Land Use Regulations, Migration and Rising House Price Dispersion in the U.S.*

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October 9, 2018

Abstract

This paper develops and solves a dynamic spatial equilibrium model of regional housing markets in which house prices are jointly determined with location-to-location migration flows. Agents optimize period-by-period and decide whether to remain where they are or migrate to a new location at the start of each period. The agent's optimal location choice and the resultant migration process is shown to be Markovian with the transition probabilities across all location pairs given as non-linear functions of wage and housing cost differentials, which are time varying and endogenously determined. On the supply side, in each location the construction firms build new houses by combining land and residential structures; with housing supplies endogenously responding to migration flows. The model can be viewed as an example of a dynamic network where regional housing markets interact with each other via migration flows that function as a source of spatial spill-overs. It is shown that the deterministic version of the model has a unique equilibrium and a unique balanced growth path. We estimate the state-level supplies of new residential land from the model using housing market and urban land acreage data. These estimates are shown to be significantly negatively correlated with the Wharton Residential Land Use Regulatory Index. The model can simultaneously account for the rise in house price dispersion and the interstate migration in the U.S.. Counterfactual simulations suggest that reducing either land supply differentials or migration costs could significantly lower house price dispersion.

JEL Classification: E0, R23, R31;
Keywords: house price dispersion, endogenous location choice, interstate migration, land-use restriction, spatial equilibrium

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*We are grateful to Alexander Chudik and Ron Smith for helpful comments.
†Wukuang Cun was a postdoc at USC Dornsife INET when research for this paper was carried out.

1 Introduction

In this paper, we develop and solve a dynamic spatial equilibrium model of regional housing markets. We model explicitly the agent's optimal location choice problem, and the dynamics of location-to-location migration flows. In contrast to the conventional demographic studies on migration that use Markov chain models with exogenously given transition probabilities across locations, we explicitly model local labor and housing markets, and allow transition probabilities that are functions of wage and housing cost differentials to endogenously respond to migration flows.[1] As a result, local wage rates and house prices are jointly determined with migration flows. Our theoretical framework can be viewed as an example of a dynamic network where regional housing markets interact with each other via migration flows that function as a source of spatial spill-overs. Because of these features, the present model provides a theoretically coherent framework to study the effects of changes in regional supply and demand conditions on house prices across all locations through endogenized migration flows.

At the start of each period, agents decide whether to remain where they are or migrate to a different location. The expected gain from migration depends on the expected differences in wage rates and housing costs between the origin and the destination, and the migration cost that consists of a route-specific element, and a stochastic idiosyncratic component. The agent's optimal location choice and the resultant migration process is shown to be Markovian with the transition probabilities across all location pairs given as non-linear functions of wage and housing cost differentials, which are time varying and endogenously determined. In each location, the construction firms build new houses by combining land and residential structures; with housing supplies endogenously responding to migration flows. It is shown that the deterministic version of the model has a unique balanced growth path, on which no location ends up with zero population.

Our modelling approach is to be distinguished from existing Rosen-Roback style spatial equilibrium models, such as, Van Nieuwerburgh and Weill (2010), and from the dynamic population allocation models adopted in the studies on spatial labor allocations by Davis et al. (2013) and Herkenhoff et al. (2018), among others. These studies rely on static models of population allocation as an outcome of spatial sorting process under perfect population mobility, or consider a representative household that centrally allocates household members (population) across locations. This paper is complementary to these studies in that it models explicitly the dynamics of location-to-location migration flows that function as a source of spatial spill-overs.[2]

We use the model to study the effects of local land-use regulations on house price dis-

[1] Conventional demographic studies on migration that use Markov chain models, such as Fuguitt (1965) and Tarver and Gurley (1965), assume that transition probabilities across locations are exogenously given, whilst in our study we allow migration flows to interact with local housing markets through endogenous and nonlinear variations in transition probabilities across location pairs and over time.

[2] Our paper also relates to empirical studies that find strong spatial spill-over effects in house price changes in the U.S., such as, Holly et al. (2010), Bailey et al. (2016), Sinai (2012), Cotter et al. (2011), and DeFusco et al. (2017). To our knowledge, the present paper is the first to explicitly model migration as the source of spatial spillover effects in regional housing markets.

persion across U.S. states and for internal migration. The house price dispersion across U.S. states has been rising since 1970s, and even after adjusting house prices for income differences, we are still left with a substantial secular rise in the dispersion of house prices relative to incomes as shown in Figure 1 below. In addition, the rise in house price dispersion is basically a between-region phenomenon, since the average within-region dispersion has been increasing much slower than the between-region dispersion as shown in Figure 2 below.[3] The secular increase in the house price dispersion in the U.S. has been the ongoing focus of empirical and theoretical research. Glaeser and Gyourko (2003), Glaeser et al. (2005), Quigley and Raphael (2005), Ihlanfeldt (2007) and Albouy and Ehrlich (2018) find that areas with faster than average growth in house prices tend to have more restrictions on residential land-use.[4] Recently, Hsieh and Moretti (2015) and Herkenhoff et al. (2018), go beyond the analysis of house prices and examine the impact of land-use regulations on spatial labor allocation. Their models predict that land-use deregulation can lead to substantial population reallocations to high-productivity cities and a considerable increase in the average labor productivity.[5] Since we explicitly modelled the dynamic interactions between migration and local housing markets, one advantage of our model in empirical application is that it allows us to simultaneously evaluate the effects of changes in land-use regulations on house price dispersion and population reallocation over time. In addition, the tractability of the model allows us to analytically solve the model, which facilitates the analysis of the evolutions of the U.S. regional housing markets between short run and long run equilibria. As will be explained below, our model can account for the rise in house price dispersion and the interstate migration in the U.S. simultaneously. In addition, our model predicts that changes in regional land-use regulations affect local house prices much more as compared to their effects on local population.

We calibrate our model on a panel of 49 states (including the District of Columbia) in the U.S. mainland. We estimate the model using the subset of the available data on interstate migration flows and state level housing market data over the period 1976-1999 (training sample), and then conduct out-of-sample forecasts and simulations over the period 2000-2014 (evaluation sample) and compare the predicted values to the actual realized values. The route-specific migration costs are estimated using the combined state-to-state migration flows and state level incomes and housing costs data. Parameters that govern local housing supplies are calibrated using state level housing market data. We estimate the state-level supplies of new residential land from the model using housing market and urban land acreage data. These estimates are shown to be significantly negatively correlated with the Wharton

[3]Similar increases in house price dispersion have also been documented across Metropolitan Statistical Areas (MSAs). The increases in house price dispersion across MSAs are mainly due to the increases in between-state dispersion, as the within-state dispersion has not increased that much. For further details, see Section S4.2 of the online supplement.

[4]Some recent studies consider also non-regulatory factors behind land supply availabilities. For example, Saiz (2010) considers the impacts of geographical constraints on land supplies, and Kahn (2011) finds that liberal cities in California grant fewer new housing permits.

[5]In addition, Hilber and Robert-Nicoud (2013) and Parkhomenko (2016) study how regional housing supply regulations are endogenously determined in political processes, and Van Nieuwerburgh and Weill (2010) and Gyourko et al. (2013) attribute the increase in house price dispersion to spatial labor sorting.

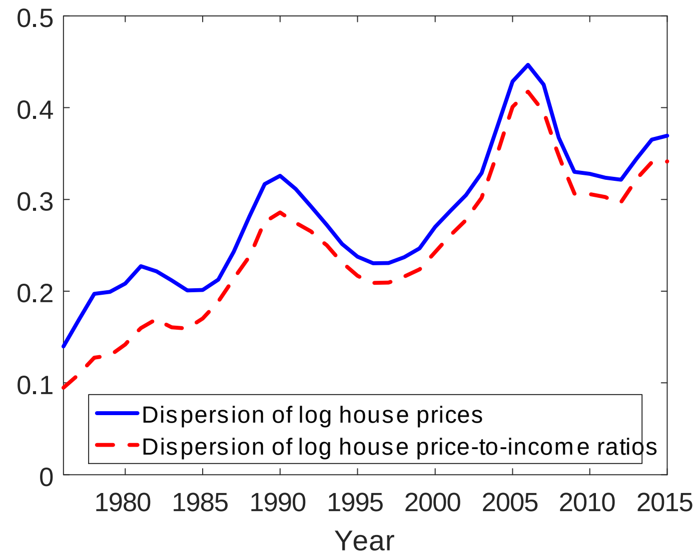


Figure 1: Dispersions of log house prices and log house price-to-income ratios across U.S. states

Notes: The solid line shows the standard deviation of log real house prices across U.S. states. The dashed line shows the standard deviation of log house price-to-income ratios across U.S. states.

Residential Land Use Regulatory Index (WRI henceforth). In the out-of-sample forecasting exercises, we examine the performance of the model in predicting the observed rise in house price dispersion during the period 2000-2014. The model predicts reasonably well the increases in the dispersions of house price-to-income ratios at both national and regional levels during the evaluation sample. In addition, the model captures the different trends at different geographical levels, i.e., the substantial increase in the between-region dispersion and the moderate increases of within-region dispersions. As will be shown in Section 9, this can be partially due to the stronger migration linkages between geographically close states that tend to prevent the house price differences between these states from increasing. Furthermore, our model captures the observed patterns of interstate migration, which complements the analysis of gross migration trends in the literature, for example, by Kaplan and Schulhofer-Wohl (2017).

To examine the importance of spatial heterogeneity in land-use regulation in driving up house price dispersion in the U.S., we conduct a counterfactual simulation over the evaluation sample (2000-2014) in which land supply growth rates of all states are set equal to the national average. The results of the counterfactual exercise show that land supply differentials are the major factor behind the rising house price dispersion in the U.S..

To examine the impacts of regional land-use regulations on local house prices and populations, we consider two counterfactual exercises: a land-use deregulation in California and a tightening of land-use regulation in Texas. These exercises show that local house prices are much more affected by changes in land use regulations than populations. For example, our model predicts that increasing the land supply growth rate of California to the national

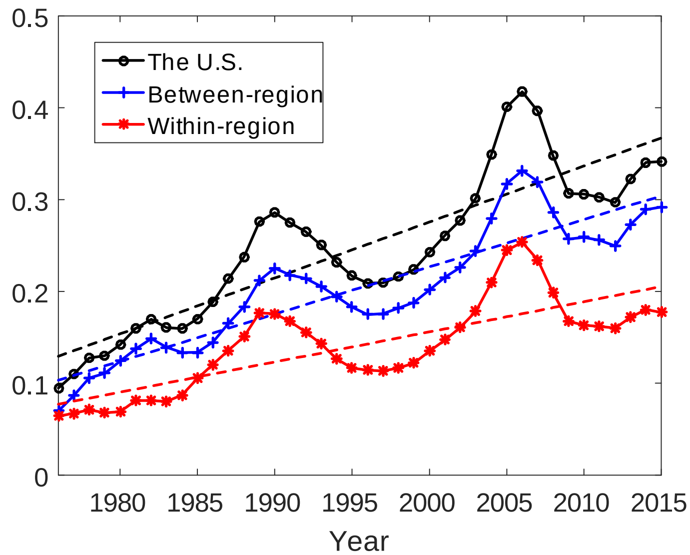


Figure 2: Dispersions of log house price-to-income ratios within and between U.S. regions

Notes: The line designated with 'o' shows the dispersion of log house price-to-income ratios across U.S. states. The line designated with '+' shows the dispersion of log house price-to-income ratios across the five U.S. regions. The line designated with '*' shows the average of within-region dispersions, where within-region dispersion is the standard deviation of log house price-to-income ratios across the states that are within a given region. See Section S5 of the online supplement for a derivation of the dispersion decomposition formula.

average from 2000 onward induces the population of California in 2014 to rise by 0.1 million (around 0.2 per cent of California population), whilst such a de-regulation could reduce the annual growth rate of real house prices from 3 per cent realized during the 2000-2014 period to a mere 0.8 per cent counterfactually. On the other extreme, reducing the land supply growth rate of Texas to the national average reduces Texas's population in 2014 by 0.1 million (around 0.4 per cent of Texas population), but increases the annual growth rate of real house prices from a realized value of 1.1 per cent to a counterfactual rate of 2.5 per cent.

To examine how land supply differentials and migration costs jointly contribute to the rise in house price dispersion, we also carry out simulations assuming different levels of land supply differentials and migration costs. The results indicate that both land supply differentials and migration costs play significant roles in driving up house price dispersion; reducing either of the two factors can significantly lower house price dispersion in the U.S.. In addition, increases in land supply differentials would lead to a larger rise in house price dispersion when migration costs are larger.

We also investigate the impulse responses of state level house prices and population to regional shocks, and consider a negative regional productivity shock to California as an example. As local productivity drops, agents migrate out from California to other states, which raises housing demand and house prices in these states. However, the responses of house prices in the neighboring states of California are faster and stronger than those of the other states. In addition, migration flows between California and its neighboring states are also more responsive to the shock. The impulse responses of the model economy to regional productivity shocks to New York, Illinois, Florida and Texas also have similar patterns. These results suggest, perhaps not surprisingly, that migrations between states that are geographically close are more responsive to changes in wage and housing cost differentials.

The rest of the paper is organized as follows. Section 2 presents the migration module, and Section 3 presents the rest of the model. Section 4 characterizes the equilibrium and proves the existence and the uniqueness of the equilibrium and the balanced growth path in the deterministic case. Section 5 estimates the model. Section 6 examines the ability of the model in predicting the observed rise in house price dispersion in the U.S.. Sections 7 and 8 study the impacts of land-use regulations on house price dispersion and internal migration. Section 9 studies the migration linkages between regional housing markets by analyzing the responses of the economy to regional shocks. Section 10 concludes.

2 A dynamic location-to-location migration model

In this section, we provide a dynamic version of the residential choice model originally developed by McFadden (1978), and explicitly model the location-to-location migration choices of agents at the start of each period. In the next section, we will provide a simultaneous determination of house prices and migration flows across space and over time.

2.1 Geography and migration flows

Time, denoted by t, is discrete and the horizon is infinite, so that $t = 0, 1, 2, ...$ There are n locations, and the collection of locations is represented by $\mathcal{I} = \{1, 2, ..., n\}$, where n is fixed but possibly large ($n \geq 2$). The economy is populated by workers who consume goods and housing services, and live for only one period. At the start of each period, workers decide whether to reside at locations where they are born, or migrate to a new location. Denote by $l_{ij}(t)$ the number of workers who are born at location i in period t, and choose to reside at location j, where i and $j \in \mathcal{I}_n$. Denote the population of workers born at location i at the start of period t by $l_{i\cdot}(t)$. Then

$$l_{i\cdot}(t) = \sum_{j=1}^{n} l_{ij}(t), \tag{1}$$

and the number of workers who choose to reside at location j in period t, denoted by $l_{\cdot j}(t)$, is given by

$$l_{\cdot j}(t) = \sum_{i=1}^{n} l_{ij}(t). \tag{2}$$

The number of workers who are born at location i at the start of period t equals to the number of workers who reside at that location in period $t - 1$, plus an intrinsic exogenously given population change.[6] Denote the intrinsic rate of population change (growth rate if

[6] The intrinsic population changes are made up of, for example, the net natural population increases (i.e. birth minus death) and the net migration flows from other countries.

positive) of location i in period t by $g_{l,it}$. Thus, the number of workers born in location i at the start of period t is given by

$$l_{i\cdot}(t) = e^{g_{l,it}} l_{\cdot i}(t-1), \tag{3}$$

where it is assumed that $g_{l,it}$ follows an exogenously given deterministic process, for $i \in \mathcal{I}_n$, to be specified below.

We model migration probabilities as a Markov process. The probability that an individual worker born at location i chooses to reside at location j in period t is denoted by $\rho_{ij}(t)$, where $\rho_{ij}(t) \geqslant 0$ and $\sum_{j=1}^{n} \rho_{ij}(t) = 1$. Workers' location choices are assumed to be conditionally independent given the location-specific wage rates and housing service prices. Thus, according to the law of large numbers, the fraction of workers born in location i who choose to reside at location j converges to $\rho_{ij}(t)$ as population increases. We ignore any randomness due to finite population and assume the migration flow from location i to location j, $l_{ij}(t)$, is determined by

$$l_{ij}(t) = l_{i\cdot}(t)\rho_{ij}(t). \tag{4}$$

Thus, by combining (2), (3) and (4), we obtain

$$l_{\cdot j}(t) = \sum_{i=1}^{n} e^{g_{l,it}} l_{\cdot i}(t-1)\rho_{ij}(t), \quad \text{for } j = 1, 2, ..., n. \tag{5}$$

The above system of equations can be re-written more compactly as

$$\boldsymbol{l}(t) = \boldsymbol{l}(t-1)\mathbf{G}(t)\mathbf{R}(t), \tag{6}$$

where $\boldsymbol{l}(t) \equiv [l_{\cdot 1}(t), l_{\cdot 2}(t), ..., l_{\cdot n}(t)]$ is the $1 \times n$ (row) vector of location-specific population, and $\mathbf{G}(t)$ is the $n \times n$ diagonal matrix of population growth rates and $\mathbf{R}(t)$ is the $n \times n$ Markovian migration probability matrix, defined by

$$\mathbf{G}(t) \equiv \begin{pmatrix} e^{g_{l,1t}} & 0 & \cdots & 0 \\ 0 & e^{g_{l,2t}} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & e^{g_{l,nt}} \end{pmatrix}, \text{ and } \mathbf{R}(t) \equiv \begin{pmatrix} \rho_{11}(t) & \rho_{12}(t) & \cdots & \rho_{1n}(t) \\ \rho_{21}(t) & \rho_{22}(t) & \cdots & \rho_{2n}(t) \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{n1}(t) & \rho_{n2}(t) & \cdots & \rho_{nn}(t) \end{pmatrix}.$$

In the standard Markov chain model of migration, transition matrix is exogenously given. However, in our model, we allow $\mathbf{R}(t)$ to be time varying and endogenously determined. We consider the endogenous determination of $\mathbf{R}(t)$ in the following sections.

