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Market thickness and the impact of unemployment on housing market outcomes☆

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ABSTRACT

A search-and-matching model is developed to study how unemployment influences the housing market in the presence of the thick-market effect. A structural estimation of the model is conducted based on Texas city-level data that covers three years—1990, 2000 and 2010. Simulations help clarify how much the thick-market effect amplifies the impact of unemployment. A three-percentage-point increase in the unemployment rate lowers the price by 10.74% and reduces the transaction volume by 5.49%. Incorporating a feedback mechanism from housing prices to unemployment strengthens the amplification magnitude of the thick-market effect.

1. Introduction

A search-and-matching model is developed in this paper to study the impact of the unemployment rate on the residential housing market when the thick-market effect is present. A structural estimation is then conducted based on Texas city-level data. The simulations using the structural estimates show that an increase in the unemployment rate generates a thinner housing market and leads to poorer matching quality. As a result, both the price and the transaction volume decline more than they would in the absence of the thick-market effect.

The collapse of housing prices and the subsequent surge in unemployment during the financial crisis of 2007–2009 generated substantial interest in understanding how housing markets interact with labor markets (see Mian and Sufi, 2014 and Liu et al., 2016). Fig. 1a shows a negative relationship between the housing price and the unemployment rate using Texas city-level data from three census years—1990, 2000 and 2010. In addition, Fig. 2b shows a negative relationship between the sales volume and the unemployment rate. Since both the housing market and the labor market are important segments of the economy, it is essential to understand the interaction between them. Recent studies have established several theoretical

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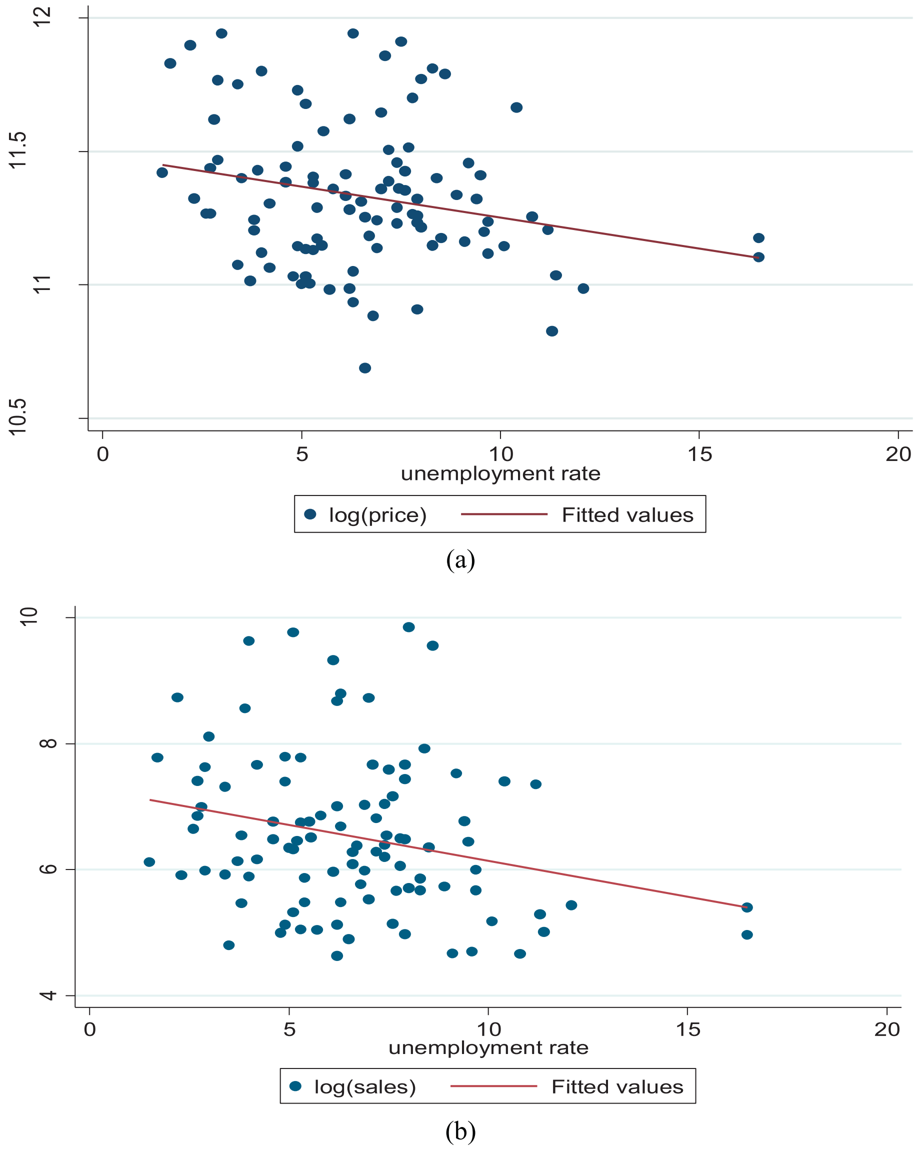

Fig. 1. (a) Housing price (in 1990 dollars) vs. unemployment rate across Texas cities (Three years 1990, 2000 and 2010 pooled together) (b) Sales volume vs. unemployment rate across Texas cities (Three years: 1990, 2000 and 2010 pooled together).

channels through which housing price can affect unemployment rate. For example, Liu et al. (2016) emphasize the collateral constraint channel while Head and Lloyd-Ellis (2012) and Rupert and Wasmer (2012) study how housing market friction causes differences in geographical mobility and unemployment rates. This paper aims to complement the aforementioned works by examining the causal relationship in the opposite direction; that is, how unemployment influences housing market outcomes in the presence of the thick-market effect. As it is well known, most macroeconomic models do not provide a fully satisfactory explanation for asset prices. In particular, the housing prices in these models are not as volatile as their counterparts in the data. It is therefore not surprising that the existing literature typically relies on large shocks to households' preferences for housing service to explain the volatility of housing prices (see e.g., Iacoviello and Neri, 2010; Liu et al., 2013, 2016). As Diamond (1982) suggests, the thick-market effect may be an important factor that compounds the impact of aggregate shocks. This paper hence provides a timely propagation mechanism for explaining the impact of aggregate shocks on housing prices in macroeconomic models.

In our model, the housing market features distinctive search friction due to heterogeneity in house characteristics and consumer tastes. In each period, each homeowner has a certain probability of being hit by some idiosyncratic shock that changes her utility flow from living in her current house. If the shock is bad enough, she will choose to move out of her current house, put the house up for sale on the market and become a potential buyer for a suitable house. Each potential

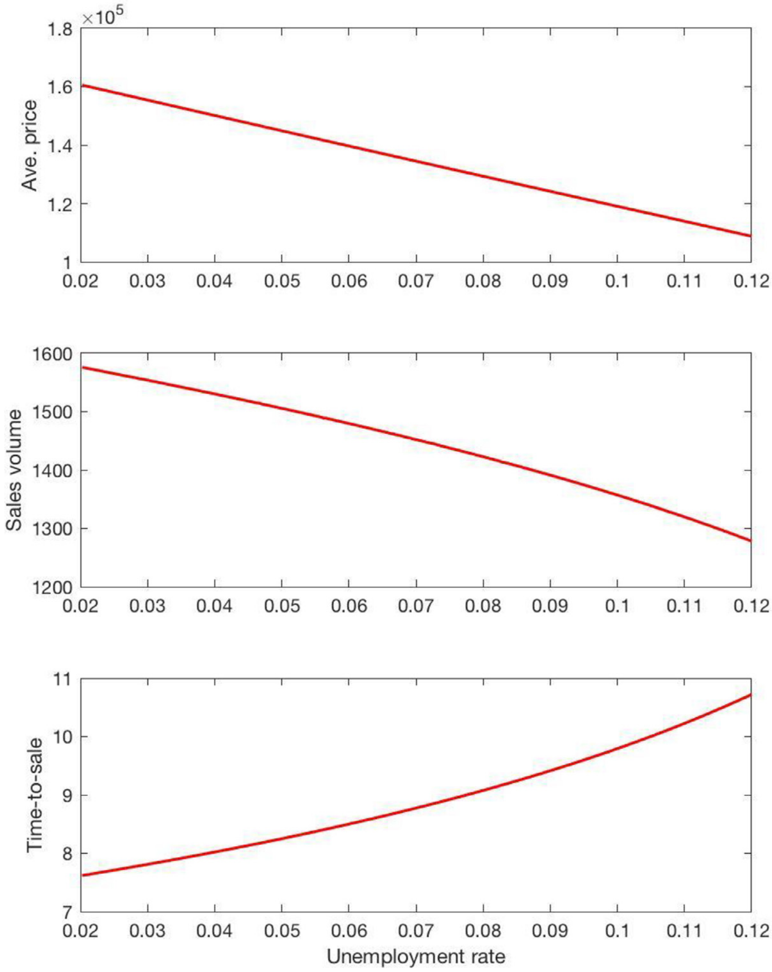

Fig. 2. Market outcomes as unemployment rate varies.

buyer has a certain probability of actually entering the market to search, which is modeled as financial constraints. On the market, buyers and sellers both search for trading partners. They only trade if they are a good match for each other. Otherwise, they will continue to search in the next period. Hence, both the number of buyers and the number of sellers are fully endogenized.

The unemployment rate influences the size of the housing market. From the demand side, it serves as a financial constraint and reduces the number of buyers as it rises. This is because being unemployed practically prevents a household from entering the housing market as a buyer because unemployed households cannot obtain mortgages. In addition, when the unemployment risk is higher, the credit conditions become tighter and vice versa; for example, the loan-to-value ratio was low in the Great Recession while the loan-to-value ratio was high during the housing boom of the early 2000s (Iacoviello and Pavan, 2013; Corbae and Quintin, 2015 and Acolin et al., 2016). From the supply side, an increase in the unemployment rate makes homeowners less willing to move because they may not be able to buy new houses due to their increased probability of becoming unemployed. Also, a higher unemployment rate increases the difficulty of selling a house and thus weakens homeowners' tendency to move. Therefore, when the unemployment rate increases (decreases), there are fewer (more) buyers and sellers. Hence the housing market becomes thinner (thicker), leading to poorer (better) matching quality on average (referred to as the thick-market effect in this paper). As a result, housing prices and transaction volumes decrease (or increase) even more. The impact of unemployment shocks is thus amplified.

To quantify this amplifying effect, we conduct a structural estimation of the model using Texas city-level data from the following three years: 1990, 2000 and 2010. The estimation explores variation in unemployment rates across city-years. The set of parameters is obtained through a weighted non-linear least squares estimation, 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. The estimation results show a large and significant marginal household disutility due to mismatch. This indicates that there is much room for the thick-market effect to play a part in the housing market by improving matching quality.

The simulations using the estimated parameters demonstrate that an increase in unemployment rate would lead to a lower housing price and a decreased sales volume, creating a positive relationship between the housing price and the transaction volume. Specifically, when the unemployment rate increases from 5% to 8%, the housing price falls by 10.74% and the sales volume falls by 5.49%. More importantly, both the price responsiveness (with respect to the unemployment rate) and the sales volume responsiveness are significantly higher in the benchmark model than in the cases where the thick-market effect is absent. Furthermore, when a feedback mechanism from housing prices to unemployment is incorporated, the thick-market effect amplifies the impact of initial unemployment shocks to an even greater extent.

Additionally, the simulation shows that in a larger city with more potential buyers and sellers, when the unemployment rate goes up, sale prices decrease by a smaller percentage than prices in a smaller city. This is consistent with the empirical findings of Smith and Tesarek (1991).

This paper makes two major contributions to the literature. First, it incorporates the unemployment rate into a search-and-matching model that includes endogenous entry of sellers and buyers. Second, this paper applies the model to Texas county-level data and conducts a structural estimation of the model. With the estimates thus obtained, it is the first to quantify the magnitude of the thick-market effect's interaction with unemployment shocks.

