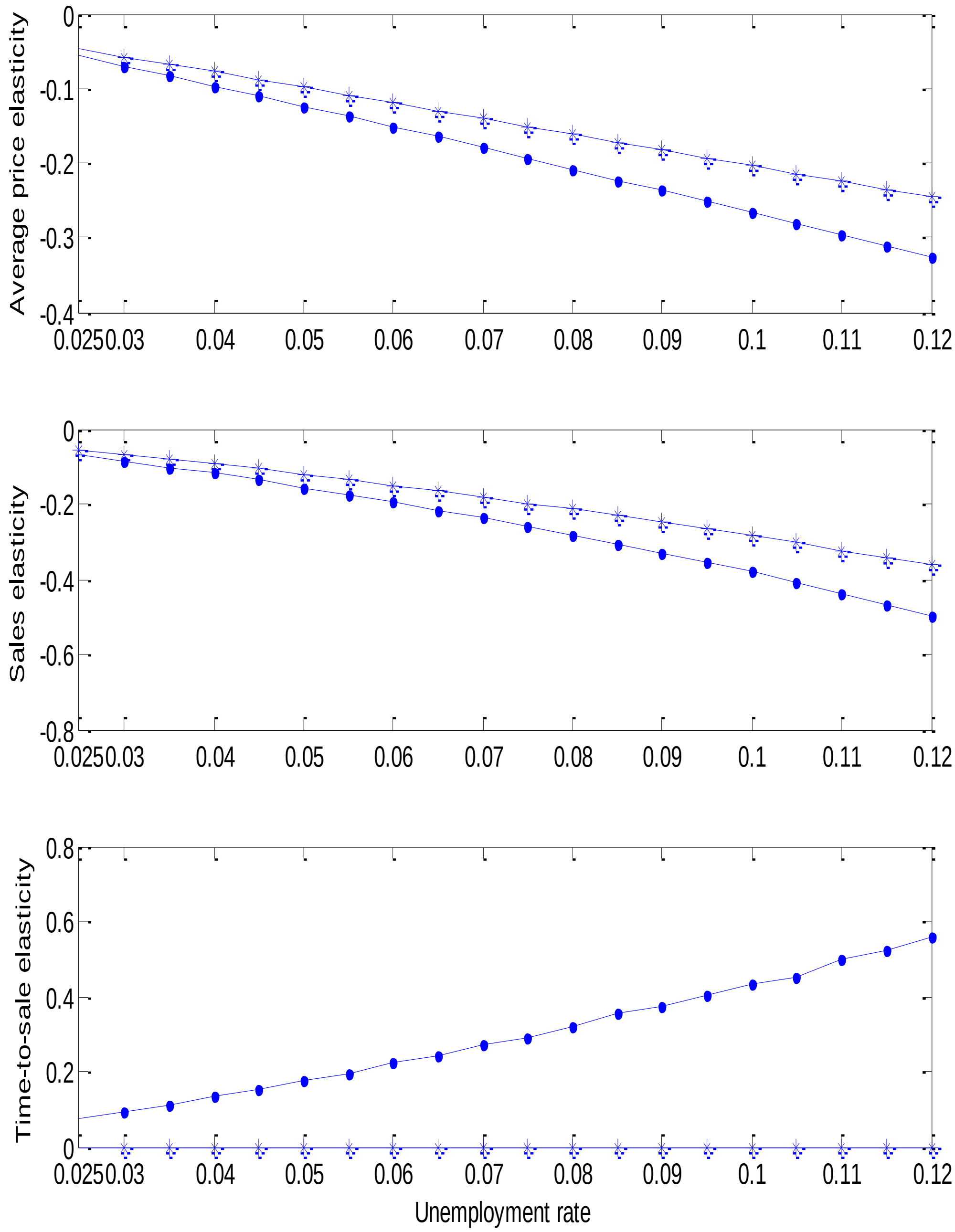

Figure 9 Long run elasticities of sale prices with respect to unemployment rate
Dotted curve: *M*= 276,460 (2010 sample mean of total number of households)
Starred curve: *M*= 14,976 (2010 sample min of total number of households)