2.2 Location choice

At the start of each period, workers decide where to reside by maximizing their utilities in terms of consumption and housing services across all locations, and then choosing the location that gives them the highest level of utility. Consider an individual worker τ who is born at location i in period t, and considers moving to location $j \in \mathcal{I}_n$, where j could be i

(namely not moving). We adopt a log-linear utility function and assume that if the worker decides to reside in location j, then her utility will be given by

$$u_{\tau,t,ij} = (1-\eta)\ln c_{\tau,t,ij} + \eta \ln s_{\tau,t,ij} - \psi \ln \alpha_{ij} + \varepsilon_{\tau,t,ij}, \tag{7}$$

where $c_{\tau,t,ij}$ and $s_{\tau,t,ij}$ are her consumption of goods and housing services, respectively, η represents the relative preference for housing service to consumption goods with $\eta \in (0,1)$, $\ln \alpha_{ij}$ is the route-specific migration cost, ψ is the relative weight of migration costs in utility function, and $\varepsilon_{\tau,t,ij}$ represents the idiosyncratic component of worker's relative location preference over (i,j) location pair. We assume $\alpha_{ij} > 1$, if $j \neq i$, and, $\alpha_{ij} = 1$, if $j = i$. In addition, suppose that $\varepsilon_{\tau,t,ij}$ is distributed independently of $c_{\tau,t,ij}$ and $s_{\tau,t,ij}$, and over time t. Also, following the literature on utility-based multiple choice decision problem, we shall assume that at each point in t, $\varepsilon_{\tau,t,ij}$ are independently and identically distributed (IID) as extreme value distribution. (see, for example, McFadden (1978)).

Each worker inelastically supplies one unit of labor and allocate her wage income between consumption of goods and housing services. Denoting the wage rate and the price of housing services at location j in period t by w_{jt} and q_{jt} respectively, the budget constraint of the worker is given as

$$c_{\tau,t,ij} + q_{jt}s_{\tau,t,ij} = w_{jt}.$$

The utility maximization is done in two steps. First, the worker maximizes her utility in terms of consumption of goods and housing services across locations. Denote by $\tilde{u}_{\tau,t,ij}$ the maximized utility of worker τ if she chooses to reside at location j. It is given as

$$\tilde{u}_{\tau,t,ij} = u_{jt} - \psi \ln \alpha_{ij} + \varepsilon_{\tau,t,ij}, \tag{8}$$

where u_{jt} is the maximal utility one can get in location j, which is determined as

$$u_{jt} \equiv \max_{\{c_{\tau,t,ij},\, s_{\tau,t,ij}\}} (1-\eta)\ln c_{\tau,t,ij} + \eta \ln s_{\tau,t,ij}, \tag{9}$$
$$s.t. \qquad c_{\tau,t,ij} + q_{jt}s_{\tau,t,ij} = w_{jt}.$$

By solving the above optimization problem, we obtain:

$$c_{jt} = (1-\eta)w_{jt}, \tag{10}$$
$$s_{jt} = \frac{\eta w_{jt}}{q_{jt}}, \tag{11}$$

where the subscripts τ and i of $c_{\tau,t,ij}$ and $s_{\tau,t,ij}$ are dropped for convenience, since the optimal levels of consumption of goods and housing services of each worker only depend on j and t. Thus, the indirect utility function associated with location j can be obtained by substituting (10) and (11) into (9) to yield:

$$u_{jt} = u_0 + \ln w_{jt} - \eta \ln q_{jt}, \tag{12}$$

where $u_0 \equiv (1-\eta)\ln(1-\eta) + \eta \ln \eta$ is a scalar.

Second, the worker chooses the location with the highest utility. Using (8) and (12), the net utility gain of worker τ migrating to location j, denoted by $v_{\tau,t,ij}$, is given by

$$\begin{aligned} v_{\tau,t,ij} &= \tilde{u}_{\tau,t,ij} - \tilde{u}_{\tau,t,ii}, \\ &= (\ln w_{jt} - \ln w_{it}) - \eta (\ln q_{jt} - \ln q_{it}) + (\varepsilon_{\tau,t,ij} - \varepsilon_{\tau,t,ii}) - \psi \ln \alpha_{ij}. \end{aligned}$$

Given the realizations of $\{\varepsilon_{\tau,t,ij}\}_{j=1}^{n}$, the worker chooses the destination with the highest $v_{\tau,t,ij}$. Let $j^*_{\tau,t,i}$ denote the location chosen by the worker. Then,

$$j^*_{\tau,t,i} = arg \max_{j \in \mathcal{I}_n} \; v_{\tau,t,ij}.$$

Since by assumption $\varepsilon_{\tau,t,ij}$ is distributed as IID extreme value, it can be shown that the probability for the worker in location i to migrate to location j is given by (see Appendix A1.1 for a derivation)

$$\rho_{ij}(t) = \frac{e^{v_{t,ij}}}{\sum_{s=1}^{n} e^{v_{t,is}}}, \tag{13}$$

where

$$v_{t,ij} \equiv (\ln w_{jt} - \ln w_{it}) - \eta (\ln q_{jt} - \ln q_{it}) - \psi \ln \alpha_{ij}. \tag{14}$$

Thus, $\rho_{ij}(t)$ is a function of wage rate differentials, $\ln w_{jt} - \ln w_{it}$, and housing cost differentials, $\ln q_{jt} - \ln q_{it}$.

3 Production and housing supplies

In this section, we discuss how output, wage rates, housing service prices, and house prices are determined.

3.1 Production

We assume that location-specific wage rates are competitively determined in local labor markets, and allow for agglomeration effects in production. We further assume that the production of final goods is given by

$$y_{it} = \phi_{it} \left(a_{it} l_{\cdot i}(t) \right)^{v_l}, \tag{15}$$

where y_{it} is the output of final goods in location i in period t, $l_{\cdot i}(t)$ is the labor used in the production, a_{it} is the location-specific labor productivity, $v_l \in (0,1)$ is the share of labor costs in output, and ϕ_{it} stands for total factor productivity given by

$$\phi_{it} = \bar{\phi}_i y_{it}^{v_\phi}, \tag{16}$$

where $\bar{\phi}_i > 0$, and $v_\phi \in [0,1)$. It is assumed that total factor productivity, ϕ_{it}, increases with production scale, which captures agglomeration effects of production. Parameter v_ϕ governs the magnitude of agglomeration effects, with $v_\phi = 0$ corresponding to no agglomeration effect. The profit of the representative final goods producer at location i is given by

$$\pi_{it}^y = y_{it} - w_{it} l_{\cdot i}(t), \tag{17}$$

where w_{it} is the wage rate in location i. The representative final goods producer chooses $l_{\cdot i}(t)$ to maximize its profits (17) subject to (15), while taking ϕ_{it} as given. The first order condition for $l_{\cdot i}(t)$ is given by,

$$w_{it} = v_l \left(\frac{y_{it}}{l_{\cdot i}(t)} \right). \tag{18}$$

By substituting (15) and (16) into (18), we obtain the labor demand function:

$$w_{it} = \tau_{w,i} a_{it}^{\lambda_a} l_{\cdot i}(t)^{-\lambda_l}, \tag{19}$$

where $\tau_{w,i} \equiv v_l \bar{\phi}_i^{1/(1-v_\phi)}$ is a location-specific scalar, and λ_a and λ_l are the elasticities of wage rate with respect to labor productivity and labor input respectively, which are defined by

$$\lambda_a \equiv \frac{v_l}{1-v_\phi}, \quad \text{and} \quad \lambda_l \equiv \frac{1-v_l-v_\phi}{1-v_\phi}. \tag{20}$$

To ensure that wage rates, w_{it}, decrease with labor inputs, $l_{\cdot i}(t)$, we assume $1 - v_l - v_\phi > 0$, which in turn implies $1 > \lambda_l > 0$.[7] We further assume that final goods producers consume all the profits they earn in each period. Thus, $c_{it}^y = \pi_{it}^y$, where c_{it}^y denotes the consumption of final goods by producers at location i in period t.

We adopt a relatively general specification of a_{it} and assume that $\ln a_{it}$ comprises of a linear trend component, $\ln a_i + g_a t$, a national common (unobserved) component, f_t, and a local component $z_{a,it}$:

$$\ln a_{it} = \ln a_i + g_a t + \lambda_i f_t + z_{a,it}, \tag{21}$$

where g_a is the national growth rate of labor productivity, and λ_i is the location-specific coefficient on the national component, with $E(\lambda_i) > 0$. In addition, $z_{a,it}$ and f_t are assumed to follow first-order autoregressive (AR(1)) processes:

$$f_t = \rho_f f_{t-1} + \sigma_f \varepsilon_{f,t}, \tag{22}$$

$$z_{a,it} = \rho_{a,i} z_{a,i,t-1} + \sigma_{a,i} \varepsilon_{a,it}, \tag{23}$$

where $\varepsilon_{f,t}$ and $\varepsilon_{a,it}$ are IID across locations and over time.

3.2 Housing supplies

We assume that location-specific housing service prices are competitively determined in local rental markets. Suppose that each unit of existing houses provides a unit of housing services

[7] It is easily seen that $\tau_{w,i} > 0$ and $\lambda_a > 0$, since $\bar{\phi}_i$ and $v_l > 0$, and $v_\phi \in [0, 1)$.

in each period, while new houses begin to provide housing services a period after they are built. Thus, the market clearing condition is given by

$$h_{i,t-1} = \left(\frac{\eta w_{it}}{q_{it}} \right) l_{\cdot i}(t), \tag{24}$$

where $h_{i,t-1}$ is the quantity of houses that are available for rent at location i in period t, $\eta w_{it}/q_{it}$ is the per capita consumption of housing services given by (11).

For determination of housing stocks, $h_{i,t}$, and house prices, $p_{i,t}$, we suppose that in each period t, a representative contractor is endowed with $\kappa_{it} > 0$ units of unused or reclaimed land in location i that can be used for new house construction. New houses are constructed by combing residential land and final goods using a Cobb-Douglas technology. Denote the amount of new houses built at location i in period t by x_{it}, and note that

$$x_{it} = \tau_{x,i} \kappa_{it}^{\alpha_{\kappa,i}} m_{it}^{1-\alpha_{\kappa,i}}, \tag{25}$$

where $\tau_{x,i} > 0$ is a scalar constant, $\alpha_{\kappa,i} \in (0,1)$ is the share of land in house value, and m_{it} is the amount of final goods used for investments in residential structures at location i. Contractors are assumed to be homogeneous and operate competitively across locations. The profit of the representative contractor in period t, denoted by π_t^c, is given as

$$\pi_t^c = \sum_{i=1}^{n} p_{it} x_{it} - m_{it}.$$

The contractor chooses $\{x_{it}, m_{it}\}_{i=1}^n$ to maximize her profits subject to house construction technology, (25), while taking the new land supplies, κ_{it}, as given. By solving the contractor's optimization problem, we obtain the supply function for new houses

$$x_{it} = \tau_{\kappa,i} \kappa_{it} p_{it}^{\lambda_{p,i}}, \tag{26}$$

where $\tau_{\kappa,i} \equiv \tau_{x,i}^{1+\lambda_{p,i}} (1-\alpha_{\kappa,i})^{\lambda_{p,i}}$ is the location-specific scalar, and $\lambda_{p,i}$ is the elasticity of the new housing supply with respect to the house price, defined by

$$\lambda_{p,i} \equiv \frac{1-\alpha_{\kappa,i}}{\alpha_{\kappa,i}} \quad . \tag{27}$$

We assume that contractors consume all the profits they earn in each period. Thus, $c_t^c = \pi_t^c$, where c_t^c denotes the consumption of contractors in period t. Housing stock depreciates at rate δ. The total supply of houses in location i in period t is given by

$$h_{it} = (1-\delta) h_{i,t-1} + x_{it}, \tag{28}$$

where $\delta \in (0,1)$ is the depreciation rate of housing stocks, and $(1-\delta)h_{i,t-1}$ is the existing houses in that location. Finally, we assume

$$\ln \kappa_{it} = \ln \kappa_i + g_{\kappa,i} t + z_{\kappa,it} \tag{29}$$

where $g_{\kappa,i}$ is the trend growth rate of new land supplies, and $z_{\kappa,it}$ is the state-specific land supply shock assumed to follow the AR(1) process:

$$z_{\kappa,it} = \rho_{\kappa,i} z_{\kappa,i,t-1} + \sigma_{\kappa,i}\varepsilon_{\kappa,it}, \tag{30}$$

where $\varepsilon_{\kappa,it}$ are IID across locations and over time.

In each location, homogeneous landlords own local housing stocks and rent them to workers, and derive utility from consuming their profits. The population of landlords in location i, denoted by l_{it}^o, grows over time at the common rate of g_l, where $g_l > 0$. Thus, $l_{it}^o = e^{g_l t} l_{i0}^o$, where $l_{i0}^o > 0$ is the initial population of landlords in location i. The life time utility of landlords (as a group) in location i is given by

$$E_t \sum_{s=0}^{\infty} (\beta e^{g_l})^s \ln(c_{i,t+s}^o), \tag{31}$$

where c_{it}^o is the consumption of the 'representative' landlord in location i, and $\beta e^{g_l} \in (0,1)$ is the adjusted discount factor that allows for the growing number of landlords. The realized net return on housing investment in location i in period t, denoted by r_{it}^o, is given by

$$r_{it}^o = (1-\theta_i)\left[\frac{q_{it} + (1-\delta)p_{it}}{p_{i,t-1}}\right], \tag{32}$$

where $\theta_i \in (0,1)$ is the location-specific cost of housing investment. The landlords' budget constraint is then given by

$$c_{it}^o l_{it}^o + p_{it} h_{it} = r_{it}^o \left(p_{i,t-1} h_{i,t-1}\right). \tag{33}$$

Landlords maximize (31) subject to (33). The Euler condition for this optimization is given by

$$E_t\left(\Lambda_{i,t+1} r_{i,t+1}^o\right) = 1, \tag{34}$$

where $\Lambda_{i,t+1}$ is the stochastic discount factor, defined by $\Lambda_{i,t+1} = \beta\left(c_{it}^o / c_{i,t+1}^o\right)$. Pre-multiplying both sides of (34) by p_{it}, and using (32), we can write the house price, p_{it}, as the sum of the expected present value of rents net of depreciation:

$$p_{it} = \sum_{s=1}^{\infty} E_t\left[(1-\delta)^{s-1}(1-\theta_i)^s \left(\prod_{v=1}^{s} \Lambda_{i,t+v}\right) q_{i,t+s}\right].$$

Since the utility function of landlords is assumed to be logarithmic, a closed form solution for landlords' optimization problem exists. The optimal rules for housing investment and consumption are given by

$$p_{it} h_{it} = \beta e^{g_l}(1-\theta_i)\left[q_{it} + (1-\delta)p_{it}\right] h_{i,t-1}, \tag{35}$$

and

$$c_{it}^o l_{it}^o = \left(1-\beta e^{g_l}\right)(1-\theta_i)\left[q_{it} + (1-\delta)p_{it}\right] h_{i,t-1}. \tag{36}$$

4 Theoretical properties

We now consider the theoretical properties of the model economy set out in Sections 2 and 3. Section 4.1 summarizes the set of equilibrium conditions by which the key variables are determined. Section 4.2 proves the existence and uniqueness of the short-run equilibrium and the balanced growth path.