In addition, this paper provides a complementary explanation to the well-documented positive correlation between housing prices and transaction volumes. Stein (1995) finds that the elasticity of transaction volume with respect to price is 4. The standard model, such as that used in Poterba (1984), does not fully explain this strong positive relationship. In the literature, the liquidity-constraint hypothesis (Stein, 1995; Genesove and Mayer 1997; Ortalo-Magné and Rady, 2006, and Sterk, 2015) and the loss-aversion hypothesis (Genesove and Mayer 2001, and Engelhardt, 2003) both provide an explanation for this relationship. Ngai and Sheedy (2015, 2017) also demonstrate that endogenous moving can largely explain this positive relationship in response to aggregate housing preference shocks. This paper studies 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.

Our study builds on the literature that has applied the search-and-matching framework to the study of housing markets (e.g., Wheaton, 1990; Arnott, 1989; Mayer 1995; Williams, 1995; Krainer, 2001; Novy-Marx, 2009; Diaz and Jerez, 2013, Novy-Marx, 2009; Piazzesi and Schneider, 2009; Ngai and Tenreyro, 2014; Ngai and Sheedy, 2015, 2017). This paper contributes to this literature by modeling and estimating the housing market thickness effect when there are unemployment shocks. Moreover, few studies model the endogenous moving decision. Exceptions include Ngai and Sheedy who show that the cleansing of existing poor matches through endogenous moving is essential to the dynamics of aggregate housing market transactions. This paper complements their papers in three ways. First, Ngai and Sheedy study the responses to an aggregate preference shock while the quality distribution of new matches in the housing market remains unchanged. This paper focuses on the responses to an unemployment shock that directly influences the market size through financial constraints. The change in market size in turn leads to changes in the quality distribution of new matches and the thick-market effect thus arises. We hence address a distinctive propagation channel for the impact of unemployment on housing markets. Second, a rental market is incorporated in the model, which implies that households may stay out of the housing market for long periods. This may interact with the housing market through individuals' moving and buying decisions. Matching the predicted rental price with the rent data in our structural estimation helps better identify the key model parameters. Finally, this paper provides an application of the model to data from Texas.

Our paper is also related to the literature that emphasizes the role of the thick-market effect in facilitating the matching process in various markets including the housing market and the labor market (e.g., Arnott, 1989; Mayer, 1995; Gan and Zhang, 2006; Zhang, 2007). A recent study by Ngai and Tenreyro (2014) applies a similar idea to explain the seasonal fluctuations in housing prices and transaction volumes. This paper complements Ngai and Tenreyro's work by presenting a micro-foundational view of how market thickness improves matching quality, and conducting structural estimations to quantify the thick-market effect.

The rest of the paper is organized as follows. Section 2 presents our benchmark model. Section 3.1 describes the estimation strategy. Section 3.2 discusses the data and the estimation results. In Section 3.3, the estimated parameters are applied to simulate the benchmark model, which demonstrates how the thick-market effect amplifies the impact of unemployment shocks on housing market outcomes. Section 4 consists of discussions and robustness checks. Section 5 concludes the paper.

2. The model

In this section we develop a search-and-matching model with endogenous moving of households to study how unemployment shocks impact the housing market. We describe the model in seven parts, denoted (a) through (f).

2.1. 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 discussion, we assume that a house cannot become an apartment, and vice versa.

The total number of houses T^H in the city is fixed.[1] All houses have the same quality but they differ in characteristics such as design, yard, etc. 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. All households differ in their preferences regarding housing characteristics. They are uniformly distributed around the circle. A buyer's location on the circle means that any house at the location would be a perfect match for the buyer. The buyer's location is private information.

The matching mechanism is as follows. At the beginning of each period, sellers post advertisements and announce the characteristics of their houses to the public. We assume that each buyer can visit at most one house per period. It is thus optimal for each buyer to choose 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 per period; it is then optimal for the seller to choose to negotiate with the visitor who best matches the seller's house and hence shows the strongest interest in the house. Although the seller cannot directly observe the preferences of her visitors, she can tell which visitor is most interested in her house.[2] If the match between the seller and the buyer is good enough, a deal is reached and the sale price is determined through bargaining.

During each period, every household who lives in her own house may be hit by a shock. When hit by such a shock, the household may choose whether or not to move to a different house. If she moves, she will need to sell her current house and buy a new one. We assume that when a household moves, she will move out of her current house and rent a place to live during the transition if she cannot immediately buy a new house to move into. This assumption allows us not to consider the situation in which a household continues living in her current house while it is for sale.

Next, let us introduce some important identity equations. First, at the beginning of time t, the number of owner-occupied houses in the city N_t^H plus the number of renters, is equal to the number of households in the city; namely $M = N_t^R + N_t^H$. Second, during time t, the number of houses for sale on the market N_t^S, reduced by the number of sales made N_t^{sales}, is equal to the number of houses left unsold at the end of this period: $U_t = N_t^S - N_t^{sales}$. Third, the number of houses for sale during this period is equal to the number of unsold houses from the previous period U_{t-1}, plus those from homeowners who move out of their houses in this period $\mu_t N_t^H$, where μ_t is a homeowner's probability of moving in this period. Namely, $N_t^S = U_{t-1} + \mu_t N_t^H$. Finally, 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}, is equal to the total number of houses in the city; that is, $T^H = N_t^H + U_{t-1}$.

Now we introduce the unemployment rate, denoted *urate,* into the model. We focus on one key channel through which unemployment influences housing demand; that is, the financial constraint. Because there is no entry cost in the housing market, the financial constraint essentially determines a household's probability of entering the market as a buyer. Both renters and home occupiers are assumed to have the same probability of being unemployed in each period. We assume that unemployed people are not in the market to buy houses because it is difficult for them to obtain mortgages. Therefore, the probability that a potential buyer (either a homeowner who moves or a renter) will actually enter the market as a buyer, denoted as γ, cannot exceed the employment rate (i.e., $\gamma < 1$-urate). Moreover, because of the financial constraint, only those households whose income is above a certain fraction of the expected house price will enter the housing market because they expect to be able to afford to buy a house. Specifically, we let

$$\gamma_t = (1 - urate) \times prob(y_t > (\tau_0 + \tau_1 urate) \times E(P_t)|employed), \tag{1}$$

where y_t is a household's income, which is assumed to be an i.i.d. draw from a Pareto distribution conditional on being employed; that is, the cdf of income is $F(y) = 1 - (y/y_{\min})^{-1/\sigma}$ if employed. $E(P_t)$ is the expected house price; $y > (\tau_0 + \tau_1 .urate) \times E(P)$ reflects the financial constraint. A positive τ_1 means the unemployment rate has an additional discouraging effect on the household's probability of entering the market as a buyer. This is because, in an environment of higher unemployment risk, the credit conditions may become tighter and vice versa. For example, the loan-to-value ratio was low in the Great Recession while the loan-to-value ratio was high during the housing boom in the early 2000s (Iacoviello and Pavan, 2013; Corbae and Quintin, 2015 and Acolin et al., 2016). Therefore, households are less likely to enter the housing market to buy houses when the unemployment rate is higher.

The total number of buyers in the market during time t, therefore, is γ_t times the sum of those homeowners who move out of their current houses, $\mu_t N_t^H$, and those people who are currently renters, N_t^R; namely, $N_t^B = \gamma_t \mu_t N_t^H + \gamma_t N_t^R$.

2.2. The seller's problem

Next, we study the decision of sellers in the search-and-matching process. Suppose at time t, seller i meets with buyer j and they negotiate the sale price. The seller's value function is as follows:

$$J_{it}^S(\pi_{ijt}^S; a_{-it}^S(\cdot), a_t^B(\cdot)) = \max_{a_{it}^S \in \{0,1\}} \pi_{ijt}^S a_{it}^S + \beta E(J_{it+1}^S; a_{-it+1}^S(\cdot), a_{t+1}^B(\cdot))(1 - a_{it}^S), \tag{2}$$

[1] We fix the total number of houses in order to better illustrate the thick-market effect's amplification of the demand side shocks to the housing market, which is the focus of this paper. In the online appendix, we discuss the case where the number of houses can be adjusted in the long run. The key intuition of the thick-market effect still stands.

[2] Albrecht et al. (2013) develop a directed-search model with private match valuations. In their setting, buyers' bids for a house increase with the private match valuation.

where $a^S_{-it}(\cdot)$ represents other sellers' decisions in the market at time t, $a^B_t(\cdot)$ are buyers' decisions and a^S_{it} is seller i's decision. If seller i decides to sell her house ($a^S_{it}=1$), her payoff π^S_{ijt} is simply the sale price P_{ijt}. If the seller decides to wait until next period ($a^S_{it}=0$), her (time-discounted) payoff is $\beta E(J^S_{it+1};a^S_{-it+1}(\cdot),a^B_{t+1}(\cdot))$. 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 her payoff from waiting. Namely, $a^S_{it}=1$ if and only if $\pi^S_{ijt}\geq \beta E(J^S_{it+1};a^S_{-it+1}(\cdot),a^B_{t+1}(\cdot))\equiv\bar{\pi}^S_{it}$, where $\bar{\pi}^S_{it}$ denotes the minimum payoff for which the seller will be willing to sell her house at time t. Following the search literature, we call $\bar{\pi}^S_{it}$ the seller's reservation payoff.

2.3. The buyer's problem

Buyers are heterogeneous in their preferences. In each time period, a buyer, denoted buyer j, searches for a house 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 per time period for any buyer to live in a perfectly matched house be u^H_0. Further, we let the utility flow per time period of buyer j from living in house i be

$$u^H_{ij}=u^H_0\exp(-c_1 d^{\alpha}_{ij}). \tag{3}$$

We assume $c_1>0$ and $\alpha>0$. Although we use a unit circle to characterize the preference space of households (the characteristic space of houses) for simplicity, the preference space (characteristic space) could be multi-dimensional in reality. Therefore, we use a curvature coefficient α here to capture the possible multi-dimensionality.[3] The parameter c_1 defines the marginal disutility from mismatch in a logarithm sense. When $d_{ij}=0$, house i is a perfect match for buyer j. When $d_{ij}>0$, there is discount in utility due to mismatch. A thicker market with more buyers and sellers has a shorter distance on average, which leads to better matching quality as reflected by a smaller discount in utility flow and a higher willingness to pay for a given house. This is referred to in this paper as the thick-market effect.

The parameter c_1 controls the sensitivity of the discount in utility to distance. When c_1 is larger, the utility discount will be greater at any positive d_{ij}, hence the thick-market effect is stronger. Therefore, a positive and substantial c_1 is crucial for the thick-market effect to play an important role in the market. In our empirical section, we will estimate c_1 and α and check if they are indeed positive and significant. Another feature of Eq. (3) is that the utility is bounded from above, which means that the thick-market effect of improving matching quality diminishes as the market gets thicker.

Buyer j's value function is as follows:

$$\begin{aligned}J^B_{jt}(\pi^B_{ijt};a^B_{-jt}(\cdot),a^S_t(\cdot)) = \max\nolimits_{a^B_{jt}\in\{0,1\}}\pi^B_{ij}a^B_{jt}+[u^R_t+\beta(\gamma E(J^B_{jt+1};a^B_{-jt+1}(\cdot),a^S_{t+1}(\cdot))\\ +(1-\gamma)E(J^{BO}_{jt+1};a^B_{-jt+1}(\cdot),a^S_{t+1}(\cdot)))](1-a^B_{jt}),\end{aligned} \tag{4}$$

where $a^B_{-jt}(\cdot)$ represents other buyers' decisions in the market at time t, $a^S_t(\cdot)$ represents all sellers' decisions at time t and a^B_{jt} denotes the decision made by buyer j at time t. If the buyer purchases the house ($a^B_{jt}=1$), her payoff is π^B_{ijt}. If the buyer decides to wait until next period ($a^B_{jt}=0$), her payoff from waiting consists of two parts. The first part of the payoff from waiting is the net utility flow from renting, denoted as u^R_t. We define the net utility as the difference between the gross utility flow from renting, u^R_0, and the paid rent R_t:

$$u^R_t\equiv u^R_0-R_t\equiv u^R_0\exp\left(-c_2N^R_t/M\right). \tag{5}$$

In (5), we let the net utility depend on the number of renters in the market N^R_t relative to the total number of households. By rearranging (5), we can obtain the equation for R_t:

$$R_t=u^R_0\left(1-\exp\left(-c_2N^R_t/M\right)\right). \tag{6}$$

We assume $c_2>0$. The rent R_t is an important endogenous variable. Note that Eq. (6) suggests that a higher rental demand (measured by N^R_t) relative to supply (approximated by M) would lead to a higher rent. While the parameter u^R_0 is simply a scale, the parameter c_2, which measures the crowdedness effect of the number of renters in the rental market, is more crucial. Both u^R_0 and c_2 will be estimated in our empirical section. We will check whether c_2 is indeed positive. We assume that rental housing markets are separate from owner-occupied housing markets. For convenience and with a little abuse of notation, we hereafter refer to rental housing units as apartments while we refer to owner-occupied housing units as houses.

The second part of the payoff from waiting is the buyer's discounted expected payoff from being a potential buyer in the next period. In the next period, the current buyer has a probability γ of remaining in the market as a buyer and earning an expected payoff of $E(J^B_{jt+1};a^B_{-jt+1}(\cdot),a^S_{t+1}(\cdot))$. With probability $(1-\gamma)$ she leaves the market in the next period and gets an expected payoff of $E(J^{BO}_{jt+1})$. Note that in the latter case, she will have to rent a place to live at $t+1$ and wait until $t+2$ when

[3] See Arnott (1989) and Zhang (2007) for further discussion.

she again has probability γ of entering the market as a buyer. Therefore, $E(J^{BO}_{jt+1})$ consists of the net utility from renting at $t+1$ and the time-discounted expected payoff of being a potential buyer at $t+2$, which is

$$E\left(J^{BO}_{jt+1}\right) = u^R_{t+1} + \beta\left[\gamma E\left(J^B_{jt+2}\right) + (1-\gamma)E\left(J^{BO}_{jt+2}\right)\right]. \tag{7}$$

The optimal decision rule of buyer j at t is $a^B_{jt} = 1$ if and only if

$$\pi^B_{ij} \geq u^R_t + \beta\left(\gamma E\left(J^B_{jt+1}; a^B_{-jt}(\cdot), a^S_t(\cdot)\right) + (1-\gamma)E\left(J^{BO}_{jt+1}\right)\right) \equiv \bar{\pi}^B_{jt},$$

where $\bar{\pi}^B_{jt}$ is the minimum payoff at which a buyer will be willing to purchase a house. In accordance with the search literature, we call $\bar{\pi}^B_{jt}$ the reservation payoff of a buyer.

2.4. Payoffs of buyers and sellers

When a trade takes place between buyer i and seller j at time t, the total 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}:

$$A_{ijt} = \pi^B_{ijt} + \pi^S_{ijt}. \tag{8}$$

The total surplus from the trade has to be larger than the sum of the reservation payoffs of both the buyer, $\bar{\pi}^B_{jt}$, and the seller, $\bar{\pi}^S_{it}$. The remaining surpluses will be shared through bargaining.

If a trade does not take place, both the buyer's and the seller's payoffs are equal to their respective reservation values. Thus, the buyer's payoff is written as

$$\pi^B_{ijt} = \bar{\pi}^B_{it} + \max\left\{\theta(A_{ijt} - \bar{\pi}^B_{it} - \bar{\pi}^S_{jt}), 0\right\}, \tag{9}$$

and the seller's payoff is written as

$$\pi^S_{ijt} = \bar{\pi}^S_{it} + \max\left\{(1-\theta)(A_{ijt} - \bar{\pi}^B_{it} - \bar{\pi}^S_{jt}), 0\right\}, \tag{10}$$

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

From Eqs. (9) and (10), we can see that a deal will be reached if and only if the total surplus is no less than the sum of the buyer's reservation payoffs and the seller's reservation payoffs; namely, $A_{ijt} \geq \bar{\pi}^S_{it} + \bar{\pi}^B_{jt}$.

2.5. Homeowners' moving decisions

In this subsection, we consider homeowners' moving decisions. Assume that in each time period, each homeowner may be hit by a shock that causes her utility flow from her current house to be lower than it was when she purchased it. The shock may be due to changes in taste, job location or family structure. Such a shock occurs with a certain probability in each period, denoted λ, which is exogenously determined by the aggregate social economic environment. The magnitude of the shock is measured by a random variable K. Assume K is uniformly distributed on $[0, 1]$. When a shock hits a household, the utility flow from her current house becomes $Ku^H_0 \exp(-c_1 d^\alpha)$, where d is the original matching distance when she purchased the house. One can see that the smaller K becomes, the bigger the negative impact of the shock. The effect of the shock persists until a new shock hits. Both the probability and the magnitude of such a shock are independent of the original matching distance d.

The household may choose to move or to stay in her current house, depending on the magnitude of the shock and the original matching quality.[4] The value function of a household with original matching distance d who is hit by a shock K at time t is

$$\begin{aligned} J^C_t(d,\ K_t) = {} & \max_{a^C_t \in \{0,1\}} a^C_t[E(J^S_t) + \gamma E(J^B_t) + (1-\gamma)E(J^{BO}_t) - MC] + (1-a^C_t)[K_t u^H_0 \exp(-c_1 d^\alpha) + \beta(1-\lambda)J^C_{t+1}(d, K_t) \\ & + \beta\lambda E_K(J^C_{t+1}(d, K_{t+1}))], \end{aligned} \tag{11}$$

where $a^C_t = 1$ indicates moving to a different house and subscript K indicates that the expectation is taken over K. The item in the first bracket is the value of moving to a different house. If the household moves, she needs to sell her current house and buy another one. Therefore, she becomes a seller and a potential buyer simultaneously. Also, she needs to pay a moving cost $MC = \chi_0 + \chi_1.E(P)$, where χ_0 is the fixed part of the moving cost and mainly reflects costs related to shipping, time

[4] In theory it is possible that a homeowner may own one or multiple unsold houses while she lives in her current house. According to our estimates, after a household moves into a new house, it takes 80 months on average until she is hit by the next moving shock. (The probability of being hit by a moving shock is estimated to be 0.0125 per month.) Because the average time to sale is 6 to 14 months according to the Texas real estate inventory data used in this paper, and also because (according to the American Household survey) the average duration of a house vacancy was 7 to 8 months at the national level between 2001 and 2005 (see Ngai and Sheedy, 2017), by the time the household gets hit by the next moving shock and contemplates whether or not to move again, the chance of her still owning an unsold house from the last move is very slim. Therefore, when we model homeowners' moving decisions, it is innocuous to treat all the homeowners as if they do not own an unsold house from a previous move.

spent on moving, emotional distress associated with moving, etc. $\chi_1.E(P)$ is the variable part of the moving cost. It includes commission fees paid to sell the house. The commission fee is usually proportional to the sale price.

The item in the second bracket is the value of staying in the current house. It has three components. The first component $K_t u_0^H \exp(-c_1 d^\alpha)$ is the utility flow from staying in the current house for this time period. The second component $\beta(1-\lambda)J_{t+1}^C(d, K_t)$ is the time-discounted value in the next period if there is no new shock. The third component $\beta\lambda E_K(J_{t+1}^C(d, K_{t+1}))$ is the expected time-discounted value in the next period if a new shock hits the household. The optimal decision rule of the household at time t is $a_t^C = 1$ if and only if the value of moving (i.e., the item in the first bracket of Eq. (11)) is greater than or equal to the value of staying in the current house (i.e., the item in the second bracket of Eq. (11)).

2.6. Market equilibrium and solution of the model

We focus on the symmetric and stationary equilibrium. We will demonstrate the key intuition of the solution in this subsection and leave the detailed derivations to the online appendix. It turns out there are two crucial steps for the solution of the model. First, the shorter the distance between a buyer and a seller, the better the match between them and thus the higher the total surplus generated if they reach a deal as suggested by Eq. (3). This implies that there exists a maximum distance $\bar{d}$ corresponding to the minimum total surplus such that a deal will be reached if and only if $d \le \bar{d}$. Second, for a homeowner who is hit by a utility shock K, conditional on her original matching distance d, her value of continuing to stay in the current house is increasing in K. The optimal decision rule of moving then suggests that there exists a threshold $\bar{K}(d)$ such that the household with original matching distance d will move to a different house if and only if the magnitude of the shock $K < \bar{K}(d)$. Below we will illustrate how to solve for $\bar{K}(d)$ and $\bar{d}$.

By definition, when $K = \bar{K}(d)$, the value of moving to a different house is the same as the value of staying in the current house. Eq. (11) and the optimal decision rule of moving imply that $E_K(J^c(d,K)) = J^c(d, \bar{K}(d)) + \frac{1}{2}\frac{(1-\bar{K}(d))^2}{1-\beta(1-\lambda)} u_0^H \exp(-c_1 d^\alpha)$.

Intuitively, the above expression says that the expected value of a homeowner with initial matching distance d who gets hit by some random shock K consists of two parts. The first part is the reservation value of staying in the current house corresponding to the threshold $\bar{K}(d)$. Note this is also equal to the value of moving. The second part needs more elaboration. Because with probability $(1-\bar{K}(d))$, the shock K that hits the household is greater than $\bar{K}(d)$, making her actual utility flow $K * u(d) > \bar{K}(d) * u(d)$, this brings in an expected utility flow increment of $0.5*(1-\bar{K}(d)) * u(d)$ above the reservation level considering K is uniformly distributed on the interval [0,1]. And such a shock K will persist with probability $(1-\lambda)$ each time from the next period on. Thus, the second part is simply the time-discounted (considering the persistence of the current shock) sum of these expected increments in utility flow above the reservation level. Plugging the above expression of $E_K(J^c(d,K))$ back into Eq. (11) and rearranging terms then gives

$$E(J^S) + \gamma E\left(J^B\right) + (1-\gamma)E\left(J^{BO}\right) - MC = \frac{\bar{K}(d)}{1-\beta} u_0^H \exp(-c_1 d^\alpha) + \frac{1}{2}\frac{(1-\bar{K}(d))^2}{1-\beta(1-\lambda)}\frac{\beta\lambda}{1-\beta} u_0^H \exp(-c_1 d^\alpha), \tag{12}$$

which defines an implicit function of $\bar{K}(d)$.[5]

The probability that a household with initial matching distance d will move when hit by a random utility shock K is thus $prob(K \le \bar{K}(d)) = \bar{K}(d)$. Note that this probability depends on the original matching quality. Notice that as the RHS of Eq. (12) is increasing in $\bar{K}(d)$ but decreasing in d, it follows that $\bar{K}(d)$ increases with d. Namely, households that initially are poorly matched are more likely to move.

Higher unemployment rates lead to thinner markets, which in turn lead to poorer matching quality on average. This may increase households' probability of moving, as Ngai and Sheedy (2015, 2017) argue. However, such an effect is secondary to the dominating negative impact of unemployment rates on the size of housing markets. From the LHS of Eq. (12), we can see that the moving probability depends on the value of being a seller ($E(J^S)$) as well as the probability of being able to buy a new house (γ), both of which are closely related to the unemployment rate. When the unemployment rate is higher, there are fewer buyers due to financial constraints. If a household moves out of her current house when the unemployment rate is higher, it is more difficult for her to sell the house at a good price in a short time period. Thus, the value of being a seller is lower, which in turn lowers the value of moving to a different house. Moreover, the probability that she can buy a new house is lower because she is more likely to become unemployed and more likely to face a tighter credit constraint, which further lowers the value of moving. As a result, current homeowners are less likely to move, and the number of sellers decreases. Along with the shrinkage on the demand side, the housing market becomes thinner when the unemployment rate is higher, and the matching quality becomes poorer as a result.