4.1 Dynamic system of equations

We first summarize the set of equilibrium conditions by which the key variables are determined. We use bold lowercase letters with only time subscripts to denote the vectors of prices and quantities for all locations. For example, $\boldsymbol{p}_t \equiv [p_{1t}, p_{2t}, ..., p_{nt}]$, which is a $1 \times n$ vector. We denote the aggregate population by $L_t \equiv \sum_{i=1}^{n} l_{\cdot i}(t)$. We focus only on the key variables that are related to migration and local housing markets, including $\boldsymbol{p}_t$, $\boldsymbol{q}_t$, $\boldsymbol{w}_t$, $\boldsymbol{x}_t$, $\boldsymbol{h}_t$, $\boldsymbol{l}(t)$ and $\mathbf{R}(t)$, and the subset of equilibrium conditions by which they are determined, which can be categorized into two groups:

- **Migration.** The first block of equilibrium conditions describe how migration probabilities, $\mathbf{R}(t)$, and local population values, $\boldsymbol{l}(t)$, are determined, given wage rates, $\boldsymbol{w}_t$, and housing service prices, $\boldsymbol{q}_t$, which include

$$\boldsymbol{l}(t) = \boldsymbol{l}(t-1)\mathbf{G}(t)\mathbf{R}(t), \tag{37}$$

where $\mathbf{G}(t) = \mathbf{diag}\left(e^{g_{l,1t}}, e^{g_{l,2t}}, ..., e^{g_{l,nt}}\right)$ is the $n \times n$ diagonal matrix of exogenous intrinsic population growth rates, $\mathbf{R}(t) = \big(\rho_{ij}(t)\big)$ is the $n \times n$ matrix of migration probabilities, and

$$\rho_{ij}(t) = \frac{\alpha_{ij}^{-\psi}\left(w_{jt}/w_{it}\right)\left(q_{jt}/q_{it}\right)^{-\eta}}{\sum_{s=1}^{n}\alpha_{is}^{-\psi}\left(w_{st}/w_{it}\right)\left(q_{st}/q_{it}\right)^{-\eta}}, \text{ for } i \text{ and } j \in \mathcal{I}_n. \tag{38}$$

- **Regional labor and housing markets**. The second block of equilibrium conditions describe how wage rates, $\boldsymbol{w}_t$, housing service prices, $\boldsymbol{q}_t$, and house prices, $\boldsymbol{p}_t$, are determined given local population, $\boldsymbol{l}(t)$, which include

$$\begin{aligned}
w_{it} &= \tau_{w,i}a_{it}^{\lambda_a}l_{\cdot i}(t)^{-\lambda_l}, \text{ for } i \text{ and } j \in \mathcal{I}_n, && (39)\\
h_{i,t-1} &= \left(\eta w_{it}/q_{it}\right)l_{\cdot i}(t), \text{ for } i \text{ and } j \in \mathcal{I}_n, && (40)\\
x_{it} &= \tau_{\kappa,i}\kappa_{it}p_{it}^{\lambda_{p,i}}, \text{ for } i \text{ and } j \in \mathcal{I}_n, && (41)\\
h_{it} &= (1-\delta)h_{i,t-1} + x_{it}, \text{ for } i \text{ and } j \in \mathcal{I}_n, && (42)\\
p_{it}h_{it} &= \beta e^{g_l}\left(1-\theta_i\right)\left[q_{it} + (1-\delta)p_{it}\right]h_{i,t-1}, \text{ for } i \text{ and } j \in \mathcal{I}_n. && (43)
\end{aligned}$$

As shown in Appendix A1.2, equations (37)-(43) can be written compactly as:

$$\begin{aligned}
\boldsymbol{\zeta}_t &= \boldsymbol{f}\left(\boldsymbol{\zeta}_{t-1}, \boldsymbol{a}_t, \boldsymbol{a}_{t-1}, \boldsymbol{\kappa}_{t-1}, \boldsymbol{g}_{l,t}; \Theta\right), && (44)\\
\boldsymbol{\chi}_t &= \boldsymbol{g}\left(\boldsymbol{\zeta}_t, \boldsymbol{a}_t, \boldsymbol{\kappa}_t; \Theta\right), && (45)
\end{aligned}$$

where Θ is a row vector that contains all the parameters, $\boldsymbol{\zeta}_t = [\boldsymbol{l}(t), \boldsymbol{q}_t]$ is a $1 \times 2n$ vector, and $\boldsymbol{\chi}_t = [\boldsymbol{p}_t, \boldsymbol{h}_t]$ is a $1 \times 2n$ vector. The stochastic processes of $\boldsymbol{a}_t$ are given by

$$\ln \boldsymbol{a}_t = \ln \boldsymbol{a} + \boldsymbol{g}_a t + \boldsymbol{\lambda} f_t + \boldsymbol{z}_{a,t}, \tag{46}$$
$$f_t = \rho_f f_{t-1} + \sigma_f \varepsilon_{f,t}, \tag{47}$$
$$\boldsymbol{z}_{a,t} = \boldsymbol{z}_{a,t-1} \mathbf{diag}(\rho_{a,1}, \rho_{a,2}, ...\rho_{a,n}) + \boldsymbol{\varepsilon}_{a,t} \mathbf{diag}(\sigma_{a,1}, \sigma_{a,2}, ...\sigma_{a,n}), \tag{48}$$

and the stochastic processes of $\boldsymbol{\kappa}_t$ are given by

$$\ln \boldsymbol{\kappa}_t = \ln \boldsymbol{\kappa} + \boldsymbol{g}_\kappa t + \boldsymbol{z}_{\kappa,t}, \tag{49}$$
$$\boldsymbol{z}_{\kappa,t} = \boldsymbol{z}_{\kappa,t-1} \mathbf{diag}(\rho_{\kappa,1}, \rho_{\kappa,2}, ...\rho_{\kappa,n}) + \boldsymbol{\varepsilon}_{\kappa,t} \mathbf{diag}(\sigma_{\kappa,1}, \sigma_{\kappa,2}, ...\sigma_{\kappa,n}). \tag{50}$$

and the values of $\boldsymbol{g}_{l,t}$, for $t = 1, 2, ...$, are exogenously given.

4.2 Equilibrium and the balanced growth path

We now consider the *non-stochastic* version of the model economy set out in Sections 2 and 3, characterize its short-run and long-run equilibria and prove the existence and uniqueness of the short-run equilibrium and the balanced growth path. The non-stochastic specification is obtained by setting to zero the innovations to the national and location-specific components of labor productivities ($\varepsilon_{f,t}$ and $\varepsilon_{a,it}$ in (22) and (23)), and the innovations to the location-specific land supply shocks ($\varepsilon_{\kappa,it}$ in (30)), namely $\varepsilon_{f,t} = 0$, $\varepsilon_{a,it} = 0$, and $\varepsilon_{\kappa,it} = 0$, for $i = 1, 2, ...n$, and $t = 1, 2, ...$ In this set up, local productivities are given by

$$a_{it} = e^{g_a t} a_i, \text{ for } i = 1, 2, ...n, \text{ and } t = 1, 2, ... \tag{51}$$

In addition, to obtain a balanced growth path we assume the same intrinsic population growth rate, g_l, across locations:

$$g_{l,it} = g_l, \text{ for } i = 1, 2, ...n, \text{ and } t = 1, 2, ... \tag{52}$$

Finally, we assume that the location-specific land supplies are given by

$$\kappa_{it} = e^{g^*_{\kappa,i} t} \kappa_i, \text{ for } i = 1, 2, ...n, \text{ and } t = 1, 2, ..., \tag{53}$$

where $g^*_{\kappa,i}$ is the state-specific land supply growth rate. On the balanced growth path, prices $\boldsymbol{p}_t, \boldsymbol{q}_t, \boldsymbol{w}_t$ (quantities $\boldsymbol{l}(t), \boldsymbol{x}_t, \boldsymbol{h}_t$) should grow at a common rate as $t \to \infty$. To find conditions under which the economy has a balanced growth path, using (41) we note that

$$\ln\left(\frac{x_{it}}{x_{i,t-1}}\right) = \ln\left(\frac{\kappa_{it}}{\kappa_{i,t-1}}\right) + \lambda_{p,i} \ln\left(\frac{p_{it}}{p_{i,t-1}}\right).$$

Note also that on the balanced growth path by definition we have $\ln(x_{it}/x_{i,t-1}) = g_l$, $\ln(\kappa_{it}/\kappa_{i,t-1}) = g^*_{\kappa,i}$, and $\ln(p_{it}/p_{i,t-1}) = g_w$, where g_w is the wage growth rate, and (39) implies $g_w = \lambda_a g_a - \lambda_l g_l$. Hence, for a balanced growth path to exist we must have

$$g^*_{\kappa,i} = (1 + \lambda_{p,i} \lambda_l)\, g_l - \lambda_{p,i} \lambda_a g_a, \text{ for } i = 1, 2, ..., n. \tag{54}$$

The above condition states that the growth rate of new land supplies, $g^*_{\kappa,i}$, and the growth of productivity for production of residential structures, g_a, should ensure that enough new houses can be produced to accommodate the housing requirements of the growing population in all locations. The land supply regime under which land growth rates are given by (54) will be referred to as the *balanced growth path land supply regime*. The analysis of the equilibrium properties of the stochastic version of the model is complicated, and will be conducted by simulations. The deterministic solution provides information on the local equilibrating properties of the stochastic version for sufficiently small-size shocks.

We use letters with stars and time subscripts to denote the corresponding detrended variables. Specifically, $w^*_{it} \equiv e^{-g_w t} w_{it}$, $\boldsymbol{w}^*_t \equiv [w^*_{1t}, w^*_{2t}, ..., w^*_{nt}]$, $p^*_{it} \equiv e^{-g_w t} p_{it}$, $\boldsymbol{p}^*_t \equiv [p^*_{1t}, p^*_{2t}, ..., p^*_{nt}]$, $h^*_{it} \equiv e^{-g_l t} h_{it}$, and $\boldsymbol{h}^*_t \equiv [h^*_{1t}, h^*_{2t}, ..., h^*_{nt}]$. Note that the detrended exogenous variables are time invariant by construction (see (51)-(53)). For example, $a^*_{it} = a_i$ and $\kappa^*_{it} = \kappa_i$. Hence equilibrium conditions (37)-(43) can be re-written in terms of the detrended variables as follows

$$\boldsymbol{l}^*(t) = \boldsymbol{l}^*(t-1)\mathbf{R}^*(t), \tag{55}$$

where $\mathbf{R}^*(t) \equiv \left(\rho^*_{ij}(t)\right)$ is the $n \times n$ matrix of migration probabilities, and

$$\rho^*_{ij}(t) = \frac{(w^*_{jt}/w^*_{it})(q^*_{jt}/q^*_{it})^{-\eta}(\alpha_{ij})^{-\psi}}{\sum_{s=1}^{n}(w^*_{st}/w^*_{it})(q^*_{st}/q^*_{it})^{-\eta}(\alpha_{is})^{-\psi}}, \text{ for } i \text{ and } j \in \mathcal{I}_n, \tag{56}$$

and

$$w^*_{it} = \tau_{w,i} a_i^{\lambda_a} \left(l^*_{\cdot i}(t)\right)^{-\lambda_l}, \text{ for } i \in \mathcal{I}_n, \tag{57}$$

$$h^*_{i,t-1} = \left(\eta w^*_{it}/q^*_{it}\right) l^*_{\cdot i}(t), \text{ for } i \in \mathcal{I}_n, \tag{58}$$

$$x^*_{it} = \tau_{\kappa,i}\kappa_i (p^*_{it})^{\lambda_{p,i}}, \text{ for } i \in \mathcal{I}_n, \tag{59}$$

$$h^*_{it} = (1-\delta)e^{-g_l} h^*_{i,t-1} + x^*_{it}, \text{ for } i \in \mathcal{I}_n, \tag{60}$$

$$p^*_{it} h^*_{it} = \beta\left(1-\theta_i\right)\left[q^*_{it} + (1-\delta)p^*_{it}\right] h^*_{i,t-1}, \text{ for } i \in \mathcal{I}_n, \tag{61}$$

Then the short-run and the balanced growth path equilibria of the economy can be defined in terms of detrended variables as follows:

Definition 1 ***(Short-run equilibrium)*** *Consider the dynamic spatial equilibrium model set up in Sections 2 and 3 by equations (37)-(43), which can be written equivalently in terms of detrended variables by equations (55) to (61). Suppose that the vectors of exogenous processes for labor productivities,* $\boldsymbol{a}_t$*, land supplies,* $\boldsymbol{\kappa}_t$*, and the intrinsic population growth rates,* $\boldsymbol{g}_{lt}$*, for* $t = 1, 2, ...$*, are given by (51)-(53), condition (54) holds, and the initial values for local population and housing stocks (* $\boldsymbol{l}_0$ *and* $\boldsymbol{h}_0$*) are strictly positive. Then, a short-run equilibrium is defined as series of non-negative prices* $[\boldsymbol{p}^*_t, \boldsymbol{q}^*_t, \boldsymbol{w}^*_t]$ *and allocations* $[\boldsymbol{l}^*(t), \boldsymbol{x}^*_t, \boldsymbol{h}^*_t]$ *that solve the system of equations (55)-(61), for given values* $l^*_{\cdot i}(t-1)$ *and* $h^*_{i,t-1}$*, for* $i \in \mathcal{I}_n$*.*

Definition 2 ***(Balanced growth path equilibrium)*** *Consider the dynamic spatial equilibrium model set up in Sections 2 and 3 by equations (37)-(43), which can be written equivalently in terms of detrended variables by equations (55) to (61). Suppose that the vectors* *of exogenous processes for labor productivities, $\boldsymbol{a}_t$, land supplies, $\boldsymbol{\kappa}_t$, and the intrinsic population growth rates, $\boldsymbol{g}_{lt}$, for $t = 1, 2, ...$, are given by (51)-(53), condition (54) holds, and the initial values for local population and housing stocks ($\boldsymbol{l}_0$ and $\boldsymbol{h}_0$) are strictly positive. Then, a balanced growth path equilibrium is defined as a path on which the economy is in short-run equilibrium in the sense set out in Definition 1 in each period, and the de-trended prices $[\boldsymbol{p}_t^*, \boldsymbol{q}_t^*, \boldsymbol{w}_t^*]$ and quantities $[\boldsymbol{l}^*(t), \boldsymbol{x}_t^*, \boldsymbol{h}_t^*]$ converge to non-negative limits as $t \to \infty$.*

The existence and uniqueness of the short-run equilibrium is established in the online supplement (see Section S1). In what follows we focus on the existence and uniqueness of the long-run balanced growth path which plays a more fundamental role in our simulation exercises.

Proposition 1 ***(Existence and uniqueness of the long-run balanced growth path)*** *Consider the dynamic spatial equilibrium model set up in Sections 2 and 3 by equations (37)-(43). Suppose that the vectors of exogenous processes for labor productivities, $\boldsymbol{a}_t$, land supplies, $\boldsymbol{\kappa}_t$, and intrinsic population growth rates, $\boldsymbol{g}_{lt}$, for $t = 1, 2, ...$, are given by (51)-(53), and condition (54) holds, and the initial values for local population and housing stocks ($\boldsymbol{l}_0$ and $\boldsymbol{h}_0$) are strictly positive. Then the model has a unique balanced growth path as set out in Definition 2.*

Proof: By post-multiplying both sides of (55) by $\boldsymbol{\tau}$, an $n \times 1$ vector of ones, we have

$$L_t^* = \boldsymbol{l}^*(t)\boldsymbol{\tau} = \boldsymbol{l}^*(t-1)\mathbf{R}^*(t)\boldsymbol{\tau} = \boldsymbol{l}^*(t-1)\boldsymbol{\tau} = L_{t-1}^*,$$

which implies

$$L_t^* = L_{t-1}^*, ..., = L_1^* = L_0, \tag{62}$$

where L_0 is the detrended aggregate population for $t = 0, 1, ...$ Using (55), $\boldsymbol{l}^*(t)$ can be written as

$$\boldsymbol{l}^*(t) = \boldsymbol{l}(0)\left[\Pi_{s=1}^t \mathbf{R}^*(s)\right], \tag{63}$$

where $\boldsymbol{l}(0) > 0$ is the vector of the initial local populations, and $\mathbf{R}^*(1), \mathbf{R}^*(2), ..., \mathbf{R}^*(t)$, are a series of stochastic matrices. Lemma A1 in Appendix A1.4 establishes the existence of the balanced growth path by showing that $\boldsymbol{l}^*(t)$ converges to some time invariant non-negative population vector $\boldsymbol{l}^*$, as $t \to \infty$.

We use letters with only stars to denote the steady states of the corresponding detrended variables. To establish that $\boldsymbol{l}^*$is unique, we first note that (62) implies

$$\sum_{i=1}^n l_{\cdot i}^* = L_0. \tag{64}$$

By imposing the balance growth path conditions, the equilibrium conditions (55) to (61) can be written as follows

$$\boldsymbol{l}^* = \boldsymbol{l}^*\mathbf{R}^*, \tag{65}$$

where $\mathbf{R}^* \equiv \left(\rho^*_{ij}\right)$ is the $n \times n$ matrix of migration probabilities, and

$$\rho^*_{ij} = \frac{(w^*_j/w^*_i)(q^*_j/q^*_i)^{-\eta}(\alpha_{ij})^{-\psi}}{\sum_{s=1}^{n}(w^*_s/w^*_i)(q^*_s/q^*_i)^{-\eta}(\alpha_{is})^{-\psi}}, \text{ for } i \text{ and } j \in \mathcal{I}_n, \tag{66}$$

and

$$w^*_i = \tau_{w,i} a_i^{\lambda_a} \left(l^*_{\cdot i}\right)^{-\lambda_l}, \text{ for } i \in \mathcal{I}_n, \tag{67}$$

$$h^*_i = \left(\eta w^*_i/q^*_i\right) l^*_{\cdot i}, \text{ for } i \in \mathcal{I}_n, \tag{68}$$

$$x^*_i = \tau_{\kappa,i}\kappa_i (p^*_i)^{\lambda_{p,i}}, \text{ for } i \in \mathcal{I}_n \tag{69}$$

$$h^*_i = \left[1 - (1-\delta)\, e^{-g_l}\right]^{-1} x^*_i, \text{ for } i \in \mathcal{I}_n, \tag{70}$$

$$p^*_i = \beta\,(1-\theta_i)\left[q^*_i + (1-\delta)p^*_i\right], \text{ for } i \in \mathcal{I}_n, \tag{71}$$

Thus, to prove the uniqueness of the balanced growth path, in what follows we show that the system of equations given by (64)-(71), has a *unique positive* solution. In the rest of the proof, we show that given $L_0, \boldsymbol{a}$ and $\boldsymbol{\kappa}$, then $\boldsymbol{w}^*, \boldsymbol{p}^*, \boldsymbol{q}^*, \boldsymbol{x}^*, \boldsymbol{h}^*, \boldsymbol{l}^*$ and $\mathbf{R}^*$ are uniquely determined.

We first show that for given values of $\boldsymbol{l}^*$, $\boldsymbol{a}$ and $\boldsymbol{\kappa}$, the solution for $\boldsymbol{w}^*, \boldsymbol{p}^*, \boldsymbol{q}^*, \boldsymbol{x}^*$ and $\boldsymbol{h}^*$ is unique and can be obtained using (67)-(71), and then ρ^*_{ij} can be written as a function of $\boldsymbol{l}^*$ as following:

$$\rho^*_{ij} = \frac{\psi_{ij}\left(l^*_{\cdot j}\right)^{-\varphi_j}}{\sum_{s=1}^{n}\psi_{is}\left(l^*_{\cdot s}\right)^{-\varphi_s}}, \tag{72}$$

where φ_j and ψ_{ij} are positive constants. See the detailed derivation of the above equation in Appendix A1.3. Recall that $\mathbf{R}^*$ is the migration probability matrix on the balanced growth path, with a typical element ρ^*_{ij} given by (66). Thus, $\mathbf{R}^*$ can be written as a function of $\boldsymbol{l}^*$, namely $\mathbf{R}^* \equiv \mathbf{R}(\boldsymbol{l}^*)$. Then, (65) can be written as

$$\boldsymbol{l}^* = \boldsymbol{l}^*\mathbf{R}(\boldsymbol{l}^*), \tag{73}$$

which is a system of non-linear equations in $\boldsymbol{l}^*$. Lemma A1 in Appendix A1.4 establishes that there exists a $\boldsymbol{l}^*$ that solves (73), and Lemma A2 establishes that (73) cannot have more than one solution. Therefore, $\boldsymbol{l}^*$ exists and is unique. Then, using the solution of $\boldsymbol{l}^*$, the other variables of the model, namely, $\boldsymbol{w}^*, \boldsymbol{p}^*, \boldsymbol{q}^*, \boldsymbol{x}^*, \boldsymbol{h}^*$and $\mathbf{R}^*$, can be solved for using equations (67) and (A.13)-(A.17) in Appendix A1.3.■

5 Estimation and calibration of the model

In order to better understand how land-use regulations affect house price dispersion and internal migration, and carry out counterfactual analyses, we first estimate the model using the subset of the available data on interstate migration flows and housing markets over the period 1976-1999 (training sample). Thus, the period indexed by 0 (i.e., the initial period) corresponds to 1976, and the periods indexed by $1, 2, ..., T_1$ correspond to the years 1977 to

1999 (inclusive). Then, we will conduct out-of-sample forecasts using the estimated model for the period 2000-2014 (evaluation sample) in Section 6, and thus the periods indexed by $T_1+1, T_1+2, ..., T$ correspond to the years 2000 to 2014.

We calibrate some of the parameters, and then estimate the rest of them using the panel data of the 49 states (including the District of Columbia) in the U.S. mainland with yearly observations over the period 1977-1999. The model parameters can be divided into five groups, which include the parameters that characterize preferences, migration flows, housing supplies and investment, labor productivities, and land supply processes. In what follows, we consider these five sets of parameters in turn.

5.1 Preference parameters

The relative weight of housing in workers' utility function (9), η, is set to 0.24, as estimated by Davis and Ortalo-Magné (2011).[8] The discount factor of landlord β is set to 0.98 to match the risk-free annual real interest rate of the U.S. over the period 1960-1999, which is estimated to be around 2 per cent. The spreads between the risk-free interest rate and the location-specific returns on housing investments are captured by the parameters θ_i, which will be calibrated in Section 5.3 below.

5.2 Migration and intrinsic population growth rates

To estimate route-specific migration cost parameters, α_{ij}, using (13), we first note that

$$\frac{\rho_{ij}(t)}{\rho_{ii}(t)} = \frac{\alpha_{ij}^{-\psi} w_{jt} q_{jt}^{-\eta}}{\alpha_{ii}^{-\psi} w_{it} q_{it}^{-\eta}}, \Rightarrow \alpha_{ij}^{\psi} = \left(\frac{w_{jt} q_{jt}^{-\eta}}{w_{it} q_{it}^{-\eta}}\right) \left(\frac{\rho_{ii}(t)}{\rho_{ij}(t)}\right) \alpha_{ii}^{\psi}.$$

Also from (4), we have $\rho_{ij}(t) = l_{ij}(t)/l_{i\cdot}(t)$, and therefore

$$\alpha_{ij}^{\psi} = \left(\frac{w_{jt} q_{jt}^{-\eta}}{w_{it} q_{it}^{-\eta}}\right) \left(\frac{l_{ii}(t)}{l_{ij}(t)}\right) \alpha_{ii}^{\psi}.$$

We set ψ to unity, and normalize α_{ii} to one, for $i = 1, 2, ..., n$. Note that the Internal Revenue Service (IRS) migration flow data that we will be using are only available from 1990 onward. Thus, we estimate α_{ij} using the above equation as follows:

$$\hat{\alpha}_{ij} = \frac{1}{10} \sum_{t=t_{1990}}^{t_{1999}} \frac{w_{jt} q_{jt}^{-\eta}}{w_{it} q_{it}^{-\eta}} \frac{l_{ii}(t)}{l_{ij}(t)}, \quad \text{for } i \neq j, \text{ and } i \text{ and } j \in \mathcal{I}_n, \tag{74}$$

where t_{1990} and t_{1999} are the time indices corresponding to 1990 and 1999, respectively, η is calibrated in Section 5.1, w_{it} are inferred using (18), and q_{it} and $l_{ij}(t)$ are observed data.

[8] These authors also provide evidence that the shares of expenditure on housing are constant over time and across U.S. MSAs.

In addition, the balanced growth path intrinsic population growth rate, g_l, defined by (52), is set to 1%, which is the average growth rate of the U.S. population over the period 1977-1999. The actual state-level intrinsic population growth rates, $g_{l,it}$, over the period 1977-1999 are measured using the IRS data. For further details, see Appendix A2.1.

5.3 Housing supplies and investment

We estimate the housing depreciation rate, δ, as the average ratio of aggregate depreciation to aggregate housing stock over the period 1977-1999 using the data from the Fixed Assets Tables compiled by the Bureau of Economic Analysis (BEA), and obtain $\hat{\delta} = 2\%$. To calibrate the state-specific supply functions for new houses, given by (26), we estimate, $\alpha_{\kappa,i}$, location-specific share of land in house values, by the state level average land values relative to total value of housing stocks over the 1977-1999 period.[9] The location-specific housing investment cost parameter, θ_i, is estimated as follows. Using the housing investment function on the balanced growth path given by (71), we have

$$\theta_i = 1 - \frac{1}{\beta}\left[\frac{q_i^*}{p_i^*} + (1-\delta)\right]^{-1},$$

which suggests the following estimate

$$\hat{\theta}_i = 1 - \frac{1}{\beta}\left[\frac{1}{\frac{1}{T_1}\sum_{t=1}^{T_1} q_{it}/p_{it} + (1-\hat{\delta})}\right], \tag{75}$$

where periods 1 and T_1 correspond to 1977 and 1999, respectively, β and δ are previously calibrated and estimated, and q_{it} and p_{it} are observed data.

5.4 Productivity processes

The share of labor costs in output, v_l, is set to 0.67 as estimated by Valentinyi and Herrendorf (2008). The agglomeration effect, v_ϕ, is set to 0.06 according to the estimation by Davis et al. (2014). To distinguish between scale effects of ϕ_{it} and a_{it} in (15), we set $\bar{\phi}_i$ defined by (16) to 1. We infer the state level wage rates, w_{it}, using (18), where the worker population, $l_{\cdot i}(t)$, is measured using the actual state level population, and the state level output, y_{it}, is measured by multiplying realized real per capita disposable income of the state by its population. To infer the state-specific labor productivities, a_{it}, we first note that (18), (19) and (20) imply

$$\ln a_{it} = -\frac{1}{1-v_\phi}\ln\bar{\phi}_i + \frac{1-v_\phi}{v_l}\ln y_{it} - \ln l_{\cdot i}(t). \tag{76}$$

Thus, the estimates of a_{it} are obtained by evaluating (76) using the parameter estimates and realized values of $l_{\cdot i}(t)$ and y_{it}, for $t = 0, 1, ..., T_1$. To estimate the stochastic process of a_{it}, defined by (21), (22) and (23), recall that a_{it} is given by

$$\ln a_{it} = \ln a_i + g_a t + \lambda_i f_t + z_{a,it}, \tag{77}$$

[9] The data on state level land share in house values are obtained from Davis and Heathcote (2007).

where $t = 1, 2, ..., T_1$ (1977-1999). To identify the unobserved common factor, f_t, we impose the following restrictions:

$$n^{-1} \sum_{i=1}^{n} \lambda_i = 1. \tag{78}$$

and

$$T_1^{-1} \sum_{t=1}^{T_1} f_t = 0, \tag{79}$$

Restriction (78) is required to distinguish between scales of λ_i and f_t, and (79) is required to separate the linear trend from the common factor. We take the common growth rate of state-level incomes, g_a, as a known parameter, and set it to match the average annual growth rate of the U.S. real per capita income during the period 1977-1999, which is around 0.02. Then, in view of (79), we estimate a_i by

$$\hat{a}_i = \exp\left[T_1^{-1} \sum_{t=1}^{T_1} (\ln a_{it} - \hat{g}_a t)\right]. \tag{80}$$

Let $e_{a,it}$ be the deviation of $\ln a_{it}$ from its trend, which is given by

$$e_{a,it} = \lambda_i f_t + z_{a,it}, \tag{81}$$

and estimated as $\hat{e}_{a,it} = \ln a_{it} - \ln \hat{a}_i - \hat{g}_a t$, for $t = 0, 1, 2, ..., T$. To estimate f_t, we first note that $n^{-1} \sum_{i=1}^{n} \lambda_i = 1$ (see (78)). By summing up both sides of (81), we have $n^{-1} \sum_{i=1}^{n} e_{a,it} = f_t + n^{-1} \sum_{i=1}^{n} z_{a,it}$, where by assumption $z_{a,it}$ are cross-sectionally independent. As a result,

$$f_t = n^{-1} \sum_{i=1}^{n} \hat{e}_{a,it} + O_p\left(T_1^{-\frac{1}{2}}\right) + O_p\left(n^{-\frac{1}{2}}\right),$$

which gives a consistent estimator of f_t:

$$\hat{f}_t = n^{-1} \sum_{i=1}^{n} \hat{e}_{a,it}. \tag{82}$$

The parameters ρ_f and σ_f in (22) are estimated by running the OLS regression of $\hat{f}_t$ on $\hat{f}_{t-1}$, for $t = 1, 2, ..., T_1$. To estimate the associated loading coefficients, λ_i, for each i we run the OLS regressions of $\hat{e}_{a,it}$ on $\hat{f}_t$, and obtain the residuals, $\hat{z}_{a,it}$, for $t = 0, 1, 2, ..., T_1$. Then, we estimate $\rho_{a,i}$ and $\sigma_{a,i}$ in (23) by running OLS regressions of $\hat{z}_{a,it}$ on $\hat{z}_{a,i,t-1}$, over the period $t = 1, 2, ..., T_1$.

5.5 Land supplies

To estimate κ_{it}, we first note that equilibrium conditions (18), (24), (26), (35) and (28) imply

$$\kappa_{it} = \frac{\gamma_{it}}{\tau_{\kappa,i}}, \tag{83}$$

where[10]

$$\gamma_{it} = \frac{\left\{\beta e^{g_l}\left(1-\theta_i\right)\left[\frac{q_{it}}{p_{it}} + (1-\delta)\right] - (1-\delta)\right\}\eta\upsilon_l\left(\frac{y_{it}}{q_{it}}\right)}{p_{it}^{(1-\alpha_{\kappa,i})/\alpha_{\kappa,i}}}. \tag{84}$$

Note that $\beta, g_l, \theta_i, \eta, \alpha_{\kappa,i}$, υ_l and δ are previously calibrated and estimated, and that y_{it}, q_{it} and p_{it} are observed data. Thus, an estimator of γ_{it} can be obtained by evaluating (84) using the parameter estimates and realized values of y_{it}, q_{it} and p_{it}, for $t = 0, 1, ..., T_1$, which corresponds to the period of 1976-1999.

We assume that *used land*, denoted by UR_{it}, is turned into *unused land* when houses on these lands are depreciated. Thus, UR_{it} would shrink at rate δ in the absence of any new constructions. Therefore, UR_{it} follows as:

$$UR_{it} = \kappa_{it} + (1-\delta)\, UR_{i,t-1}. \tag{85}$$

To estimate $\tau_{\kappa,i}$ in (83), we make use of published data on major land uses in the U.S. compiled by the U.S. Department of Agriculture (USDA). We consider only the observations before 2000 and estimate $\tau_{\kappa,i}$ using the USDA urban area size data for 1978 and 1992 as follows. Note that (85) implies

$$UR_{i,t_{1992}} = \sum_{t=t_{1979}}^{t_{1992}} (1-\delta)^{t_{1992}-t}\, \kappa_{i,t} + (1-\delta)^{14}\, UR_{i,t_{1978}}, \tag{86}$$

where t_{1978}, t_{1979} and t_{1992} are the time indices for 1978, 1979, and 1992. Using (83) in (86) to eliminate κ_{it}, we obtain the following estimator of $\tau_{\kappa,i}$:

$$\hat{\tau}_{\kappa,i} = \frac{\sum_{t=t_{1979}}^{t_{1992}} (1-\delta)^{t_{1992}-t}\, \hat{\gamma}_{i,t}}{UR_{i,t_{1992}} - \left(1-\hat{\delta}\right)^{14} UR_{i,t_{1978}}}. \tag{87}$$

Then, we compute $\hat{\kappa}_{it}$ using (83) as

$$\ln \hat{\kappa}_{it} = \ln \hat{\gamma}_{it} - \ln \hat{\tau}_{\kappa,i}, \;\; \text{for } i = 1, 2, ..., n \text{ and } t = 0, 1, ..., T_1. \tag{88}$$

We estimate κ_i and $g_{\kappa,i}$ in (29) by running OLS regressions of $\ln \hat{\kappa}_{it}$ on a linear time trend (including a constant), for $i = 1, 2, ..., n$, and obtain the residuals, $\hat{z}_{\kappa,it}$, for $t = 0, 1, ..., T_1$.[11] Finally, for each i we estimate $\rho_{\kappa,i}$ and $\sigma_{\kappa,i}$ by running OLS regressions of $\hat{z}_{\kappa,it}$ on $\hat{z}_{\kappa,i,t-1}$, over the period $t = 1, 2, ..., T_1$.

Figure 3 plots $\hat{g}_{\kappa,i}$ versus the state level Wharton Residential Land Use Regulatory Index, which are complied by Gyourko et al. (2008) and denoted by WRI_i, for the 48 states on the U.S. mainland. Washington, D.C. is excluded since its WRI data is not available. Note that WRI_i is an index constructed from surveys carried out in 2004 and is intended to characterizes the local residential land-use regulatory environment, which increases with the

[10] For details of the derivations, see Appendix A1.5.

[11] It is worth noting that our estimates of $g_{\kappa,i}$ reflect the average tightness of state-level land-use regulations over the period 1977-1999, and need not to be good proxies for particular years or sub-periods.

tightness of land-use regulation.[12] Therefore, the data used to construct WRI_i have little overlap with the time series data and parameter calibrations we employ to back out κ_{it}. Thus, the significant negative correlation between $\hat{g}_{\kappa,i}$ and WRI_i, as shown in Figure 3, indicates that the land use regulation can be an important factor that affects local house prices through the supplies of new land. By running an OLS regression of $\hat{g}_{\kappa,i}$ on WRI_i, for the 48 states on the U.S. mainland, we obtain

$$\hat{g}_{\kappa}(WRI_i) = \underset{(0.0115)}{0.0468} - \underset{(0.0116)}{0.0607}WRI_i, \quad R^2 = 0.37 \tag{89}$$

where $\hat{g}_{\kappa}(WRI_i)$ is the fitted value, R^2 is the squared correlation coefficient, and the figures in brackets are standard errors of the estimated coefficients.

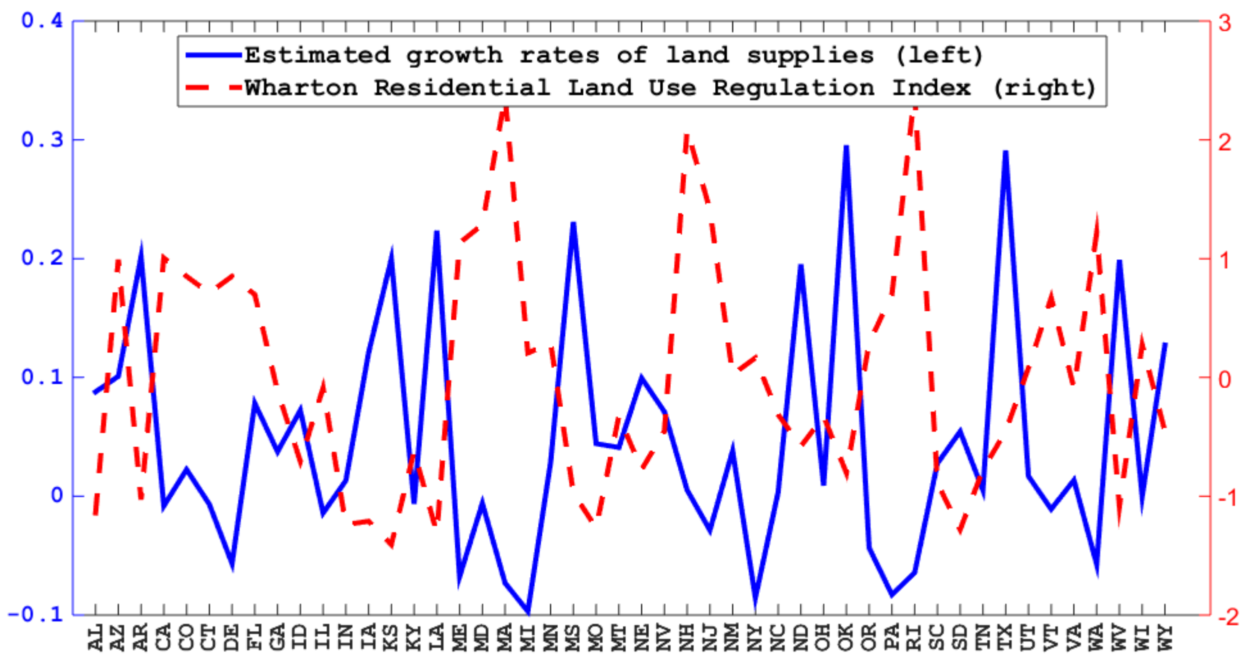


Figure 3: Estimated land supply growth rates and the WRI

Notes: This figure shows the estimated state level growth rates of land supplies and the state level Wharton Residential Land Use Regulatory Index (WRI), complied by Gyourko et al. (2008), of the 48 states on the U.S. mainland. Washington, D.C. is excluded since its WRI data is not available.

[12] More specifically, the Wharton Residential Land Use Regulatory Index is based on the Wharton survey on land-use regulations conducted in 2004, and complied by Gyourko et al. (2008), who use factor analysis to create the aggregate index, which is then standardized so that its sample mean is zero and its standard deviation equals one. Since Alaska and Hawaii are excluded from our analysis, we re-scale the WRIs of the remaining states so that the mean and the standard deviation of the sub-sample we use are zero and one, respectively.