Next, by definition, at the maximum matching distance $\bar{d}$, the sum of the seller's reservation payoff $\beta E(J^S)$ and the buyer's reservation payoff $E(J^{BO})$ is equal tothe total surplus of the match which is just the buyer's valuation of the house; namely,

$$\beta E(J^s) + E(J^{BO}) = A(\bar{d}) = \frac{G(\bar{d})}{1-\beta(1-\lambda)} + \frac{\beta\lambda\left[E(J^S) + \gamma E\left(J^B\right) + (1-\gamma)E\left(J^{BO}\right) - MC\right]}{1-\beta(1-\lambda)} \tag{13}$$

[5] In the online appendix, we discuss the conditions that are sufficient to ensure that $\bar{K}(d)$ has an interior solution in the interval [0,1]. Later on, when we conduct structural estimates of our model using the Texas data, we find that all of the conditions for interior $\bar{K}$ are satisfied.

where $G(d) \equiv [1 + \frac{\beta\lambda}{2}\frac{(1-\bar{K}(d))^2}{1-\beta(1-\lambda)}]u_0^H \exp(-c_1 d^\alpha)$. The first part on the RHS of Eq. (13) is the time-discounted sum of utility flow from staying in the house of initial matching distance $\bar{d}$. Note the expression of $G(d)$ has taken account of the possible reduction in utility flow in the future when a random shock K hits. Because starting from the next time, each period the homeowner gets hit by a shock with probability λ, the time discount factor must be adjusted to $\beta(1-\lambda)$. The second part is the time-discounted sum of expected payoffs if the homeowner moves out of the current house in the future.

Finally, in the stationary equilibrium,$E(J^S)$, $E(J^B)$ and $E(J^{BO})$ can all be expressed as functions of $\bar{d}$ and $K(\bar{d})$. Hence, Eq. (13) can be used to pin down the equilibrium $\bar{d}$. Once $\bar{d}$ is determined, solving the rest of the endogenous variables is straightforward. Please see the online appendix for detailed deduction of the equilibrium endogenous variables.

3. Estimation and simulations

In this section, we will first discuss the estimation strategy in Section 3.1. Then data and estimation results will be presented in Section 3.2. Thirdly, simulations based on the structural estimated will be conducted in Section 3.3, through which we shall identify the role of the thick market effect.

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. Given that we do not have data on individual housing units matched with household information, we use city-level data in our empirical analysis, which we will discuss in detail later.

The estimation strategy is to find a set of parameters that minimizes the differences between some of the observed endogenous variables and the corresponding equilibrium outcomes generated from the model. We use non-linear least squares to conduct the estimation. We do not use GMM because the standard way of constructing the moment conditions requires some difficult derivatives of the implicit functions of the equilibrium outcomes from the model with respect to the parameter set. Instead, we adopt a consistent, albeit less efficient, weighted nonlinear estimator.

In principle we can use any subset of the endogenous variables and their corresponding equilibrium outcomes. Here we match the endogenous variables for which we have data. They include the rent R, the price of a house P, the number of sales transactions that occur and the time to sale, which is the inverse of the probability of selling a house q^S. These four variables represent key housing market outcomes. Therefore, we have four equations:

$$R_k = R(\Theta, X_k) + \varepsilon_1, \tag{14.1}$$

$$P_k = P(\Theta, X_k) + \varepsilon_2, \tag{14.2}$$

$$N^{sales}{}_k = N^{sales}(\Theta, X_k) + \varepsilon_3, \tag{14.3}$$

$$TS_k = 1/\left[q^S(\Theta, X_k)\right] + \varepsilon_4, \tag{14.4}$$

where R_k in (14.1) is the observed monthly rent of city k while $R(\Theta, X_k)$ is the equilibrium rent R from the model based on the information from city k, denoted X_k, and a given set of parameters Θ. Obtaining $R(\Theta, X_k)$ requires solving the entire model, which we do numerically.

Similarly, P_k in (14.2) is the observed housing price in city k, and $P(\Theta, X_k)$ is the equilibrium expected sale price of a house from the model conditional on Θ and X_k. N_k^{sales} in (14.3) is the observed monthly transaction volume in city k and $N^{sales}(\Theta, X_k)$ is the equilibrium number of sales from the model. Finally, TS_k in (14.4) is the observed time to sale in city k. Because we do not have the time-to-sale data at the city level, we use inventory as a proxy that measures the number of months it would take to sell all unsold housing stock on the market.[6] $q^s(\Theta, X_k)$ is the equilibrium probability of selling a house from the model based on Θ and X_k. Its inverse is the time to sale. Like $R(\Theta, X_k)$, solving for $P(\Theta, X_k)$, $N^{sales}(\Theta, X_k)$ and $q^s(\Theta, X_k)$ requires solving for all endogenous variables in the equilibrium described in the previous section.

We assume that $E(\varepsilon_i|X_k) = 0$ for $i = 1, 2, 3, 4$ and that the 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 in order to capture the possible heteroskedasticity $\text{Var}(\varepsilon_i) \neq \text{Var}(\varepsilon_j)$ and the correlation $\text{Cov}(\varepsilon_i, \varepsilon_j) \neq 0$. A weighted nonlinear least square estimator is given by

$$\min_{\Theta} \frac{1}{K}\sum_{k=1}^{K} \begin{pmatrix} R_k - R(\Theta, X_k) \\ P_k - P(\Theta, X_k) \\ N^{sales}{}_k - N^{sales}(\Theta, X_k) \\ TS_k - \left[1/q^S(\Theta, X_k)\right] \end{pmatrix}' \Sigma^{-1} \begin{pmatrix} R_k - R(\Theta, X_k) \\ P_k - P(\Theta, X_k) \\ N^{sales}{}_k - N^{sales}(\Theta, X_k) \\ TS_k - \left[1/q^S(\Theta, X_k)\right] \end{pmatrix}, \tag{15}$$

[6] Diaz and Jerez (2013) and Piazzesi and Schneider (2009) use the average time-to-sale data at the national level.

where K is the total number of cities. Note that 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 Eq. (15) with Σ as the identity matrix and use the residuals to construct an estimate of $\hat{\Sigma}$. The final estimate of (15) is conducted using the estimated $\hat{\Sigma}$.

The set of parameters Θ includes: τ_0 and τ_1, which characterize the financial constraint in the equation that defines the probability of entering the housing market as a buyer; λ, the probability of being hit by a utility shock; χ_0 and χ_1 in the equation for the moving cost; c_1 and α, which determine the marginal disutility from mismatch and the degree of mismatch; utility flow or willingness to pay for a perfectly matched house u_0^H; c_2, which measures the effect of crowdedness in the rental market; u_0^R, the utility flow or willingness to pay for a rental apartment; and θ, the bargaining power of buyers versus sellers. The parameter set also includes two constant parameters. One is the time discount rate β. We let the monthly time discount rate $\beta = 0.997$, which corresponds to a yearly time discount factor of 0.965. The other is the parameter σ in the Pareto distribution of income. In accordance with the literature, we let $\sigma = 0.6$ (see Jones, 2015). These two parameters are not our focus, so we choose to hold them constant. All of the other parameters will be estimated in our empirical analysis.

Before we discuss the data to be used in the estimation, we consider a slight complication of the model. Our model focuses on matching between individual households' tastes and characteristics of houses in the housing market *within a city*. It ignores the quality differences of the houses or apartments *across cities* and suggests that geographical variations in housing market outcomes may be due only to market size (which varies with unemployment rate) and the thick-market effect. Empirically, in order to control for quality differences across cities, we collect information on the average housing and neighborhood characteristics for different cities. We allow the utility from (or willingness to pay for) living in a perfectly matched house u_0^H and the gross rental utility u_0^R to be dependent on these housing and neighborhood characteristics. Specifically, we let u_0^H and u_0^R be

$$\ln u_0^H = a_0 + a_1 HouseRooms + a_2 HouseAge + a_3 WhitePct + a_4 D_{2000} + a_5 D_{2010} + a_6 income \tag{16}$$

$$\ln u_0^R = b_0 + b_1 AptRooms + b_2 Crime + b_3 WhitePct + b_4 D_{2000} + b_5 D_{2010} + b_6 income. \tag{17}$$

In Eqs. (16) and (17), *WhitePct* is the percentage of the city's population that is white. *HouseRooms* in (16) is the average number of rooms in a house in the city and *HouseAge* in (16) is the average number of years since the city's houses were built. *AptRooms* in (17) is the average number of rooms in the city's rental apartments and *Crime* in (17) is the city's crime rate. Another important factor that may influence households' willingness to pay for housing (either owner-occupied or rental) is income. A standard bid-rent model that incorporates internal urban structure and commuting cost would suggest that urban income influences people's willingness to pay to live in a city (see Duranton and Puga, 2004). We thus include city average income in both Eqs. (16) and (17). Finally, D_{2000} is the dummy for the year 2000 and D_{2010} is the dummy for the year 2010. The coefficients for these two dummy variables in both Eqs. (16) and (17) capture changes in the aggregate environment that affect the willingness to pay for housing in all cities in these two years, such as changes in demographics.

We first conduct auxiliary hedonic regressions of average housing prices and average rental prices on characteristics of houses and apartments (e.g., number of rooms, years since construction) and location amenities such as white population percentage, crime rate, etc., as is typical in the real estate literature. Then we apply the estimates thus obtained to the above equations for u_0^H and u_0^R.

The search-and-matching model developed in this paper basically seeks to capture the variations in housing market outcomes across cities that cannot be explained by differences in quality or willingness to pay (either for a perfectly matched house or a rental apartment). In sum, the set of parameters to be estimated includes: τ_0 and τ_1, which characterize the financial constraint in the equation that defines the probability of entering the housing market as a buyer; λ, the probability of being hit by a utility shock; χ_0 and χ_1 in the equation for the moving cost; c_1 and α, which determine the marginal disutility from mismatch and the degree of mismatch; a_0 and a_6 in the equation for willingness to pay for a perfectly matched house; c_2, which measures the effect of crowdedness in the rental market; b_0 and b_6 in the equation for willingness to pay for a rental apartment; and θ, the bargaining power of buyers versus sellers. The total number of parameters to be estimated is thirteen. The estimation is carried out by the nonlinear least squares procedure described in Eq. (15).

The four dependent variables in (15) are important housing market outcome variables that can help to identify the key parameters in our model. For example, both the time to sale and the sale price are sensitive to the parameters related to search-and-matching friction (c_1 and α), and the bargaining power of buyers versus sellers (θ) is critical to the sale price. Also, the sales volume depends crucially on the parameters shaping the moving decision (i.e., moving cost parameters χ_0 and χ_1 and moving shock probability λ) as well as the probability of entering the market as a buyer (τ_0 and τ_1 in the financial constraint equation).

As for the explanatory variables, we have unemployment rates, total number of households, household income, total number of houses (imputed) and hedonic housing characteristics such as number of rooms (for both houses and apartments), house age and location amenities such as crime rate and white percentage of population, etc. We also include the time dummies in the estimation. These exogenous variables determine the market thickness and the fundamentals of the housing markets.

Table 1
Summary statistics for Texas cities.

Variable descriptions	Year	Mean	Std dev	Min	Max	# of cities
Rents per month ($) (1990 dollars)	1990	375	38.1	282	453	27
	2000	426.0	79.6	308.5	613.8	38
House prices ($) (1990 dollars)	2010	441.3	60.1	341.6	617.4	37
	1990	70,648	16,426	43,800	111,400	27
	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	33,617	27
	2000	5854	11,081	308	52,459	38
	2010	5756	11,577	317	56,804	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 ($)	1990	37,166	5,210	24,602	46,641	27
(1990 dollars)	2000	46,666	8,757	27,881	72,453	38
	2010	45,888	6,652	32,043	64,186	37
Household size	1990	3.38	0.34	2.84	4.65	27
	2000	3.35	0.31	2.70	4.48	38
	2010	3.26	0.27	2.69	4.17	37
Rooms in a house	1990	5.840	0.186	5.557	6.288	27
	2000	5.926	0.336	5.3	7.3	38
	2010	5.839	0.389	5.3	7.7	37
Age of a house	1990	21.1	5.451	12	34	27
	2000	27.2	6.675	10	38.7	38
	2010	34.5	7.855	18	47	37
Rooms in an apartment	1990	4.0	0.198	3.695	4.401	27
	2000	3.9	0.242	3.4	4.4	38
	2010	4.0	0.410	3.4	5.8	37
Percentage of white	1990	59.0%	16.3%	21.9%	83.3%	27
	2000	50.4%	17.3%	7.7%	81.4%	38
	2010	47.8%	16.9%	13.7%	80.2%	37
Crime	1990	1062.6	417.3	226.1	1977.8	27
	2000	627.9	262.5	53.3	1193.7	38
Construction cost ($) (1990 dollars)	2010	411.6	94.8	246.5	665.3	37
	1990	85,963	22,475	41,400	118,300	27
	2000	93,070	22,319	41,479	134,475	38
	2010	104,385	28,805	47,423	188,650	37

3.2. Data and estimation results

Next we will first describe the data and then present the estimation results.