6 Can the model predict the rise in house price dispersion?

We now consider whether the estimated model can quantitatively account for the observed rise in the house price dispersion in the U.S.. To this end, we simulate the estimated model over the evaluation sample (2000-2014), and compare the predicted values to the realized ones. Recall that the periods indexed by $T_1 + 1, T_1 + 2, ..., T$ correspond to the years 2000 to 2014.

To simulate the model given by (44) and (45), we need to set the initial values and the exogenous variables. In the out-of-sample simulation, the initial values, $\boldsymbol{\zeta}_{T_1}$, correspond to the realized values in 1999. Recall that $\boldsymbol{\zeta}_t \equiv [\boldsymbol{l}(t), \boldsymbol{q}_t]$, and $\boldsymbol{l}(T_1)$ and $\boldsymbol{q}_{T_1}$ are observed data. We take the intrinsic population growth rates, $\boldsymbol{g}_{l,t}$, as deterministic exogenous variables, and set $\boldsymbol{g}_{l,t}$, for $t = T_1 + 1, T_1 + 2, ..., T$, to their balanced growth path level, g_l. The state level productivities and land supplies for the initial period, $\boldsymbol{a}_{T_1}$ and $\boldsymbol{\kappa}_{T_1}$, correspond to the realized values in 1999, and $\boldsymbol{a}_t$ and $\boldsymbol{\kappa}_t$, for $t = T_1 + 1, T_1 + 2, ..., T$, are simulated using the estimated versions of (46) - (50).[13] We simulate the model for five hundred replications, and the mean values are approximated as the averages across replications.

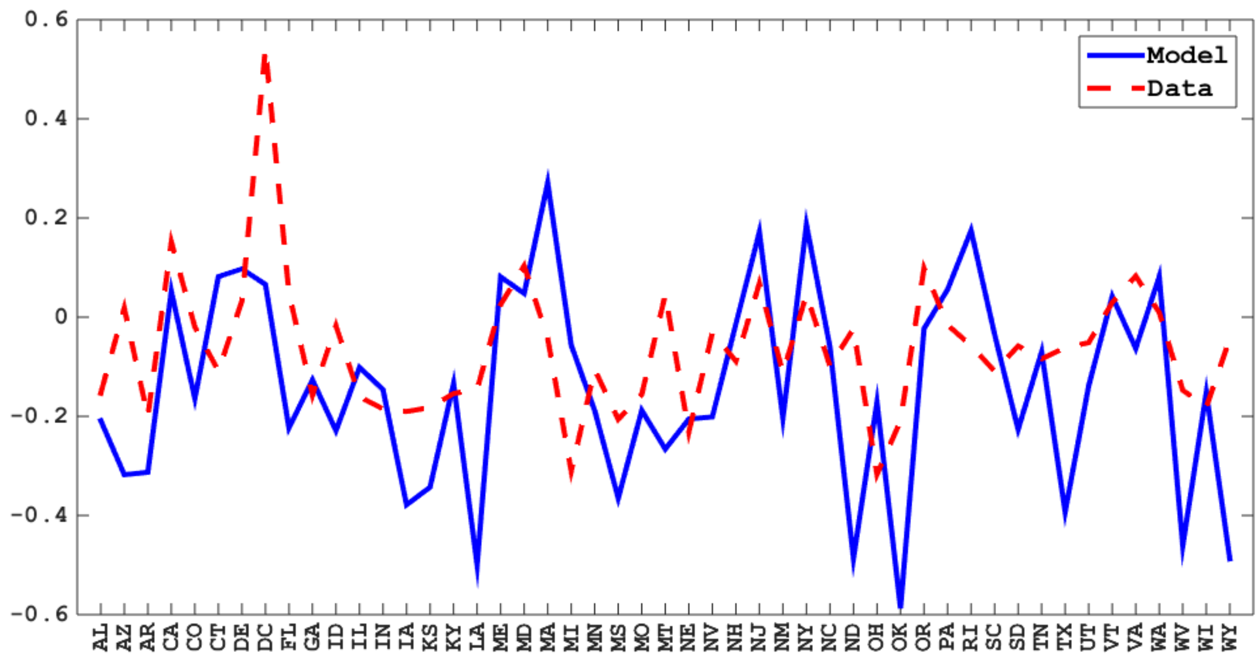


Figure 4: Changes in log house price-to-income ratios of U.S. states over the evaluation sample (2000-2014)

Notes: This figure displays the model predicted changes in log house price-to-income ratios of U.S. states during the evaluation sample (2000-2014) against the counterpart realized values.

[13] For further details, see Appendix A3.1.

The simulation results are summarized as follows: *First*, the model can capture the trends in the house price-to-income ratios at state level as shown in Figure 4.

Second, the model replicates reasonably well the trends in the dispersions of house price-to-income ratios at both national and regional levels, as shown in Figure 5. The model generated between-state dispersion increases from 0.24 to 0.39 during the evaluation sample (2000-2014), while the associated realized value rises from 0.24 to 0.34. In addition, the model captures the different trends at different geographical levels, i.e., the substantial increase in the between-region dispersion and the moderate increases of within-region dispersions. As will be shown in Section 9, this can be partially due to the stronger migration linkages between states that are geographically close, which tends to prevent the house price differences between these states from increasing.

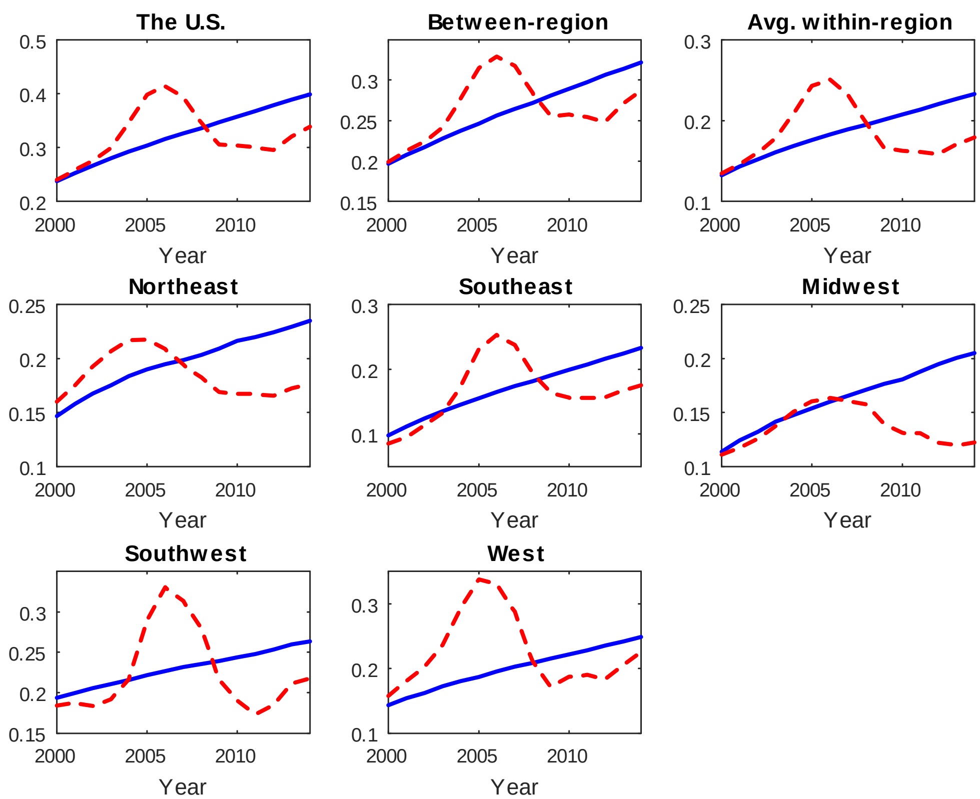


Figure 5: Dispersions of log house price-to-income ratios between- and within- U.S. regions during the evaluation sample (2000-2014) (Solid-blue: simulated; Dashed-red: data)

Notes: This figure plots the realized and simulated dispersions of log house price-to-income ratios between- and within- U.S. regions over the evaluation sample (2000-2014). Average within-region dispersion refers to the average of the within-region dispersions of the five U.S. regions.

Third, the model matches the observed trends in the interstate migration. Figure 6 compares the actual accumulated net migration inflows of the U.S. states during the evaluation sample (2000-2014) with the model generated counterparts. As can be seen, the model captures the significant migration outflows from states with rising house price-to-income ratios, such as California, and New York, and the substantial inflows towards states with decreasing house price-to-income ratios, such as Florida and Texas.

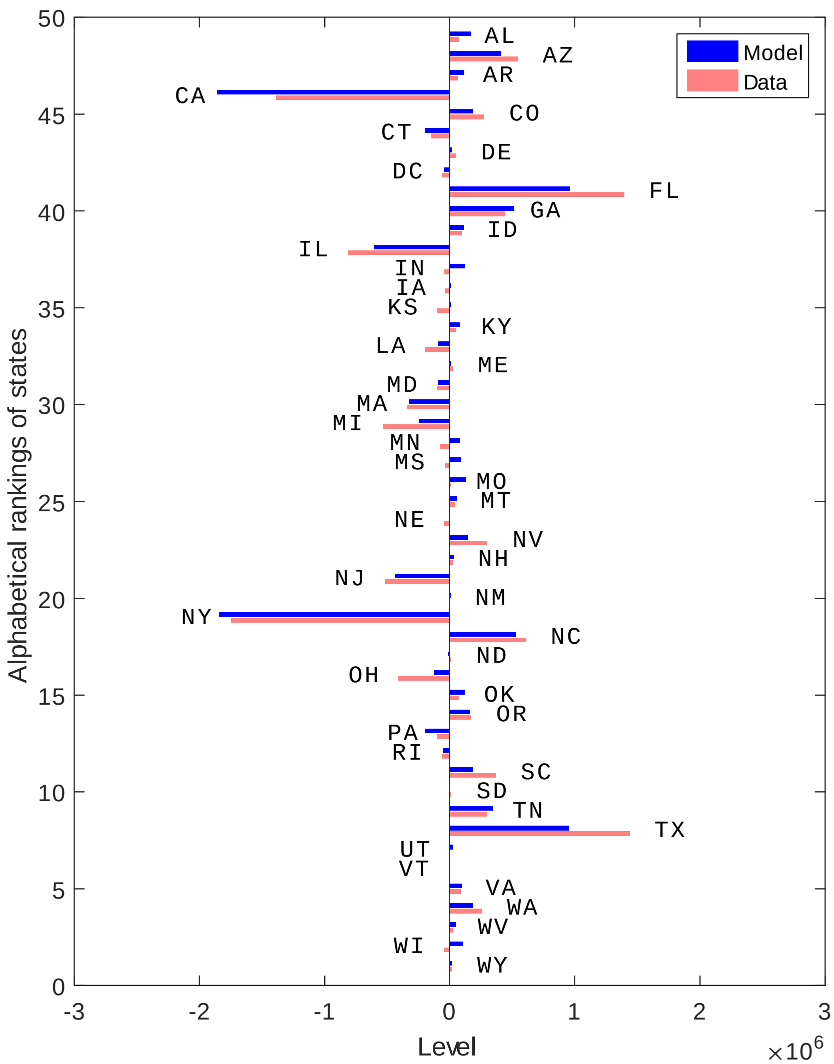


Figure 6: Net inward migration flows by states during the evaluation sample (2000-2014) (Upper-blue: simulated; Lower-red: data)

Notes: This figure shows the realized and simulated accumulated net migration inflows towards U.S. states during the evaluation sample (2000-2014). States are arranged from top to bottom in alphabetical order.

7 Land-use regulations and house price dispersion

We now conduct a series of counterfactual exercises to examine the contributions of spatial heterogeneities of land-use regulations in driving up house price dispersion in the U.S.. In addition, we investigate the impacts of the land-use regulations in California and Texas on local house prices and populations and conduct counterfactual simulations by varying the land supply growth rates of California and Texas, in turn.

7.1 Land-use regulations in the U.S.

Baseline: In this case, we simulate the model using the realized state level productivities, land supplies and intrinsic population growth rates. To do so, we take productivities, land supplies and intrinsic population growth rates, i.e., $\boldsymbol{a}_t$, $\boldsymbol{\kappa}_t$ and $\boldsymbol{g}_{l,t}$, as deterministic exogenous variables, and set them to their realized values, for $t = T_1 + 1, T_1 + 2, ..., T$.[14] The initial values, $\boldsymbol{\zeta}_{T_1}$, correspond to the realized values in 1999 as before. As shown in the Panel (2) of Table 1, the simulated values are in line with the associated realized values.

Land supply growth rates proxied by the WRI: To examine the extent to which the heterogeneity in regulatory environments, as measured by WRI_i, can explain the rising house price dispersion, we use WRI_i to proxy the state level growth rates of land supplies according to (89).[15] Then, we set the state-specific land supplies, $\ln \kappa_{it}$, as $\ln \kappa_{it} = \ln \hat{\kappa}_{iT_1} + \hat{g}^{wri}_{\kappa,i} t + \hat{\boldsymbol{z}}_{\kappa,it}$, for $i = 1, 2, ..., 49$ and $t = T_1 + 1, T_1 + 2, ..., T$, where $\hat{g}^{wri}_{\kappa,i}$ are the state-specific land supply growth rates proxied by WRI_i, and $\hat{\boldsymbol{z}}_{\kappa,it}$ are the realized land supply shocks. Then, we conduct a simulation using the counterfactual land supplies with proxied land supply growth rates, while keeping everything else the same as in the baseline simulation. As shown in the Panel (3) of Table 1, the results are not changed much from those of the baseline simulation, which suggests that the rising house price dispersion can be largely explained by the spatial heterogeneity in land-use regulations.

Homogeneous land supply growth rates: To examine the importance of spatial heterogeneity in land supply growth rates in driving up the house price dispersion, we conduct a counterfactual simulation in which land supply growth rates of all states are set equal to their national average, denoted by $\bar{\hat{g}}_\kappa = \frac{1}{49}\sum_{i=1}^{49} \hat{g}_{\kappa,i}$, where $\hat{g}_{\kappa,i}$ is the state-specific land supply growth rate estimated in Section 5.5. Then, we set the state-specific land supplies, $\ln \kappa_{it}$, as $\ln \kappa_{it} = \ln \hat{\kappa}_{iT_1} + \bar{\hat{g}}_\kappa t + \hat{z}_{\kappa,it}$, for $i = 1, 2, ..., 49$ and $t = T_1 + 1, T_1 + 2, ..., T$. Then, we conduct simulations using the counterfactual land supplies with homogeneous land supply growth rates, while keeping everything else the same as in the baseline simulation. As shown in Panel (4) of Table 1, the model fails to capture the upward trends in house price-to-income ratio dispersions when land supply growth rates are assumed to be the same across states, which suggests that spatial heterogeneity in land supply growth rates is an essential factor behind the increasing house price dispersion.

[14] For further details, see Appendices A2.1 and A3.2.

[15] Since the WRI data is not available for Washington, D.C., we keep D.C.'s land supply growth rate as it is in the baseline simulation.

Table 1: The level and the dispersion of realized and simulated log house price-to-income ratios

	Actual		**Simulated**					
	(1) Data		(2) Baseline simulation		(3) Land supply growth rates proxied by the WRI		(4) Homogeneous land supply growth rates	
Year	*2000*	*2014*	*2000*	*2014*	*2000*	*2014*	*2000*	*2014*
			I. Level					
The U.S.	1.53	1.47	1.53	1.49	1.53	1.46	1.52	1.38
Northeast	1.56	1.57	1.56	1.58	1.55	1.44	1.54	1.25
Southeast	1.43	1.37	1.43	1.39	1.43	1.39	1.43	1.39
Midwest	1.42	1.21	1.42	1.23	1.42	1.13	1.42	1.16
Southwest	1.28	1.21	1.28	1.21	1.30	1.40	1.30	1.41
West	1.93	2.02	1.93	2.06	1.93	2.07	1.92	1.81
			II. Disperison					
The US	0.24	0.34	0.24	0.35	0.24	0.37	**0.23**	**0.25**
Between-region	0.20	0.29	0.20	0.30	0.20	0.31	0.19	0.22
Northeast	0.16	0.18	0.16	0.19	0.16	0.27	0.16	0.09
Southeast	0.09	0.18	0.09	0.19	0.09	0.21	0.08	0.13
Midwest	0.11	0.12	0.11	0.12	0.11	0.12	0.11	0.11
Southwest	0.18	0.22	0.18	0.21	0.18	0.20	0.18	0.15
West	0.16	0.23	0.16	0.23	0.16	0.26	0.15	0.13

Notes: This table reports the levels and the dispersions of realized and simulated log house price-to-income ratios at different geographical levels. Panel (2) reports the results from the baseline simulation. Panel (3) reports the simulation results when the growth rates of state level land supplies are proxied by the WRI as (89). Panel (4) corresponds to the counterfactual simulation in which land supply growth rates of all U.S. states are homogeneous.

7.2 Land-use regulations in California and Texas

According to Gyourko et al. (2015), the residential land-use regulatory environments of some areas in the U.S. started to become stricter from 1970s onward. Land-use regulations can have important implications not only for local house prices but could also for the spatial allocation of population. Deregulation in states with stricter land-use restrictions can affect the population allocation across U.S. states through the house price channel. Here, we investigate the impacts of local land-use regulations, which are the main factors that determine the land supplies for housing, on house prices and population allocation. In particular, we consider California and Texas in our counterfactual experiments, which are at the two extreme poles of land-use regulation continuum, with California being the most regulated state, and Texas being the least regulated state. In what follows, we let the land supply growth rates of California and Texas to vary between their actual values and the national average land supply growth rate. Let $g_{\kappa,CA}(\varrho)$ and $g_{\kappa,TX}(\varrho)$ denote the counterfactual land supply growth rates of California and Texas, and consider the following rates

$$g_{\kappa,i^*}(\varrho) = (1-\varrho)\hat{g}_{\kappa,i^*} + \varrho\bar{\hat{g}}_{\kappa}, \text{ for } i^* = CA, TX, \quad (90)$$

with $\varrho \in [0,1]$, where $\bar{\hat{g}}_{\kappa}$ is the national average of land supply growth rate, and $\hat{g}_{\kappa,i^*}$ is the estimated actual land supply growth rate of state i^*. Then, we set the land supplies of state i^*, $\ln \kappa_{i^*,t}$, as

$$\ln \kappa_{i^*,t} = \ln \hat{\kappa}_{i^*,T_1} + g_{\kappa,i^*}(\varrho)t + \hat{\boldsymbol{z}}_{\kappa,i^*,t}, \text{ for } t = T_1+1, T_1+2, ..., T, \text{ for } i^* = CA, TX, \quad (91)$$

where $\hat{\boldsymbol{z}}_{\kappa,i^*,t}$ are the actual land supply shocks.

Table 2: Effects of loosening of land-use regulations in California

California						
	units	Baseline	Counterfactual increases in land supply growth			
ϱ		0	1/4	1/2	3/4	1
Real house price in 2014	Thousands $	274.0	253.1	233.3	214.6	197.1
Avg. yearly growth rate of real house prices (2000-2014)	Per cent	3.027	2.499	1.956	1.400	0.832
Population in 2014	Millions	29.75	29.77	29.79	29.81	29.83
Avg. yearly growth rate of population (2000-2014)	Per cent	1.112	1.116	1.120	1.125	1.130

Notes: This table shows the impacts of land-use deregulation in California on the local house prices and population. The third column reports the results from the baseline simulation. The fourth to last columns report the results from the counterfactual simulations in which the land supply growth rate of California is set to $g_{\kappa,CA}(\varrho)$, given by (90), where $\varrho = \{1/4, 1/2, 3/4, 1\}$.

We first consider the effects of a land-use deregulation in California. To this end, we simulate the model while setting the land supply growth rate of California to $g_{\kappa,CA}(\varrho)$, given by (90), for $\varrho = \{1/4, 1/2, 3/4, 1\}$, and its land supply $\kappa_{CA,t}$ according to (91), while keeping everything else the same as in the baseline simulation described in Section 7.1. Note that the estimated land growth rate of California, $\hat{g}_{\kappa,CA}$, is less than the national average, $\bar{\hat{g}}_{\kappa}$. Thus, a larger ϱ corresponds to a higher degree of deregulation. As shown in Table 2, the land supply growth rate of California has considerable impacts on the local house prices, but by comparison has small impacts on the local population. For example, our model predicts that increasing the average land supply growth rate of California to the national average from 2000 onward induces the population of California in 2014 to rise by 0.1 million (around 0.2 per cent of California population), whilst such a de-regulation could reduce the annual growth rate of real house prices from 3 per cent realized during the 2000-2014 period to a mere 0.8 per cent counterfactually. In addition, the reallocation of population towards California are mainly from Texas, and the neighboring states of California, such as Arizona, Nevada, Oregon, and Washington. For further details, see Section S4.3 of the online supplement.

Table 3: Effects of tightening of land-use regulations in Texas

Texas						
	units	Baseline	Counterfactual decreases in land supply growth			
ϱ		0	1/4	1/2	3/4	1
Real house price in 2014	Thousands $	95.2	100.4	105.9	111.7	117.7
Avg. yearly growth rate of real house prices (2000-2014)	Per cent	1.066	1.421	1.776	2.128	2.480
Population in 2014	Millions	20.76	20.73	20.71	20.69	20.67
Avg. yearly growth rate of population (2000-2014)	Per cent	1.769	1.761	1.754	1.747	1.740

Notes: This table shows the impacts of tightening land-use regulation in Texas on the local house prices and population. The third column reports the results from the baseline simulation. The fourth to last columns report the results from the counterfactual simulations in which the land supply growth rate of Texas is set to $g_{\kappa,TX}(\varrho)$, given by (90), where $\varrho = \{1/4, 1/2, 3/4, 1\}$.

We then consider the effects of a tightening of land-use regulation in Texas. To this end, we simulate the model while setting the land supply growth rate of Texas to $g_{\kappa,TX}(\varrho)$, given by (90), for $\varrho = \{1/4, 1/2, 3/4, 1\}$, and its land supply $\kappa_{TX,t}$ according to (91), while keeping everything else the same as in the baseline simulation. Since the estimated land growth rate of Texas, $\hat{g}_{\kappa,TX}$, is higher than the national average, $\bar{\hat{g}}_{\kappa}$, then a larger ϱ corresponds to more tightened land-use regulation. Similar to the deregulation experiment in California, tightening land-use regulation in Texas significantly impact local house prices, but only has marginal effects on the State's population (see Table 3). For example, reducing the average land supply growth rate of Texas to the national average reduces Texas's population in 2014 by 0.1 million (around 0.4 per cent of Texas population), but increases the annual growth rate of real house prices from a realized value of 1.1 per cent to a counterfactual rate of

2.5 per cent. In addition, the reallocation of population from Texas are mainly towards California, Florida, and the neighboring states of Texas, such as Louisiana and Oklahoma. For further details, see Section S4.3 of the online supplement.

Overall, our counterfactual exercises do show that changes in local land-use regulations can affect population allocation via the house price channel, but its effects tend to be moderate. However, changes in land use regulations affect house prices much more as compared to their effects on allocation of population.

8 Mobility and house price dispersion

To examine how land supply growth differentials and migration costs jointly contribute to the rise in house price dispersion, we now carry out simulations assuming different levels of land supply growth differentials and migration costs. We experiment with different levels of migration costs through changing the weight of migration cost, ψ, in the utility function (see (14)). As ψ increases, population mobility drops. In addition, we adjust the degree of land supply growth differentials by letting the state level land supply growth rates vary between their actual levels and the national average. Let ϱ denote the counterfactual land supply regime. Under regime ϱ, the growth rates of land supplies are given as before by $g_{\kappa,i}(\varrho) = (1-\varrho)\hat{g}_{\kappa,i} + \varrho\bar{\hat{g}}_{\kappa}$, for $i = 1, 2, ..., n$, and the state-specific land supplies, $\ln \kappa_{it}$, are set as $\ln \kappa_{it} = \ln \hat{\kappa}_{iT_1} + g_{\kappa,i}(\varrho)t + \hat{\boldsymbol{z}}_{\kappa,it}$, for $t = T_1 + 1, T_1 + 2, ..., T$ and $i = 1, 2, ..., n$ (see (90) and (91)). Thus, the level of land supply differentials is measured by $1 - \varrho$.

We simulate the model for different pairs of (ϱ and ψ) = $(0.60, 0.80, 1, 1.2, 1.4)$, whilst keeping everything else the same. The results are summarized in Table 4, and show that the dispersion of log house price-to-income ratios would be significantly lower if migration costs are reduced. For example, when $\varrho = 0$, dispersion would be around 0.4 (0.6) less when ψ is reduced to 0.8 (0.6). Decreases in ψ also lower the national log house price-to-income ratio, since more people would move out of high price growth states as migration costs are reduced. However, it has much smaller impacts on the level than on the dispersion of house price-to-income ratios. In addition, both land supply growth differentials and migration costs play important roles in driving up house price dispersion; reducing either of them can significantly lower house price dispersion in the U.S.. Moreover, increases in land supply growth differentials would lead to larger rises in house price dispersion when migration costs are larger. For example, when $\psi = 0.6$ dispersion increases by 0.085, from 0.248 to 0.333, as the level of land supply growth differentials, $1 - \varrho$, increases from 0.6 to 1.4. But, when $\psi = 1.4$, dispersion would increase by 0.111, from 0.318 to 0.429, as $1 - \varrho$ increases from 0.6 to 1.4.

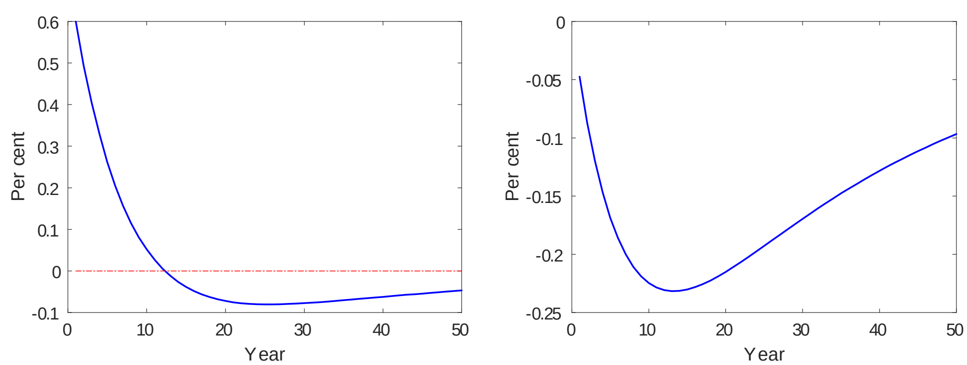
Table 4: The level and the dispersion of simulated 2014 log house price-to-income ratios under different parameter values

Land Supply Differentials $1-\varrho$ \ Migration Costs Ψ		Lower		Bechmark	Higher		Lower		Bechmark	Higher	
		60%	*80%*	*100%*	*120%*	*140%*	*60%*	*80%*	*100%*	*120%*	*140%*
		I. Level					II. Dispersion				
Lower	*60%*	1.413 (0.948)	1.432 (0.961)	1.446 (0.970)	1.451 (0.973)	1.452 (0.974)	0.248 (0.713)	0.264 (0.760)	0.298 (0.858)	0.314 (0.903)	0.318 (0.914)
	80%	1.434 (0.962)	1.454 (0.976)	1.468 (0.985)	1.473 (0.988)	1.474 (0.989)	0.265 (0.762)	0.284 (0.818)	0.322 (0.926)	0.339 (0.975)	0.343 (0.987)
Benchmark	*100%.*	1.455 (0.976)	1.475 (0.990)	**1.490** **(1.000)**	1.495 (1.003)	1.496 (1.004)	0.285 (0.821)	0.308 (0.885)	**0.348** **(1.000)**	0.366 (1.053)	0.371 (1.066)
Higher	*120%*	1.476 (0.990)	1.496 (1.004)	1.511 (1.014)	1.516 (1.018)	1.518 (1.019)	0.308 (0.887)	0.333 (0.958)	0.375 (1.079)	0.394 (1.135)	0.399 (1.149)
	140%	1.495 (1.004)	1.516 (1.018)	1.532 (1.028)	1.537 (1.032)	1.539 (1.033)	0.333 (0.959)	0.360 (1.036)	0.404 (1.162)	0.424 (1.220)	0.429 (1.235)

Notes: This table reports the average and the dispersion of model simulated log house price-to-income ratios across U.S. states in 2014 for different land supply regimes and migration costs. A larger ϱ corresponds to a higher level of land supply differentials. A larger Ψ corresponds to higher migration costs.

9 Spatial impulse responses of regional shocks

To better understand the migration linkages between regional housing markets, we analyze the responses of the economy to a regional shock. In particular, we assume that the economy is initially on the balanced growth path and consider a one standard deviation negative regional productivity shock to California. The simulated innovations used in the computation of the impulse responses are independently drawn from the standard normal distribution. For the details of the computation of the impulse responses, see Section S2 of the online supplement. The impulse responses are shown in Figures 7-10. Figure 7 shows the responses of the house price-to-income ratio (left panel) and the population (right panel) of California after the shock. As can be seen from these figures, the adjustments of population and house prices to the shock are very slow, taking decades to complete. This is due to the slow depreciation of housing stocks and the sluggishness in the migration flows. Figures 8 and 9 show the responses of house price-to-income ratios and populations of U.S. states to the negative regional productivity shock to California, where the states are ordered by their distances to California. Figure 10 shows the snapshots of the responses of house price-to-income ratios of U.S. states. Each panel shows the responses in the period noted at the top. In each panel, the horizontal axis corresponds to state's rank in terms of their geographical closeness to California. In response to the shock, house price-to-income ratios rise in all states. However, the responses in the neighboring states (e.g., Nevada and Arizona), and in some of the West Coast states (e.g., Washington, D.C. and New York) are quicker and stronger. The responses in these states reach their peaks more quickly, and their peak values tend to be larger as well. Thus, the snapshots of the responses tend to be U shaped.



Log house price-to-income ratio

Log population

Figure 7: Reponses of California to a negative regional shock to local productivity

Notes: This figure shows the responses of log house price-to-income ratio and log population of California to a one standard deviation negative regional shock to local productivity.

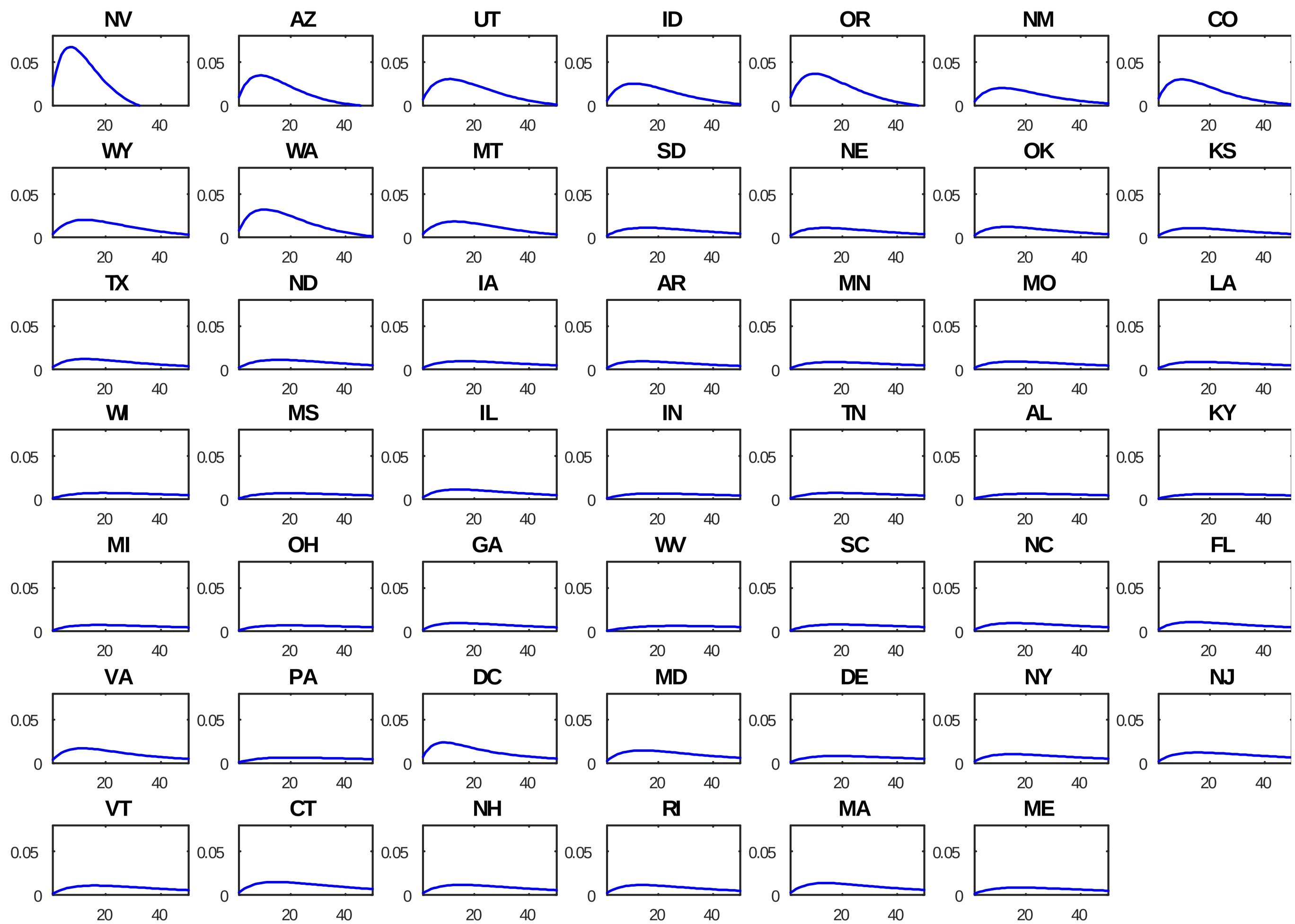


Figure 8: Responses of log house price-to-income ratios of U.S. states to a negative regional productivity shock to California

Notes: This figure shows the responses of log house price-to-income ratios of U.S. states (except for California) to a one standard deviation negative regional productivity shock to California. States are ordered ascendingly by their distances to California. The unit on the horizontal axis is year. The unit on the vertical axis is per cent.