3.2.1. The data

The data set consists of city-level data from Texas that covers 28 cities in 1990, 37 cities in 2000, and 37 cities in 2010. In the data we find complete information regarding all relevant variables. All cities in the 1990 data show up again in 2000 and 2010 except for the city of Texarkana, for which there is information in 1990 but not in later years. Four cities that appear 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 definition of a given city may vary across these three years due to changes in the multiple-listing service markets. Therefore, this paper does not utilize the panel aspect of the data. Instead, it treats a city that appears in 1990, 2000 and 2010 as three different cities. We thus carry out a non-linear least squares estimation of four simultaneous equations, using a sample of 102 observations.

The city-level total number of houses sold, average price and inventory are obtained from Texas Real Estate Center[7] and are gathered from various multiple-listing service markets. Other variables are constructed based on information from censuses. The construction cost of a given city is the average cost of new houses in that city.

Table 1 lists the summary statistics of the variables used in the estimation. Several observations merit mentioning here. First, there are substantial differences across cities. The ratio of the number of households in the biggest city to the number

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

in 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 is mostly due to the fact that the smallest city in the samples of 2000 and 2010, San Marcos, is not included in the sample year 1990. San Marcos was considered part of Austin in 1990. The ratios of the highest city unemployment rate to the lowest are 5.89 in 1990, 8.07 in 2000, and 3.11 in 2010. This paper exploits these variations. It suggests that the variations in housing prices are partly due to variations in factors such as the total number of households and the unemployment rate. These factors may also simultaneously affect other housing market outcomes such as transaction volumes, rental prices, and time to sale.

Second, there are substantial differences across the three years. The economy in general and the housing market in particular were doing poorly in 1990 in the state of Texas. However, in 2000, both the economy and the housing market had significantly improved. In 2010, similarly to the U.S. national economy, the Texas economy had barely recovered from the worst recession since World War II. 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, while the samples in 1990 and 2000 are not directly comparable, the average housing price increased by 28.5%, from \$70,648 (in 1990 dollars) for the 28 cities in 1990 to \$89,316 (in 1990 dollars) for the 37 cities in 2000. The average housing price then increased by just 6.7% from \$89,316 in 2000 to \$95,303 in 2010. Similarly to the average housing price, the average rent increased by 15.5% from \$375 per month in 1990 to \$433.3 per month in 2000. In contrast, however, it increased only slightly between 2000 and 2010. Note that a significant part of the differences in housing prices and rental prices across the three years are captured by the coefficients for the dummy variables D_{2000} and D_{2010} in Eqs. (16) and (17). The time to sale was 14.3 months in 1990, 6.48 months in 2000 and 9.15 months in 2010.

It is worth noting that our model treats the total number of houses in each city as exogenously given. However, the total number of existing houses T^H is not always observed in the data. In this case, we use a simple method to impute its value. According to the census, 64% of households in Texas are homeowners. 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 model estimation. Let M be the total number of households in a city; the imputed number of houses in the city is thus calculated as $M * 64\%/(100\% - 2\%)$.

It is also important to point out that, because of data constraints, this paper assumes that all houses and households in a given city comprise a single market. This assumption is obviously not accurate. Cities such as Houston, Dallas, San Antonio and Austin probably have more locality-based markets than small cities such as Bryan-College Station. Houses of different types or 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 markets will be discussed later as a robustness check in Section 4.3.

3.2.2. Estimation results

Table 2 reports the estimates of the parameters of the model. The first panel of Table 2 lists two constants: β, the monthly time discount rate and σ, the parameter in the cdf of the Pareto distribution of income. The second panel in Table 2 reports the weighted non-linear least square estimation results of the model. Part A lists the estimates of the parameters in the equation that determines a household's probability of entering the market as a buyer. In addition to the direct impact on eligibility for a mortgage application discussed earlier, an increase in the unemployment rate may tighten the credit conditions for buying a house, which may reflect concerns about households' future job security. This additional effect is captured by τ_1 in Eq. (1) and it is estimated to be significant at 1.019 with a standard error of 0.127. If we set all the other exogenous variables at the 2010 sample mean level, when the unemployment rate increases from 5% to 7%, the probability of entering the market as a buyer would drop from 0.237 to 0.213. When the unemployment rate decreases from 9% to 7%, the probability would rise from 0.192 to 0.213. So increasing unemployment rates have a negative impact on the number of buyers in the housing market.

Part B reports the estimates of the parameters that are crucial to determining a household's per-month probability of moving. The monthly probability of being hit by a utility shock that might trigger moving, λ, is estimated at 0.0125 with a standard error of 0.0008. It is statistically significant. This means that after a household moves into a house, it will take 80 months on average before she gets hit by a shock that changes her utility flow from the house. The fixed part of the moving cost χ_0 is estimated at 4617.245 with a standard error of 870.218. And the effect of sale price on the variable part of the moving cost χ_1 is estimated at 0.0134 with a standard error of 0.00253. Both are statistically significant. The total estimated moving cost is about 4.78% of the sample mean price, which is quite reasonable. If we set all the other exogenous variables at the 2010 sample mean level, based on our estimates, when the unemployment rate increases from 5% to 7%, the probability of moving to a different house drops from 0.0087 to 0.0086. When the unemployment rate decreases from 9% to 7%, the probability rises from 0.0085 to 0.0086. So an increase in the unemployment rate has a negative impact on both the number of sellers and the number of buyers and leads to a thinner market. Notice that at the sample mean unemployment rate of 7.5%, according to our predicted moving probability, the average time that a homeowner will stay in her current house is about 120 months, fairly close to the average ownership duration of 11 years based on the American Household survey in 2005 (see Ngai and Sheedy, 2017).

Part C reports the estimates of the parameters in the house utility flow Eqs. (3) and (16). The key parameters of this paper are the coefficients in Eq. (3): the coefficient for marginal disutility from mismatch, c_1, and the curvature coefficient,

Table 2
Parameter estimates of the benchmark structural model.

Parameter	Value	Standard error
Constants		
Monthly time discount rate β	0.997	
Parameter in the Pareto distribution of income σ	0.6	
Estimated coefficients		
A. Coefficients determining the probability of entering the market as a buyer:		
Financial constraint: intercept τ_0	0.3800	0.0408
Financial constraint: effect of the unemployment rate τ_1	1.0193	0.1274
B. Coefficients determining the probability of moving:		
Probability of being hit by a utility shock λ	0.0125	0.0008
Moving cost: intercept χ_0	4617.2452	870.2184
Moving cost: effect of the average sale price χ_1	0.0134	0.0023
C. Coefficients determining the house utility flow:		
Curvature parameter α	0.5081	0.0095
Percentage of utility discount from per-unit mismatch c_1	226.4562	4.0000
Parameters in the willingness-to-pay equation:		
Intercept a_0	9.4627	0.0909
Rooms in a house a_1	0.3205	0.0586
Age of house a_2	−0.0055	0.0026
White percentage a_3	−0.2894	0.1333
Dummy for year 2000 a_4	0.2360	0.0684
Dummy for year 2010 a_5	0.4576	0.0967
Household income a_6	1.1025	0.1008
D. Coefficients determining the rental utility flow:		
Crowdedness effect c_2	12.8589	5.7666
Parameters in the willingness-to-pay equation:		
Intercept b_0	5.6265	0.0834
Rooms in an apartment b_1	−0.1320	0.0551
Crime rate b_2	$-7.83e^{-5}$	0.0000
White percentage b_3	0.1334	0.0849
Dummy for year 2000 b_4	0.1807	0.0389
Dummy for year 2010 b_5	0.3461	0.0563
Household income b_6	1.3046	0.1080
E. Bargaining power of buyers		
θ	0.5163	0.0650

α, which reflects the multi-dimensionality of housing characteristics. While c_1 defines the marginal disutility due to mismatch in a logarithmic sense, $1 - \exp(-c_1 d^{\alpha})$ measures the utility discount ratio that captures the degree of mismatch. The estimate is 226.456 with a standard error of 4.0 for c_1 and 0.508 with a standard error of 0.0095 for α; both are at more than 1% significance level. As discussed earlier, since both c_1 and α are positive, increasing the number of buyers and sellers in the market would result in higher matching qualities and higher transaction prices on average. The economic significance of these parameters will be discussed more in the simulation section.

For the parameters in the equation for willingness to pay for a perfectly matched house, Eq. (16), the household income coefficient is positive and significant, which indicates that higher income generates higher willingness to pay for houses as discussed earlier. As for the parameters of the hedonic characteristics of housing, we obtain them from an auxiliary housing price regression. 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. The coefficient for the percentage of whites in the city is negative. The dummy variables for year 2000 and year 2010 are both positive and significant.

Part D reports the estimates of the parameters in the rental utility flow Eqs. (6) and (17). The crowdedness effect reflected by parameter c_2 in the net rental utility Eq. (6) is estimated at a significant positive value of 12.859. The positive sign suggests that an increase in renters would increase the rental price given the number of apartments. For the parameters in the equation for willingness to pay for rental apartments, Eq. (17), the household income coefficient is positive and significant. As for the parameters of the hedonic characteristics of rental housing, we obtain them from an auxiliary rental price regression. The coefficient for the percentage of whites in a given city is positive and significant while the coefficient for the crime rate in a given city is negative and significant as expected. It may initially seem surprising that the coefficient for the number of rooms is negative. However, as shown in Table 1, the average apartment in 1990 had 4.047 rooms while the average apartment in 2000 had 3.895 rooms. This shows that older apartments have more rooms than newer apartments, and hence the number of rooms in an apartment may be negatively associated with the rental price. The dummy variables for years 2000 and 2010 are both positive and significant.

Part E reports the estimate of the bargaining power of buyers versus sellers. It is estimated at 0.516 with a standard error of 0.065. In sum, the estimates of all the parameters in our model are significant (please see Table 2), suggesting that the key relationships they characterize are indeed important in determining the housing market outcomes in the real data.

To check closeness of fit, we calculate R^2 for the four matched endogenous variables. They are 0.439, 0.734, 0.348 and 0.05 for housing price, transaction volume, rental price and time to sale, respectively. The closeness of fit is reasonable for housing price, transaction volume and rental price. However, it is low for time to sale. This may be due to limitations in our data. Because we do not have the time-to-sale data at the city level, we use inventory as a proxy that measures the number of months it would take to sell all unsold housing stock on the market. This proxy captures the expected selling probability of a typical house during a month in a city. The implicit assumption is that each house in a city has the same ex-ante expected selling probability, which is consistent with our model. This proxy may be inaccurate if there are heterogeneous housing markets within a given city. As a robustness check, we carry out the estimation with only the three equations for housing price, transaction volume and rental price. Our main results still hold.

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 otherwise noted, our simulations are conducted at the 2010 sample mean level for all exogenous variables except for the unemployment rate and the household income.

At the aggregate level, changes in the unemployment rate are typically associated with changes in the income level. As such, we develop a simple theoretical framework with labor market friction in which an exogenous productivity shock causes both employment and income to change in the same direction. Based on this model we derive a linear relationship between income and unemployment rate; namely, $income = \delta_0 - \delta_1 urate$. We present the theoretical deduction in the online appendix. Using the Texas city-level data on average household income and unemployment rate, we estimate the coefficients of the above equation. δ_0 and δ_1 are estimated at 0.682 and 3.030, respectively. In the simulations, we let the mean of income change with unemployment according to this estimated relationship. By doing so, we set our simulations in an environment that more closely matches reality.

At any given unemployment rate, we apply the parameter estimates from Table 2 and numerically solve for the equilibrium set of housing market outcomes including 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 simulation results of the model.