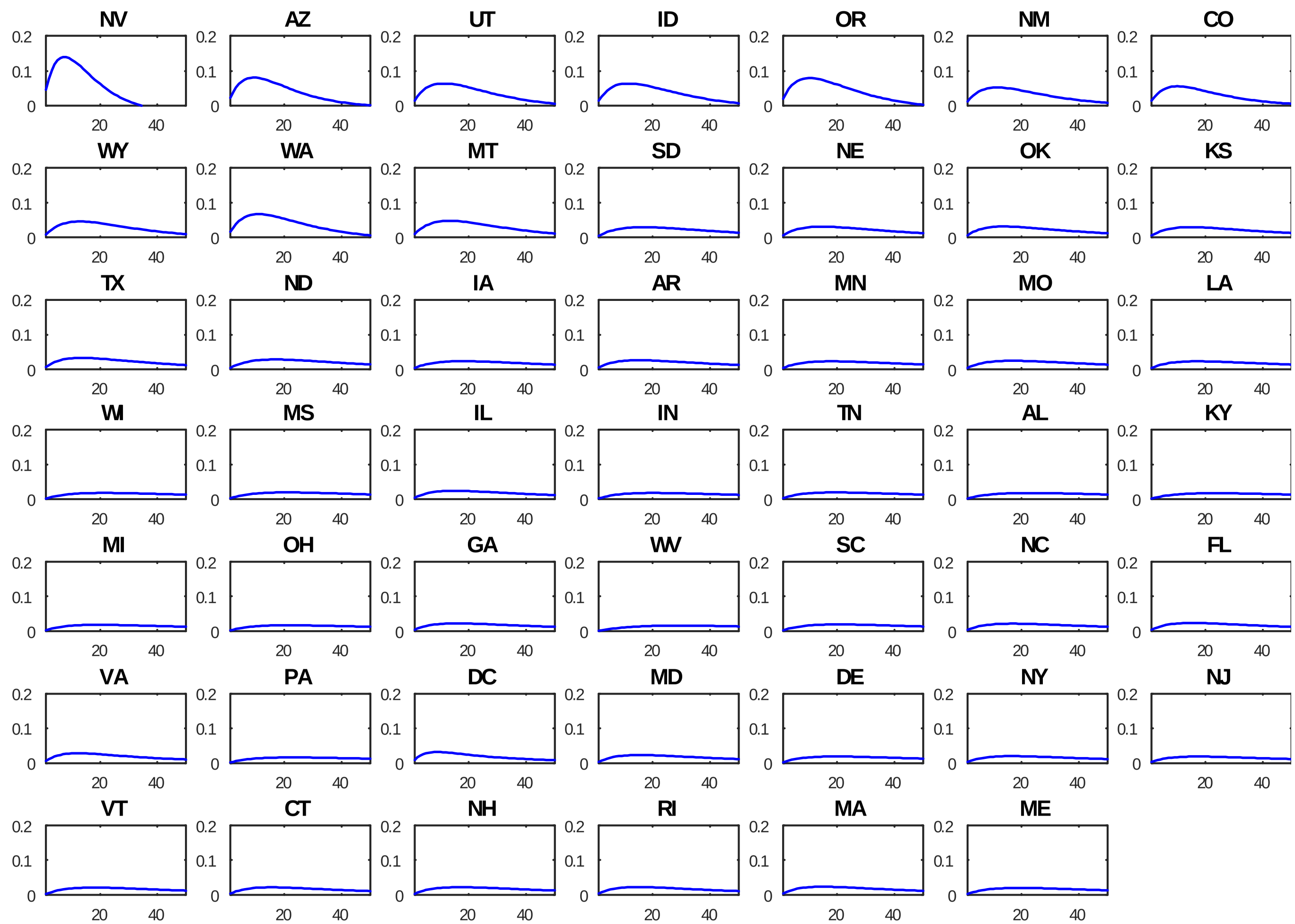


Figure 9: Responses of log populations of U.S. states to a negative regional productivity shock to California

Notes: This figure shows the responses of log populations of U.S. states (except for California) to a one standard deviation negative regional productivity shock to California. States are ordered ascendingly by their distances to California. The unit on the horizontal axis is year. The unit on the vertical axis is per cent.

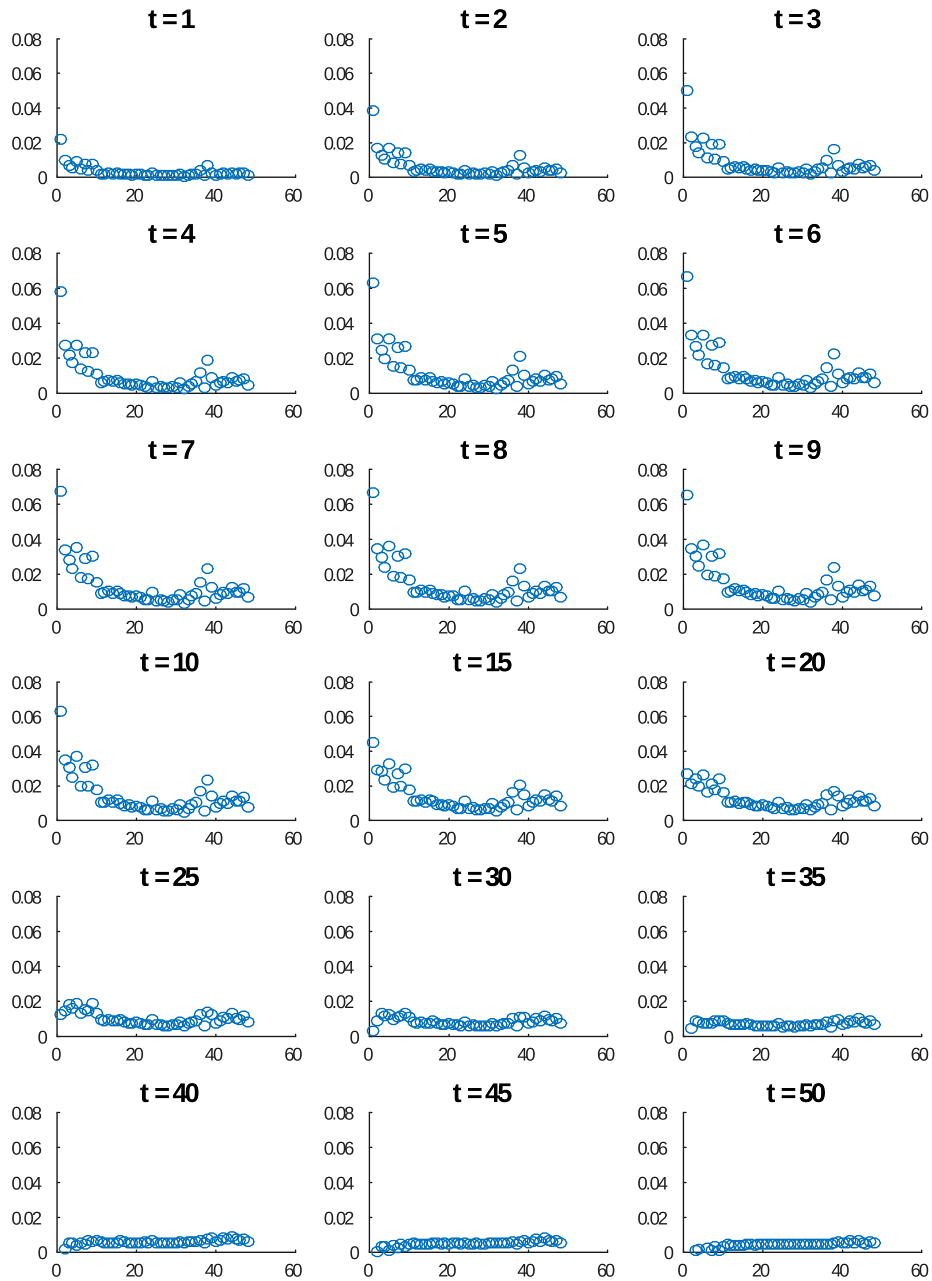


Figure 10: Snapshots of the responses of the log house price-to-income ratios of U.S. states to a negative regional productivity shock to California

Notes: Each panel shows the responses of the log house price-to-income ratios of U.S. states (except for California) to a one standard deviation negative regional productivity shock to California for the period noted at the top. The unit of t is year. States are ordered ascendingly by their distances to California. The horizontal axis corresponds state's rank in terms of distance to California. The unit on the vertical axis is per cent.

10 Concluding remarks

This paper presents and solves a dynamic spatial equilibrium model of regional housing markets in which regional house prices are jointly determined with migration flows. It extends existing studies on regional housing markets by explicitly modelling location-to-location migration flows. The model can be viewed as an example of a dynamic network where regional housing markets interact with each other via migration flows, and provides a theoretically coherent framework to study the effects of changes in regional supply and demand conditions on regional house prices through endogenized migration flows. The theoretical model can also be adapted to study other types of spatial spill-overs in regional economies that operate through migration; for example, spill-over effects in regional labor markets.

The model is utilized to study the effects of land-use regulations on house price dispersions and interstate migrations in the U.S.. The estimated model can simultaneously account for the observed rises in the house price dispersions at both national and regional levels, and the observed interstate migration flows over the period 2000-2014. As a result, our work bridges the gap between the studies on house price dispersions in the U.S. and those on the impacts of land-use regulations on spatial allocation of population. In addition, our model can further account for the observed differences in trends in house price dispersions within and between U.S. regions. Finally, in addition to spatial heterogeneity in land-use regulations, degree of population mobility is also found to be an important factor in determining house price dispersion. Spatial house price dispersion tends to rise when mobility is low and fall when mobility is high.

The analysis of this paper on regional housing markets can be extended in a number of directions. The financial side of the housing market can be incorporated into the analysis, with the aim of investigating possible implications of rising house price dispersion for macroeconomic fluctuations. An econometrically estimated version of the model can also be used for the analysis and predication of house price diffusion across states or MSAs. Finally, given the importance of labor mobility for a stable spatial house price dispersion, it is also worth considering the factors that determine population mobility, their nature and variations overtime and across space.

Appendices

A1 Mathematical derivations and proofs

A1.1 Derivation of migration probabilities

Here we derive the migration probability equation (13). For the worker τ who is born in location i, the probability of residing in location j^* is

$$Prob\ (j^* \text{ is chosen}) = Prob\ \left(v_{\tau,t,ij^*} > v_{\tau,t,ij}\ \forall j \neq j^*\right),$$

where

$$v_{\tau,t,ij} = (\ln w_{jt} - \ln w_{it}) - \eta\,(\ln q_{jt} - \ln q_{it}) + (\varepsilon_{\tau,t,ij} - \varepsilon_{\tau,t,ii}) - \psi \ln \alpha_{ij}.$$

Recall that $\varepsilon_{\tau,t,ij}$ is IID for all τ, t, i and j, and has an extreme value distribution, with the cumulative distribution function $F(\varepsilon) = e^{-e^{-\varepsilon}}$, and the probability density function $f(\varepsilon) = e^{-\varepsilon}e^{-e^{-\varepsilon}}$. Consider the following decomposition of $v_{\tau,t,ij}$,

$$v_{\tau,t,ij} = v_{t,ij} + (\varepsilon_{\tau,t,ij} - \varepsilon_{\tau,t,ii})$$

where

$$v_{t,ij} = (\ln w_{jt} - \ln w_{it}) - \eta\,(\ln q_{jt} - \ln q_{it}) - \psi \ln \alpha_{ij}.$$

Note that $v_{t,ij}$ is known by worker τ, and will be treated as given. The probability that worker τ selects region j^* as her migration destination can be written as

$$\begin{aligned} Prob\ (j^* \text{ is chosen}) &= Prob\ \left(v_{t,ij^*} + \varepsilon_{\tau,t,ij^*} - \varepsilon_{\tau,t,ii} > v_{t,ij} + \varepsilon_{\tau,t,ij} - \varepsilon_{\tau,t,ii},\ \forall j \neq j^*\right), \\ &= Prob\ \left(\varepsilon_{\tau,t,ij^*} + v_{t,ij^*} - v_{t,ij} > \varepsilon_{\tau,t,ij},\ \ \forall j \neq j^*\right). \end{aligned}$$

Conditional on $\varepsilon_{\tau,t,ij^*}$, the probability that location j^* is chosen by worker τ is given by

$$Prob\ (j^* \text{ is chosen}\ |\varepsilon_{\tau,t,ij^*}) = \prod_{j \neq j^*} F\left(\varepsilon_{\tau,t,ij^*} + v_{t,ij^*} - v_{t,ij}\right).$$

Since $\varepsilon_{\tau,t,ij^*}$ is also random, the probability that location j^* is chosen is the integral of $Prob\ (j^* \text{ is chosen}\ |\varepsilon_{\tau,t,ij^*})$ over its support and weighted by its density function, namely

$$\begin{aligned} Prob\ (j^* \text{ is chosen}) &= \int_{-\infty}^{+\infty} \left[\prod_{j \neq j^*} e^{-e^{-\left(\varepsilon + v_{t,ij^*} - v_{t,ij}\right)}}\right] e^{-\varepsilon} e^{-e^{-\varepsilon}} d\varepsilon \\ &= \int_{-\infty}^{+\infty} \left[\prod_{j \neq j^*} e^{-e^{-\left(\varepsilon + v_{t,ij^*} - v_{t,ij}\right)}}\right] e^{-\varepsilon} e^{-e^{-\left(\varepsilon + v_{t,ij^*} - v_{t,ij^*}\right)}} d\varepsilon \\ &= \int_{-\infty}^{+\infty} \left[\prod_{j} e^{-e^{-\left(\varepsilon + v_{t,ij^*} - v_{t,ij}\right)}}\right] e^{-\varepsilon} d\varepsilon \\ &= \int_{-\infty}^{+\infty} exp\left[-e^{-\varepsilon} \sum_{j} e^{-\left(v_{t,ij^*} - v_{t,ij}\right)}\right] e^{-\varepsilon} d\varepsilon. \end{aligned}$$

Define $s = e^{-\varepsilon}$. Thus, $ds = -e^{-\varepsilon} d\varepsilon$. Then,

$$\begin{aligned} Prob\ (j^* \text{ is chosen}) &= \int_0^{+\infty} exp\left[-s\sum_j e^{-\left(v_{t,ij*}-v_{t,ij}\right)}\right] ds \\ &= -\left.\frac{exp\left[-s\sum_j e^{-\left(v_{t,ij*}-v_{t,ij}\right)}\right]}{\sum_j e^{-\left(v_{t,ij*}-v_{t,ij}\right)}}\right|_0^{+\infty} \\ &= \frac{1}{\sum_j e^{-\left(v_{t,ij*}-v_{t,ij}\right)}} = \frac{e^{v_{t,ij*}}}{\sum_j e^{v_{t,ij}}}. \end{aligned}$$

A1.2 Compact form of equilibrium conditions

To derive the compact form of the equilibrium conditions, i.e., (44)-(45), we first note that (43) implies

$$p_{it} = \frac{\beta e^{g_l}\left(1-\theta_i\right) q_{it}}{h_{it}/h_{i,t-1} - \beta e^{g_l}\left(1-\theta_i\right)\left(1-\delta\right)}. \tag{A.1}$$

Also, by substituting (41) into (42), we have

$$h_{it} = (1-\delta)h_{i,t-1} + \tau_{\kappa,i}\kappa_{it}p_{it}^{\lambda_{p,i}}. \tag{A.2}$$

Then, substituting (A.1) into (A.2) we obtain

$$\begin{aligned} h_{it} &= (1-\delta)h_{i,t-1} + \\ & \tau_{\kappa,i}\kappa_{it}\left[\frac{\beta e^{g_l}\left(1-\theta_i\right) q_{it}}{h_{it}/h_{i,t-1} - \beta e^{g_l}\left(1-\theta_i\right)\left(1-\delta\right)}\right]^{\lambda_{p,i}}. \end{aligned} \tag{A.3}$$

Then, by substituting (40) into (A.3), we can eliminate h_{it} and $h_{i,t-1}$, and after lagging the resultant equation by one period we have

$$\begin{aligned} \eta\left(\frac{w_{it}}{q_{it}}\right) l_{\cdot i}(t) &= (1-\delta)\eta\left(\frac{w_{i,t-1}}{q_{i,t-1}}\right) l_{\cdot i}(t-1) + \\ & \tau_{\kappa,i}\kappa_{i,t-1}\left[\frac{\beta e^{g_l}\left(1-\theta_i\right) q_{i,t-1}}{\left(\frac{w_{it}}{w_{i,t-1}}\right)\left(\frac{l_{\cdot i}(t)}{l_{\cdot i}(t-1)}\right)\left(\frac{q_{i,t-1}}{q_{it}}\right) - \beta e^{g_l}\left(1-\theta_i\right)\left(1-\delta\right)}\right]^{\lambda_{p,i}}. \end{aligned} \tag{A.4}$$

Thus, equations (37), (38) and (39), together with (A.4), provide $2n$ non-linear dynamic equations in $l_{\cdot i}(t)$, $i = 1, 2, ..., n$, and q_{it}, $i = 1, 2, ..., n$, which can be written compactly as:

$$\boldsymbol{\zeta}_t = \boldsymbol{f}\left(\boldsymbol{\zeta}_{t-1}, \boldsymbol{a}_t, \boldsymbol{a}_{t-1}, \boldsymbol{\kappa}_{t-1}, \boldsymbol{g}_{l,t}; \Theta\right), \tag{A.5}$$

where Θ is a row vector that contains all the parameters, $\boldsymbol{\zeta}_t = [\boldsymbol{l}(t), \boldsymbol{q}_t]$ is a $1 \times 2n$ vector. In addition, using (39), (40) in (A.2) and (A.1) to eliminate w_{it} and $h_{i,t-1}$, we have

$$p_{it} = \frac{\beta e^{g_l}(1-\theta_i) q_{it}}{h_{it} q_{it} / \left(\eta \tau_{w,i} a_{it}^{\lambda_a} l_{\cdot i}(t)^{1-\lambda_l}\right) - \beta e^{g_l}(1-\theta_i)(1-\delta)}, \tag{A.6}$$

$$h_{it} = (1-\delta)\left(\frac{\eta \tau_{w,i} a_{it}^{\lambda_a}}{q_{it}}\right) l_{\cdot i}(t)^{1-\lambda_l} + \tau_{\kappa,i}\kappa_{it} p_{it}^{\lambda_{p,i}}. \tag{A.7}$$

Note that using (A.6) and (A.7), we can solve for p_{it} and h_{it}, for given values of $l_{\cdot i}(t), q_{it}, a_{it}$ and κ_{it}. Thus, $\boldsymbol{p}_t$ and $\boldsymbol{h}_t$ are functions of $\boldsymbol{l}(t)$, $\boldsymbol{q}_t$, $\boldsymbol{a}_t$ and $\boldsymbol{\kappa}_t$:

$$\boldsymbol{\chi}_t = \boldsymbol{g}\left(\boldsymbol{\zeta}_t, \boldsymbol{a}_t, \boldsymbol{\kappa}_t; \Theta\right), \tag{A.8}$$

where $\boldsymbol{\chi}_t = [\boldsymbol{p}_t, \boldsymbol{h}_t]$ is a $1 \times 2n$ vector.