3.3.1. Housing market outcomes and unemployment rate

Fig. 2 shows housing market outcomes (sale price, sales volume, and time to sale) at various unemployment rates. Consider the case where the unemployment rate drops from 7% to 5%, corresponding to the change in the average unemployment rate in Texas between 1990 and 2000. From Fig. 2, the average sale price increases by 7.74%, from \$134,500 to \$144,900; the sales volume increases by 3.67%, from 1452 houses to 1505 houses; and the time to sale decreases by 5.96%, from 8.77 months to 8.25 months.

We also worked through the contrasting case where the unemployment rate increased from 5% to 8%, corresponding to the change in the average unemployment rate in Texas between 2000 and 2010. The average sale price decreases by 10.74%; the sales volume decreases by 5.49%; and the time to sale increases by 10.0%.

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

3.3.2. Identifying the thick-market effect

Next, we demonstrate the role of the thick-market effect in amplifying the impact of unemployment shocks by improving matching quality. Market thickness is measured by the average mutual distance between a seller and a buyer. The thicker the market, the shorter the average mutual distance. 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,

$$ave\_dist = E\left(D|D \leq \frac{1}{2N^S}\right), \tag{18}$$

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.

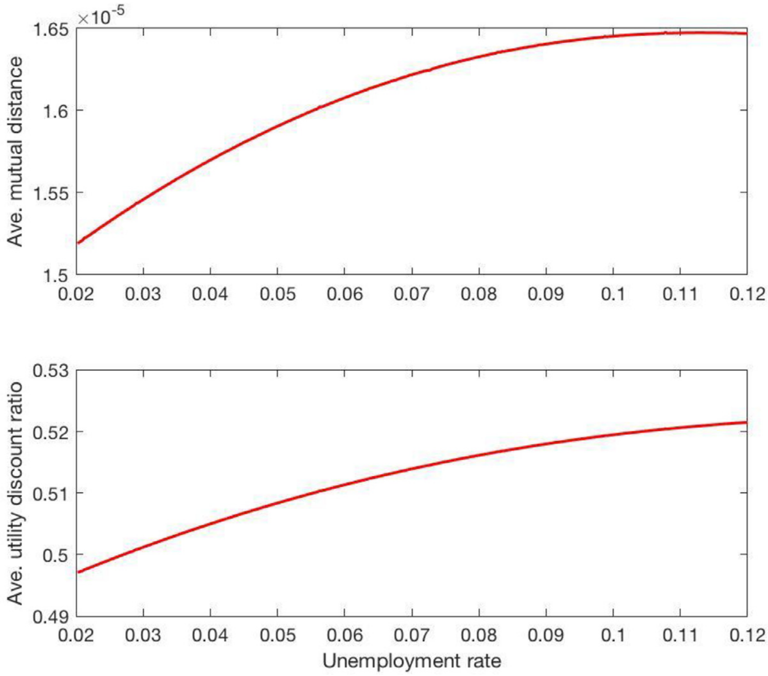

Fig. 3. Market thickness and matching quality as unemployment rate varies.

We measure the average matching quality by the average discount ratio in the utility flow of housing services, calculated as follows:

$$ave\_discount = 1 - E\left(\exp(-c_1 D^{\alpha})|D \leq \frac{1}{2N^S}\right). \tag{19}$$

The shorter the mutual distance, the better the match and thus the smaller the utility discount resulting from mismatch.

Fig. 3 illustrates how market thickness and matching quality vary with the unemployment rate. At the estimated parameter values, in particular at $c_1 = 226.456$, 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. As shown in Fig. 3, when the market becomes thinner as the unemployment rate rises, the average matching quality worsens at the same time. This is the micro-foundation of the thick-market effect. Specifically, according to Fig. 3, when the unemployment rate increases from 5% to 8%, the average discount ratio in the utility flow increases from 0.50 to 0.52.

Next, we illustrate the extent to which the thick-market effect amplifies the impact of unemployment changes on housing market outcomes. First, as we discussed in our benchmark model in Section 2, the marginal disutility due to mismatch, c_1, is critical. If c_1 is small or insignificant, there is less room for market thickness to play its role of improving the matching quality in the housing market. We hence consider the extreme case, a control model in which all of the houses are homogeneous, c_1 is essentially zero, and there would be no utility discount from mismatch. Therefore, the thick-market effect would not be able to amplify the impact of unemployment shocks by changing matching quality. By design, there is no search friction or matching friction in this model. A single price immediately clears the market. We refer to this control model as the Walrasian model from now on in this paper. We present the Walrasian model in more details in the online appendix. The unemployment rate continues to affect the housing market in the Walrasian model, the comparison of the responses of the housing market outcomes with respect to the unemployment rate between the Walrasian model and the benchmark model can help identify the thick-market effect, which plays its role by facilitating matching.

Fig. 4 presents the quasi-elasticity of housing market outcome variables[8] (such as average sale price, sales volume and time to sale) with respect to the unemployment rate in two different scenarios. The red curve is based on the simulations of the benchmark model we presented in Section 2; all of the parameters are set at the estimated values shown in Table 2. The blue curve is based on the simulations of the Walrasian model; all the parameters used are the same as those in our structural estimates of the benchmark model except that we do not have to use the parameters that determine the matching quality. As shown in Fig. 4, in the Walrasian model where there is no search-and-matching friction and hence no room for the thick-market effect to play, the quasi-elasticities of the average sale price, sales volume and time to sale are

[8] Suppose z is a housing market outcome variable. We define the quasi-elasticity of z with respect to the unemployment rate as $\partial \ln z / \partial urate$. This represents the percentage change in the housing outcome variable caused by a one-percentage-point change in the unemployment rate.

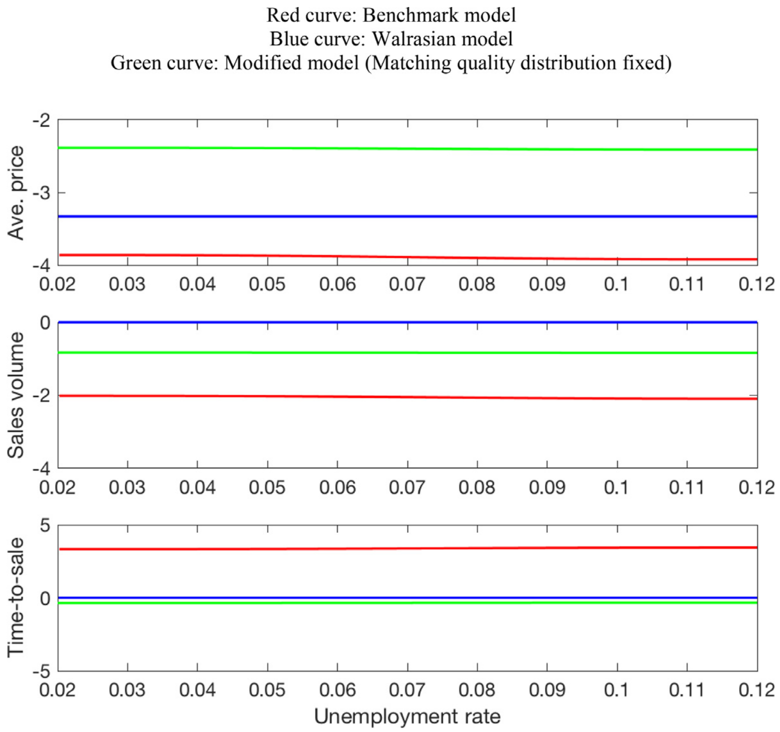

Fig. 4. Quasi-elasticity of market outcomes with respect to unemployment rate.
Red curve: Benchmark model.
Blue curve: Walrasian model.
Green curve: Modified model (Matching quality distribution fixed).
Note: Suppose z is a housing market outcome variable. We define the quasi-elasticity of z with respect to the unemployment rate as $\partial \ln z / \partial urate$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

significantly smaller in absolute value than the corresponding quasi-elasticities in the benchmark model. For example, at the sample mean unemployment rate of 7.5%, in the benchmark model, the quasi-elasticities of the sale price, sales volume and time to sale are −3.885, −2.040 and 3.368, respectively, while in the Walrasian model the corresponding numbers are −3.331, −0.002, and 0. Note that the selling probability is always 1 in the Walrasian model. We can see that compared to the Walrasian model, both the sales volume and time to sale are much more responsive to unemployment shocks in the benchmark model. The thick-market effect increases the responsiveness of the sale price to unemployment shocks by 16%, which is also remarkable. Therefore, our simulation demonstrates that the thick-market effect significantly strengthens the impact of unemployment rate changes by improving matching quality.

We also compare the percentage changes of the housing market outcomes between the benchmark model and the Walrasian model when the unemployment rate changes from 2% (or 7.5%) to 12%. In the benchmark model, both the sale price and the sales volume decrease by 32.30% (or 17.52%) and 18.87% (or 11.06%), respectively, while the time to sale increases by 40.74% (or 20.16%). In the Walrasian model, both the sale price and the sales volume decrease by 28.09% (or 13.92%) and 0.02% (or 0.01%), respectively, while the change in the time to sale is zero. Through comparison, we can see that the thick-market effect contributes 13% (or 20.6%) of the overall price change.[9] And it explains most of the change in the sales volume and all of the change in the time to sale.

Finally, because the Walrasian model is an extreme case, we also do an experiment where we fix the quality distribution of new matches the same as the one corresponding to the benchmark model at the unemployment rate of 7.5%. The remaining part of the model is unchanged. In doing so, we still allow for the search and match friction in the model, but we shut down the channel through which the thick-market effect influences the matching quality distribution (and hence the average matching quality). We use the same set of parameter estimates as before in the simulation. In such a case, when the unemployment rate changes from 2% (or 7.5%) to 12%, both the sale price and the sales volume decrease by 21.14% (or 10.99%) and 7.98% (or 3.91%), respectively. The time to sale does not increase. In fact, it even shortens slightly on the contrary to the benchmark case. This may be because when we fix the matching quality distribution unchanged, the sellers do not need to wait extra time for a better match in response to negative demand shocks. Through comparison, we can

[9] To make the sale prices of the two models comparable, we adjust the willingness to pay for a perfectly matched house u_0^H in the Walrasian model by a scalar so that at the initial unemployment rate, the sale prices in the two models are the same.

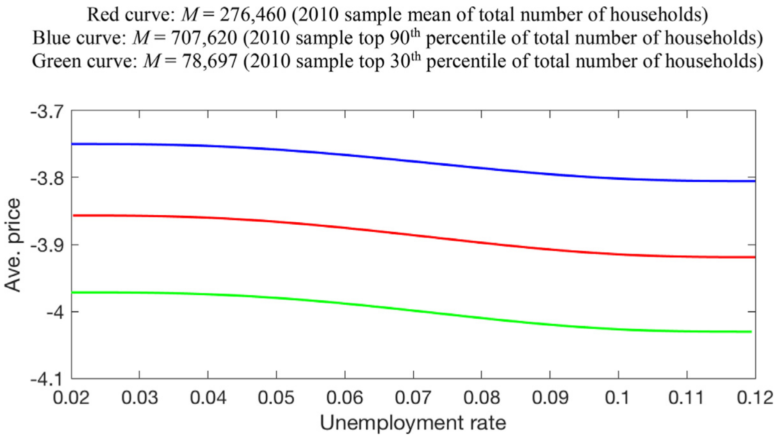

Fig. 5. City size and quasi-elasticities of average prices with respect to unemployment rate.
Red curve: $M = 276{,}460$ (2010 sample mean of total number of households).
Blue curve: $M = 707{,}620$ (2010 sample top 90th percentile of total number of households).
Green curve: $M = 78{,}697$ (2010 sample top 30th percentile of total number of households).
Note: Suppose z is a housing market outcome variable. We define the quasi-elasticity of z with respect to the unemployment rate as $\partial \ln z / \partial urate$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

see that the thick-market effect, by improving matching quality, contributes 35% (or 37%) of the overall price change and 58% (or 66%) of the overall sales volume change. And it explains all of the increase in the time to sale. In Fig. 4, we also show the quasi-elasticity of the above three market outcome variables with respect to the unemployment rate for this modified model that fixes the matching quality distribution. (Please see the green curves.) It is clear that the housing market's responsiveness to unemployment shocks is much weaker compared to the benchmark case.

3.3.2.1. Separating income's effect on willingness to pay. In our model, unemployment shocks influence the thickness of housing markets through the financial constraint channel, which in turn affects housing market outcomes. Because changes in unemployment rates are associated with changes in income, which in turn affect households' willingness to pay for housing services as captured by u_0^H and u_0^R, unemployment shocks may also affect housing prices through the willingness-to-pay channel.

We conduct the following simulation exercise to separate the income effect on willingness to pay from the overall effect of unemployment shocks by fixing u_0^H and u_0^R. Hence only the financial constraint channel, through which the unemployment rate influences the market thickness, works. Through simulations, we show that in such a case, an unemployment shock from 2% (or 7.5%) to 12% would lead to an 8.69% (or 5.35%) decrease in the sale price. This accounts for 27% (or 30.5%) of the overall change in the sale price. Moreover, when the willingness-to-pay channel is shut down, the change in the transaction volume in response to unemployment shocks is fairly close to its overall change in the benchmark case, as is the change in the time to sale. Thus, even if the income-to-willingness-to-pay channel is shut down, unemployment shocks can still influence market thickness through the financial constraint channel and can still impact housing market outcomes rather significantly.

3.3.2.2. Additional evidence. Finally, Fig. 5 shows the quasi-elasticity of the average sale price with respect to the unemployment rate for different city sizes as measured by the total number of households M. The red curve is drawn at $M = 276{,}460$, the sample mean level, the blue curve is drawn at $M = 707{,}620$, the sample's top 90th percentile level and the green curve is drawn at $M = 78{,}697$, the sample's 30th percentile. As shown in the figure, smaller cities are more responsive to changes in the unemployment rate. For example, at an unemployment rate of 7.5%, the price elasticity with respect to the unemployment rate is about -3.775, -3.885 and -3.996 when $M = 707{,}620$, $M = 276{,}460$, and $M = 78{,}697$, respectively. It decreases in absolute value as M gets larger. The reason is that as the market becomes thicker, the thick-market effect diminishes, and its amplifying function becomes weaker according to Eq. (3), as long as $c_1 > 0$ and $\alpha > 0$. Also, a larger city is more likely to generate a thicker housing market in equilibrium. Smith and Tesarek (1991) show that the prices of more expensive houses rose by larger percentages during the housing market boom and dropped by larger percentages during the bust. Their finding is consistent with our simulation result given that high-priced houses are typically in thinner markets with fewer buyers and sellers.

4. Discussions

This section provides further discussions on the extensions and caveats of our model and results.

Table 3
Feedback mechanism and amplification magnitude of the thick-market effect.

η	0.000	0.031	0.062	0.092	0.123	0.154	0.185	0.200
φ	0.000	2.16e^{-07}	4.31e^{-07}	6.47e^{-07}	8.63e^{-07}	1.08e^{-06}	1.29e^{-06}	1.40e^{-06}
A. Quasi-elasticity of Price								
Benchmark	−3.923	−4.417	−4.977	−5.921	−7.084	−8.986	−12.327	−15.461
Walrasian	−3.331	−3.687	−4.132	−4.705	−5.476	−6.591	−8.297	−9.137
Amplification Magnitude	0.178	0.198	0.205	0.258	0.294	0.363	0.486	0.692
Modified benchmark	−2.388	−2.560	−2.760	−3.006	−3.272	−3.716	−4.184	−4.424
Amplification Magnitude	0.643	0.725	0.803	0.970	1.165	1.418	1.946	2.495
B. Quasi-elasticity of Sales								
Benchmark	−2.058	−2.322	−2.696	−3.148	−3.950	−4.909	−7.102	−9.711
Walrasian	−0.002	−0.003	−0.003	−0.003	−0.004	−0.005	−0.006	−0.007
Amplification Magnitude	897.916	914.731	947.499	970.959	1045.570	1077.704	1216.672	1443.943
Modified benchmark	−0.830	−0.892	−0.963	−1.049	−1.144	−1.293	−1.457	−1.543
Amplification Magnitude	1.480	1.604	1.800	2.000	2.452	2.796	3.876	5.295
C. Quasi-elasticity of Time to sale								
Benchmark	3.410	3.845	4.425	5.187	6.399	7.980	11.265	14.742
Walrasian	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Amplification Magnitude	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf

Note: φ is related to the elasticity of the employment rate with respect to the housing price, η. Specifically, we let $\varphi = \eta * 0.075/E(P_{0.075})$ where $E(P_{0.075})$ is the average housing price at the sample mean unemployment rate of 0.075. In the Table 3 simulations, we choose different $\eta \in [0, 0.20]$. This range contains various values of employment elasticity with respect to the housing price documented in the literature (for example, see Miao et al., 2016 and Mian and Sufi, 2014).
Suppose z is a housing market outcome variable. We define the quasi-elasticity of z with respect to the unemployment rate as $\partial \ln z/\partial urate$. The amplification magnitude of the thick-market effect is measured by the difference between the quasi-elasticity of the benchmark model and that of the comparison model divided by the quasi-elasticity of the comparison model. In panel A (B) of Table 3, the first row is the quasi-elasticity of the housing price (sales volume) under the benchmark model; the second row is the quasi-elasticity under the Walrasian model; the third row is the amplification magnitude of the thick-market effect with the Walrasian model as the comparison reference; the fourth row is the quasi-elasticity under the modified benchmark model where the matching quality distribution is fixed; the fifth row is the amplification magnitude of the thick-market effect with the modified benchmark model as the comparison reference.

4.1. Feedback from housing markets to unemployment

Our main purpose is to study how unemployment shocks affect housing market outcomes and how this impact is amplified by the thick-market effect. We have therefore treated unemployment as exogenous in our model. The exogenous unemployment rate can be viewed as a reduced form of the endogenous unemployment process from a structural model. Indeed, we construct a stripped-down version of the Diamond-Pissarides-Mortsen model in the online appendix to show that if there are exogenous productivity shocks, then the resulting unemployment will mimic them. In such a model, unemployment has only a one-way impact on housing prices. However, the housing price may affect the demand for firms' products or household spending (through the wealth-effect channel, see Mian and Sufi, 2014 and Liu et al., 2016). Therefore, there would be interesting feedback from housing price to unemployment even if the initial shocks came from the labor market. It is hence important to see whether the thick-market effect still holds in the presence of such feedback. We thus conduct a simple exercise in which we add into our benchmark model a feedback mechanism from the housing price to unemployment. Specifically, we introduce

$$urate' = urate - \varphi \times (E(P) - const),$$

where $urate$ is the initial unemployment rate and $urate'$ is the ending unemployment rate. $E(P)$ is the average sale price corresponding to the initial unemployment rate. In the online appendix, we show how to formally derive the above feedback equation. *Const* is a constant that is set at a level such that $urate' = urate$ given φ, when $urate$ is at the sample mean unemployment rate, 0.075. If the coefficient φ is zero, then $urate'$ is always equal to $urate$ and there is no feedback from housing price to unemployment. The larger φ becomes, the stronger the feedback effect of the housing price on unemployment.

We conduct simulations of both the benchmark model and the Walrasian model with the feedback mechanism added in, using the set of estimated parameters reported in Table 2. We then calculate the quasi-elasticity of the sale price with respect to the initial unemployment rate for different values of $\varphi \geq 0$. We can see from Table 3 that for either the benchmark model or the Walrasian model, the price quasi-elasticity becomes higher in absolute value as φ becomes larger. More importantly, the magnitude of the thick-market effect in amplifying the impacts of initial unemployment shocks on housing prices increases monotonically with φ. The intuition is that when the unemployment rate initially increases, the market becomes thinner and the housing price declines. If the feedback effect is stronger, lower housing prices will generate an even higher unemployment rate which will in turn lead to an even thinner market and even lower housing prices. We also present in Table 3 the quasi-elasticity of the sales volume and time to sale with respect to the initial unemployment rate for different values of $\varphi \geq 0$, under both the benchmark model and the Walrasian model. The patterns are similar.

In addition, we present in Table 3 the quasi-elasticity of both housing prices and sales volumes with respect to the initial unemployment rate under *the modified model where we fix the matching quality distribution* as we did in Section 3.3.2. We also report the corresponding amplification magnitude of the thick-market effect using this modified model as the comparison reference. Again, the amplification magnitude increases as φ increases.

4.2. Different entry probability of homeowners and renters

In the benchmark model, we assume that all the households have the same probability of entering the housing market as buyers. In reality, the probability of entering the market as a buyer may vary for different types of households because they may have different housing net worth values and thus different abilities to obtain a mortgage. It is important to understand how this will affect the main predictions of our benchmark model. However, we encountered difficulties in explicitly incorporating this into the paper's framework. On the theory side, because the time to sale of a seller as well as the time to buy of a renter can be a span of any length in theory, a household may own multiple unsold houses at the same time. The model would become very complicated and intractable if we considered the heterogeneity of households with respect to the number of unsold houses they own. For tractability, we thus make a simplifying assumption that homeowners and renters have different entry probabilities while within the same group the entry probability is the same; namely,

$$\gamma^i = (1 - urate) \times prob\big(y > (\tau_0^i + \tau_1 urate) \times E(P) | employed\big), \tag{1'}$$

where $i \in \{owner,\ renter\}$ and $\tau_0^{owner} \neq \tau_0^{renter}$. Intuitively, when a homeowner moves out of her current house, the net worth of the house can help cover the down-payment required to purchase a new house, which implies that $\tau_0^{owner} < \tau_0^{renter}$. We can solve the modified benchmark model while letting homeowners and renters have different τ_0.

It would be ideal if we could separately estimate different τ_0's in our structural estimation. If we had data on certain key household characteristics such as house net worth, we may have been able to estimate how the difference between τ_0^{renter} and τ_0^{owner} is associated with such characteristics by exploring their variations in data. However, the lack of this key information prevented us from identify different probabilities of entering the housing market as a buyer by household type. We hence tried another way. Based on Chen et al. (2013)'s use of the refinancing application index from the Mortgage Bankers Association and the data on cash-out value from Freddie Mac, the dollar cash-out ratio of refinance loan to income is $0.12*1.41 = 0.169$. Because the housing price in our sample is roughly 2.07 times the household income at the 2010 sample mean, we infer that the cash-out value of the current house is about 0.08 times the housing price. This implies that in (1′), $\tau_0^{owner} = \tau_0^{renter} - 0.08$.

We then run simulations of the modified benchmark model with different τ_0^{owner} and the corresponding $\tau_0^{renter} = \tau_0^{owner} + 0.08$ in order to see whether our main results are robust when we allow for different entry probabilities for homeowners and renters. Generally speaking, the housing price changes with the unemployment rate in a fairly similar way to that of Fig. 2 of the benchmark model, as do the transaction volume and the time to sale, although not surprisingly the level of each outcome variable varies across different τ_0^{owner}. For example, for the cases where $\tau_0^{owner} = 0.311$, $\tau_0^{owner} = 0.331$, and $\tau_0^{owner} = 0.361$,[10] when the unemployment rate increases from 5% to 8%, the housing price (or the sales volume) falls by 10.89% (or 5.54%), 11.06% (or 5.55%), and 11.28% (or 5.60%) for each of the above τ_0^{owner}, respectively. These percentage changes are close to the corresponding ones (10.74% for the price and 5.49% for the volume) in the benchmark model.

More importantly, the thick-market effect still significantly amplifies the impact of the unemployment rate on the three key outcome variables. For example, in Fig. 6, for the cases where $\tau_0^{owner} = 0.311$, $\tau_0^{owner} = 0.331$, and $\tau_0^{owner} = 0.361$ and for each market outcome variable, we draw three quasi-elasticity curves (with respect to unemployment rate) corresponding to 1) the modified benchmark model with different entry probabilities, 2) the Walrasian model with different entry probabilities, and 3) the modified model with different entry probabilities and fixed matching quality distribution. They all show patterns similar to those of Fig. 4 of the benchmark model, suggesting that our main results concerning the thick-market effect remain robust even with different entry probabilities for homeowners and renters.

4.3. Bargaining power of buyers and sellers

In our model, the bargaining power of buyers and of sellers plays an important role in linking the matching quality to the equilibrium sale price. The bargaining power of buyers is estimated to be 0.516 with a standard error of 0.061. The estimate is very significant, which indicates that bargaining power is indeed important in determining the equilibrium housing market outcomes.

To further illustrate the influence of bargaining power on the magnitude of the thick-market effect, we conduct simulations of the benchmark model by setting the bargaining power at different values. In Fig. 7, the red curves represent the quasi-elasticity of housing market outcomes based on simulations in which the bargaining power of buyers is set to be $\theta = 0.3$; the blue curves are based on simulations in which the bargaining power of buyers is set to be $\theta = 0.7$. All of the other parameters use the parameter estimates reported in Table 2. Fig. 7 shows that the sale price becomes much less

[10] The benchmark model estimate of τ_0 is 0.38. We have experimented with τ_0^{owner} ranging from 0.22 to 0.45. All show patterns similar to those of the benchmark model.

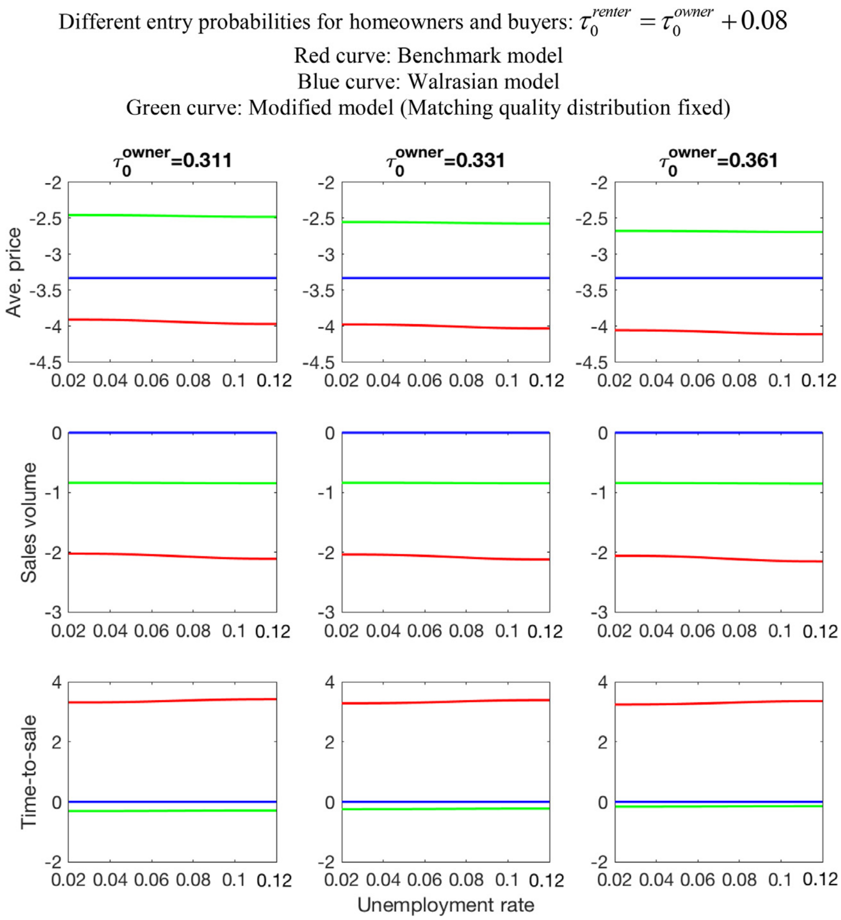

Fig. 6. Quasi-elasticity of market outcomes with respect to unemployment rate.
(Different entry probabilities forhomeowners and buyers: $\tau_0^{renter} = \tau_0^{owner} + 0.08$).
Red curve: Benchmark model.
Blue curve: Walrasian model.
Green curve: Modified model (Matching quality distribution fixed).
Note: Suppose z is a housing market outcome variable. We define the quasi-elasticity of z with respect to the unemployment rate as $\partial \ln z/\partial urate$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

responsive to unemployment shocks when θ is high. This is because when the buyer's bargaining power is high, the seller's payoff bears only a small fraction of the gain or loss from the changes in the matching quality caused by changes in unemployment. However, the responsiveness curves for the sales volume and the time-to-sale do not shift as much as the sale price shifts when the bargaining power varies. This is because these two outcome variables are not directly related to the seller's payoff, which depends crucially on the bargaining power.

4.4. Measurement of potential market size

Due to data limitations, we assume that each metropolitan area consists of a single market. Therefore, differences in city size (i.e., total number of households) are used to map the differences in potential market size (not of the actual market size, which is endogenously determined). One may concern that the difference in total households across cities overstates the difference in potential market size because a large city may consist of several local housing markets.

For a robustness 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 actual city size for the ith metropolitan area, and M_i^n is the new potential market size for the ith city we use in this robustness check. The scale a is determined such that $\bar{M} = a\sqrt{\bar{M}}$ where $\bar{M}$ is the mean city size across all cities. This ensures that the transformed city size is equal to the original city size at the mean level.

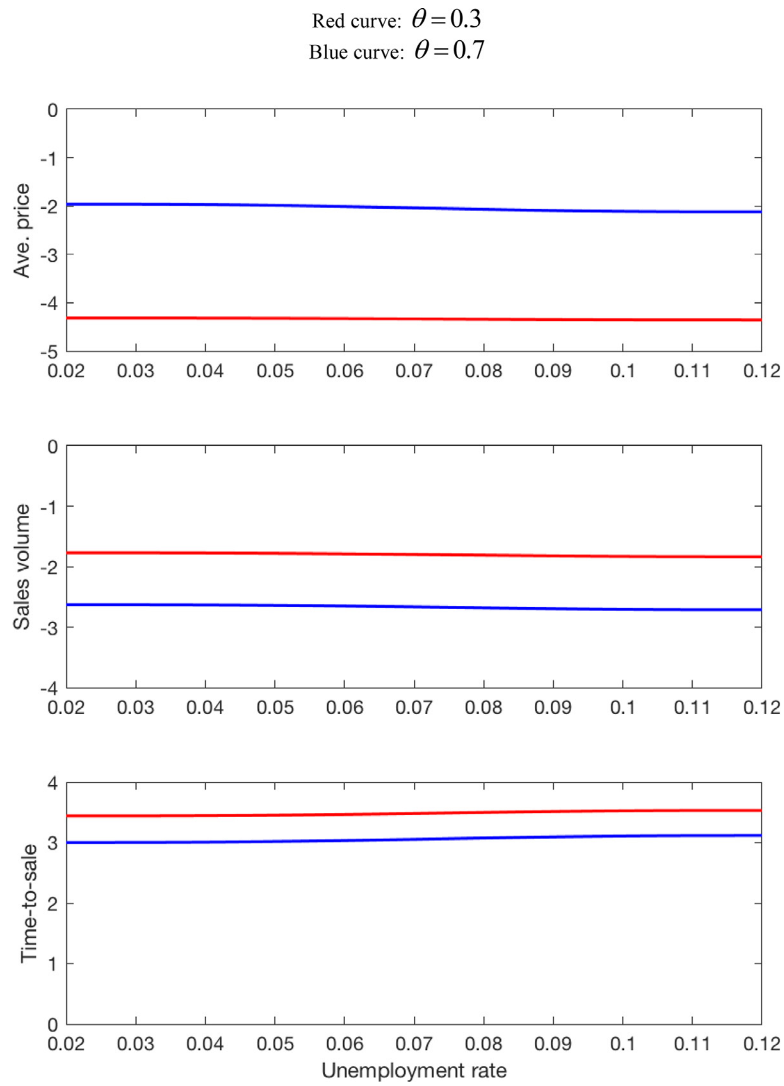

Fig. 7. Bargaining power and quasi-elasticities of market outcomes with respect to unemployment rate.
Red curve: $\theta = 0.3$.
Blue curve: $\theta = 0.7$.
Note: Suppose z is a housing market outcome variable. We define the quasi-elasticity of z with respect to the unemployment rate as $\partial \ln z / \partial urate$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

With this newly constructed potential market size, we re-estimate our model.[11] All of the results remain qualitatively the same. The key coefficient, the marginal disutility from mismatch, is $c_1 = 221.59$. It is significant and its value is fairly close to the previous estimate of 226.46. Simulations based on this set of new estimates again show that the thick-market effect amplifies the impact of the unemployment rate on housing market outcomes.

Another concern is that heterogeneous submarkets may exist within a city. Markets of different types may respond differently to unemployment shocks. For example, lower-end markets for lower-income households may be more susceptible to unemployment shocks. This means that the coefficients of the equations in our model may vary by market type. Unfortunately, we do not have housing data at the submarket level to test such heterogeneity. What we estimate in this paper is an average effect using city-level data. It would be interesting to explore this heterogeneity issue in the future when submarket data becomes available.

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

4.5. Correlation between transaction volumes and prices

Transaction volumes and prices are both endogenous variables in this model. They change in the same direction in response to changes 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 7.5%, based on simulations that use the set of estimated parameters reported in Table 2. Then we calculate the weighted average of the two elasticities with the weight for each city being its number of households divided by the aggregate number of households in all cities. The ratio of the weighted average transaction volume elasticity to the weighted price elasticity is 2.67. This is a bit smaller than the value of 4 roughly estimated by Stein (1995). We also use the set of estimates obtained from the robustness check in Section 4.4 to calculate the price elasticity and the transaction volume elasticity. The corresponding ratio of the weighted average transaction volume elasticity to the weighted price elasticity is 1.40.

Notice that our model setup does not consider the effects of liquidity constraints as do Genesove and Mayer (1997), nor does it incorporate loss aversion as do Genesove and Mayer (2001). If those two effects were incorporated, the thick-market effect would become even stronger through its interactions with them. This is because those two effects would likely lead to greater decreases in the number of sellers in the market when there is a negative demand shock.

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 one percentage point due to some exogenous factors. In this case, the total reduction in the transaction volume resulting from both the loss-aversion effect and the liquidity-constraint effect is 0.375 percentage points,[12] which is also smaller than the Stein estimate.

5. Conclusions

In this paper, we develop a search-and-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 buyers and sellers is better in a thicker market. A higher unemployment rate prevents households from entering the housing market as buyers. This is due to two factors. One is that it is very difficult for the unemployed to obtain mortgage loans. The other is that the credit condition becomes tighter in an environment of higher unemployment risk. Higher unemployment rates also reduce current homeowners' probability of moving due to increased job insecurity and longer time to sale. 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 decline more than they would 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 sale 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 changes on housing market outcomes. In our benchmark model, the quasi-elasticities of housing price, sales volume and time to sale at the sample mean unemployment rate are −3.885, −2.040 and 3.368, respectively, significantly larger than the corresponding quasi-elasticities –3.331, −0.002 and 0 in the Walrasian model where the thick-market effect is absent. A three-percentage-point increase in the unemployment rate (from 5% to 8%) would lower the sale price by 10.77%, reduce the sales volume by 5.49%, and increase the time to sale by 10.0%. In addition, a larger city, which typically has more buyers and sellers, experiences a smaller percentage change in price in response to a change in the unemployment rate.

Moreover, we also show that when a feedback mechanism from the housing price to the unemployment rate is incorporated, the magnitude of the thick-market effect becomes even greater. For example, in our benchmark model, when the employment elasticity with respect to housing prices is set at 0.12, the quasi-elasticities of housing price, sales volume and time to sale with respect to the initial unemployment rate are −7.084, −3.950 and 6.399, respectively at the sample mean unemployment level, much larger than the corresponding elasticities −5.476, −0.004 and 0 in the Walrasian case where the thick-market effect is absent.

Our model helps to explain the interaction between housing markets and aggregate unemployment shocks. The simulations in this paper demonstrate that the thick-market effect plays an important role in amplifying the impact of unemployment rate changes on housing market outcomes. Moreover, our analysis sheds light on the micro-foundation of the thick-market effect; that is, its improvement of the average matching quality between buyers and sellers.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2018.04.007.

[12] We calculate the elasticity using Tables VI and VII from Genesove and Mayer (2001).

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