A1.3 Derivation of balanced growth path migration probabilities

To derive the balanced growth path migration probability equation (72), we first observe that the long run rent-to-price ratio in location i can be obtained from (71) and is given by

$$\frac{q_i^*}{p_i^*} = \Gamma_i, \tag{A.9}$$

where Γ_i is given by

$$\Gamma_i = \frac{1}{\beta(1-\theta_i)} - (1-\delta). \tag{A.10}$$

Note that β and $\theta_i \in (0,1)$, which implies $\beta^{-1}(1-\theta_i)^{-1} > 1$. Since $\delta > 0$, it follows that $\Gamma_i > \delta > 0$. Using this result in (68), we obtain the long-run demand function for housing in location i:

$$h_i^* = \frac{\eta w_i^* l_{\cdot i}^*}{\Gamma_i p_i^*} \tag{A.11}$$

By substituting (70) into (69), we obtain the long-run housing supply function in location i:

$$h_i^* = \tilde{\delta}^{-1} \tau_{\kappa,i} \kappa_i (p_i^*)^{\lambda_{p,i}}, \tag{A.12}$$

where $\tilde{\delta} \equiv 1 - (1-\delta) e^{-g_l}$. By substituting (A.12) into (A.11) for h_i^*, we have

$$\tilde{\delta}^{-1} \tau_{\kappa,i} \kappa_i (p_i^*)^{\lambda_{p,i}} = \frac{\eta w_i^* l_{\cdot i}^*}{\Gamma_i p_i^*}.$$

Using the above equation, we can solve for p_i^*

$$p_i^* = \left(\frac{\tilde{\delta}\eta}{\tau_{\kappa,i}\kappa_i}\right)^{\frac{1}{1+\lambda_{p,i}}} \Gamma_i^{-\frac{1}{1+\lambda_{p,i}}} \left(w_i^* l_{\cdot i}^*\right)^{\frac{1}{1+\lambda_{p,i}}}, \tag{A.13}$$

and by substituting (A.13) into (A.9) for p_i^*, we have

$$q_i^* = \left(\frac{\tilde{\delta}\eta}{\tau_{\kappa,i}\kappa_i}\right)^{\frac{1}{1+\lambda_{p,i}}} \Gamma_i^{\frac{\lambda_{p,i}}{1+\lambda_{p,i}}} \left(w_i^* l_{\cdot i}^*\right)^{\frac{1}{1+\lambda_{p,i}}}. \tag{A.14}$$

By substituting (A.13) into (A.12) for p_i^*, we obtain

$$h_i^* = \left(\frac{\tilde{\delta}}{\tau_{\kappa,i}\kappa_i}\right)^{-\frac{1}{1+\lambda_{p,i}}} \left(\frac{\eta}{\Gamma_i}\right)^{\frac{\lambda_{p,i}}{1+\lambda_{p,i}}} \left(w_i^* l_{\cdot i}^*\right)^{\frac{\lambda_{p,i}}{1+\lambda_{p,i}}}. \tag{A.15}$$

Finally, by substituting (A.15) into (70) for h_i^*, we obtain

$$x_i^* = \left(\frac{1}{\tau_{\kappa,i}\kappa_i}\right)^{-\frac{1}{1+\lambda_{p,i}}} \left(\frac{\tilde{\delta}\eta}{\Gamma_i}\right)^{\frac{\lambda_{p,i}}{1+\lambda_{p,i}}} \left(w_i^* l_{\cdot i}^*\right)^{\frac{\lambda_{p,i}}{1+\lambda_{p,i}}}, \tag{A.16}$$

Therefore, p_i^*, q_i^*, x_i^* and h_i^* can be obtained uniquely in terms of $l_{\cdot i}^*, w_i^*$,and κ_i using (68) - (71).

By substituting (67) and (A.14) into (66) for $q_i^*$and w_i^*, then ρ_{ij}^* can be written as a function of $\boldsymbol{l}^*$:

$$\rho_{ij}^* = \frac{\psi_{ij}\left(l_{\cdot j}^*\right)^{-\varphi_j}}{\sum_{s=1}^n \psi_{is}\left(l_{\cdot s}^*\right)^{-\varphi_s}}, \tag{A.17}$$

where

$$\begin{aligned} \varphi_j &= \frac{\eta}{1+\lambda_{p,j}} + \lambda_l\left(1 - \frac{\eta}{1+\lambda_{p,j}}\right), \\ \psi_{ij} &= \alpha_{ij}^{-\psi}\left(\frac{\tilde{\delta}\eta}{\tau_{\kappa,j}\kappa_j}\right)^{-\frac{\eta}{1+\lambda_{p,j}}} \Gamma_j^{-\frac{\eta\lambda_{p,j}}{1+\lambda_{p,j}}} \left(\tau_{w,j} a_j^{\lambda_a}\right)^{1-\frac{\eta}{1+\lambda_{p,j}}}. \end{aligned}$$

Since λ_l and $\lambda_{p,j} > 0$, and $\eta \in (0,1)$, it follows that $\varphi_j > 0$, for any $i \in \mathcal{I}_n$. In addition, note that $\psi_{ij} > 0$, for any i and $j \in \mathcal{I}_n$, since $\alpha_{ij}, \tilde{\delta}, \eta, \tau_{\kappa,i}, \tau_{w,i}, \kappa_j$ and $a_j > 0$, and Γ_j, given by (A.10), is strictly positive as previously shown.

A1.4 Lemmas: statements and proofs

Lemma A1 *Consider the following Markovian process in* $\boldsymbol{l}^*(t)$

$$\boldsymbol{l}^*(t) = \boldsymbol{l}^*(t-1)\mathbf{R}^*(t) \tag{A.18}$$

where $\boldsymbol{l}^*(t) = [l_{\cdot 1}^*(t), l_{\cdot 2}^*(t), ..., l_{\cdot n}^*(t)]$ *is the* $1\times n$ *row vector of detrended population values, and* $\mathbf{R}^*(t) = (\rho_{ij}^*(t))$ *is the* $n\times n$ *transition matrix with the typical element,* $\rho_{ij}^*(t)$ *defined by (56) that depends non-linearly on* $\boldsymbol{l}^*(t)$*, and* n *is a fixed integer. Suppose that the initial population vector,* $\boldsymbol{l}^*(0) = \boldsymbol{l}(0)$*, is given and satisfies the conditions* $\boldsymbol{l}(0) > 0$*, and* $\sum_{i=1}^n l_{\cdot i}(0) = L_0$*, where* $0 < L_0 < K$*. Then* $\boldsymbol{l}^*(t)$ *converges to a finite population vector,* $\boldsymbol{l}^*(\infty)$*, or simply* $\boldsymbol{l}^* = [l_{\cdot 1}^*, l_{\cdot 2}^*, ..., l_{\cdot n}^*]$*, as* $t \to \infty$*, with* $l_{\cdot i}^* \geq 0$*, and* $\sum_{i=1}^n l_{\cdot i}^* = L_0$

Proof: We first note that by construction $0 \leq \rho_{ij}^{*}(t) \leq 1$ for all i and j, and $\sum_{j=1}^{n} \rho_{ij}^{*}(t) = 1$, for all j. Hence, for each t, $\mathbf{R}^{*}(t)$ is a right stochastic matrix with $\mathbf{R}^{*}(t)\boldsymbol{\tau}_n = \boldsymbol{\tau}_n$, where $\boldsymbol{\tau}_n$ is an $n \times 1$ vector of ones, for all t. Recursively solving (A.18) forward from $\boldsymbol{l}^{*}(0)$, we have

$$\boldsymbol{l}^{*}(t) = \boldsymbol{l}^{*}(0)\left[\Pi_{s=1}^{t}\mathbf{R}^{*}(s)\right],$$

But it is easily seen that $\left[\Pi_{s=1}^{t}\mathbf{R}^{*}(s)\right]\boldsymbol{\tau}_n = \boldsymbol{\tau}_n$, and hence

$$\sum_{i=1}^{n} l_{\cdot i}^{*}(t) = \boldsymbol{l}^{*}(t)\boldsymbol{\tau}_n = \boldsymbol{l}^{*}(0)\boldsymbol{\tau}_n = L_0. \tag{A.19}$$

Also, since $\boldsymbol{l}^{*}(0) = \boldsymbol{l}(0) > 0$, $\rho_{ij}^{*}(t) \geq 0$, and n is finite, then $\boldsymbol{l}^{*}(t) = [l_{\cdot 1}^{*}(t), l_{\cdot 2}^{*}(t), ..., l_{\cdot n}^{*}(t)] \geq 0$, for all t, and in view of (A.19) we have $\sup_{it}(l_{\cdot i}^{*}(t)) \leq L_0 < K$. Therefore, $\boldsymbol{l}^{*}(t)$ must converge to some vector $\boldsymbol{l}^{*}$ which is bounded in t, as $t \to \infty$. ■

Lemma A2 *Consider the system of non-linear equations in $l_{\cdot i}$, for $i \in \mathcal{I}_n$:*

$$\boldsymbol{l} = \boldsymbol{l}\mathbf{R}(\boldsymbol{l}) \tag{A.20}$$

where $\boldsymbol{l} = [l_{\cdot 1}, l_{\cdot 2}, ..., l_{\cdot n}]$, $\boldsymbol{l} \geq 0$, $\sum_{i=1}^{n} l_{\cdot i} = L_0$, $0 < L_0 < K$, n is fixed, and the typical element of matrix $\mathbf{R}$ is given by

$$\rho_{ij} = \frac{\psi_{ij}\,(l_{\cdot j})^{-\varphi_j}}{\sum_{s \in \mathcal{I}_n} \psi_{is}\,(l_{\cdot s})^{-\varphi_s}}, \tag{A.21}$$

where ψ_{ij} and $\varphi_j > 0$, for any i and $j \in \mathcal{I}_n$. Then, the solution to (A.20) must be strictly positive, $l_{\cdot i} > 0$ for $i \in \mathcal{I}_n$, and unique.

Proof. We first show that $l_{\cdot i} > 0$, and hence $1 > \rho_{ij} > 0$, for all i and $j \in \mathcal{I}_n$. Consider a population vector $\boldsymbol{l}$ that solves (A.20). Note that $\sum_{i=1}^{n} l_{\cdot i} > 0$, and $l_{\cdot i}$ is non-negative for any $i \in \mathcal{I}_n$. Thus, $l_{\cdot i} > 0$ has to hold for at least one i. Without loss of generality, we assume

$$l_{\cdot 1} > 0. \tag{A.22}$$

Note also that since $l_{\cdot 1}$ is the first element in $\boldsymbol{l}$, then from (A.20) we have

$$l_{\cdot 1} = \sum_{i=1}^{n} \rho_{i1} l_{\cdot i}, \tag{A.23}$$

where, upon using (A.21), ρ_{i1} is given by

$$\rho_{i1} = \frac{1}{1 + \sum_{s \neq i}\left(\frac{\psi_{is}}{\psi_{i1}}\right)\frac{(l_{\cdot 1})^{\varphi_1}}{(l_{\cdot s})^{\varphi_s}}}, \text{ for } i = 1, 2, ..., n. \tag{A.24}$$

Note that by assumption ψ_{ij} and $\varphi_j > 0$, and it is supposed that $l_{\cdot 1} > 0$. Hence, if $l_{\cdot s} = 0$, for any $s \in \{2, 3, ..., n\}$, then $\rho_{i1} = 0$, for all $i \in \mathcal{I}_n$, and using (A.23) it follows that $l_{\cdot 1} = 0$, which contradicts our supposition. The same line of reasoning can be applied to any other elements of $\boldsymbol{l}$, and we must have $l_{\cdot i} > 0$, for any $i \in \mathcal{I}_n$.

Given that $l_{\cdot i} > 0$, for all i, we now show that (A.20) cannot have more than one solution. Suppose there exist two solutions $\boldsymbol{l}^{(1)}$ and $\boldsymbol{l}^{(2)}$, with $\boldsymbol{l}^{(1)}$ and $\boldsymbol{l}^{(2)} > 0$, $\boldsymbol{l}^{(1)} \neq \boldsymbol{l}^{(2)}$, such that $\boldsymbol{l}^{(1)} = \boldsymbol{l}^{(1)}\boldsymbol{R}\left(\boldsymbol{l}^{(1)}\right)$ and $\boldsymbol{l}^{(2)} = \boldsymbol{l}^{(2)}\boldsymbol{R}\left(\boldsymbol{l}^{(2)}\right)$. Denote the j^{th} elements of $\boldsymbol{l}^{(1)}$ and $\boldsymbol{l}^{(2)}$ by $l_{\cdot j}^{(1)}$ and $l_{\cdot j}^{(2)}$, respectively. Split the locations into two groups, $\mathcal{I}_n^+$ and $\mathcal{I}_n^-$, where $\mathcal{I}_n^+ \equiv \{j \mid l_{\cdot j}^{(2)} > l_{\cdot j}^{(1)}, j \in \mathcal{I}_n\}$, and $\mathcal{I}_n^- \equiv \{j \mid l_{\cdot j}^{(2)} \leq l_{\cdot j}^{(1)}, j \in \mathcal{I}_n\}$, and note that $\mathcal{I}_n^+ \cap \mathcal{I}_n^- = \emptyset$ and $\mathcal{I}_n^+ \cup \mathcal{I}_n^- = \mathcal{I}_n$. That is,

$$l_{\cdot j}^{(2)} \begin{cases} > l_{\cdot j}^{(1)} & \text{if } j \in \mathcal{I}_n^+ \\ \leq l_{\cdot j}^{(1)} & \text{if } j \in \mathcal{I}_n^- \end{cases} . \tag{A.25}$$

Further, since $\sum_{j=1}^{n} l_j^{(1)} = \sum_{j=1}^{n} l_j^{(2)} = L_0$, and $\boldsymbol{l}^{(1)} \neq \boldsymbol{l}^{(2)}$, it also follows that neither $\mathcal{I}_n^+$ nor $\mathcal{I}_n^-$ can be empty. Thus, we have

$$\sum_{j\in\mathcal{I}_n^+} l_{\cdot j}^{(2)} > \sum_{j\in\mathcal{I}_n^+} l_{\cdot j}^{(1)}. \tag{A.26}$$

Recall that $\rho_{ij}^{(1)}$ and $\rho_{ij}^{(2)}$ are the typical elements of $\boldsymbol{R}\left(\boldsymbol{l}^{(1)}\right)$ and $\boldsymbol{R}\left(\boldsymbol{l}^{(2)}\right)$, respectively. For any $i \in \mathcal{I}_n$, using (A.21), we have (recall that $l_{\cdot j}^{(1)} > 0$ and $l_{\cdot j}^{(2)} > 0$)

$$\frac{\sum_{j\in\mathcal{I}_n^+} \rho_{ij}^{(2)}}{\sum_{j\in\mathcal{I}_n^-} \rho_{ij}^{(2)}} = \frac{\sum_{j\in\mathcal{I}_n^+} \psi_{ij}\left(l_{\cdot j}^{(2)}\right)^{-\varphi_j}}{\sum_{j\in\mathcal{I}_n^-} \psi_{ij}\left(l_{\cdot j}^{(2)}\right)^{-\varphi_j}}, \tag{A.27}$$

$$\frac{\sum_{j\in\mathcal{I}_n^+} \rho_{ij}^{(1)}}{\sum_{j\in\mathcal{I}_n^-} \rho_{ij}^{(1)}} = \frac{\sum_{j\in\mathcal{I}_n^+} \psi_{ij}\left(l_{\cdot j}^{(1)}\right)^{-\varphi_j}}{\sum_{j\in\mathcal{I}_n^-} \psi_{ij}\left(l_{\cdot j}^{(1)}\right)^{-\varphi_j}}. \tag{A.28}$$

Since by (A.25), $l_{\cdot j}^{(2)} > l_{\cdot j}^{(1)}$, if $j \in \mathcal{I}_n^+$, and $l_{\cdot j}^{(2)} \leq l_{\cdot j}^{(1)}$, if $j \in \mathcal{I}_n^-$, then (recall that $\psi_{ij} > 0$ and $\varphi_j > 0$)

$$\begin{aligned} \sum_{j\in\mathcal{I}_n^+} \psi_{ij}\left(l_{\cdot j}^{(2)}\right)^{-\varphi_j} &< \sum_{j\in\mathcal{I}_n^+} \psi_{ij}\left(l_{\cdot j}^{(1)}\right)^{-\varphi_j}, \\ \sum_{j\in\mathcal{I}_n^-} \psi_{ij}\left(l_{\cdot j}^{(2)}\right)^{-\varphi_j} &\geq \sum_{j\in\mathcal{I}_n^-} \psi_{ij}\left(l_{\cdot j}^{(1)}\right)^{-\varphi_j}. \end{aligned}$$

Hence, using the above results in (A.27) and (A.28) we have

$$\frac{\sum_{j\in\mathcal{I}_n^+} \rho_{ij}^{(2)}}{\sum_{j\in\mathcal{I}_n^-} \rho_{ij}^{(2)}} < \frac{\sum_{j\in\mathcal{I}_n^+} \rho_{ij}^{(1)}}{\sum_{j\in\mathcal{I}_n^-} \rho_{ij}^{(1)}}, \qquad \forall\ i \in \mathcal{I}_n,$$

and it follows that

$$\frac{\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(2)}+\sum_{j\in\mathcal{I}_n^-}\rho_{ij}^{(2)}}{\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(2)}} > \frac{\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(1)}+\sum_{j\in\mathcal{I}_n^-}\rho_{ij}^{(1)}}{\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(1)}}, \qquad \forall\ i\in\mathcal{I}_n.$$

Since $\rho_{ij}^{(1)}$ and $\rho_{ij}^{(2)}$ are migration probabilities,

$$\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(2)}+\sum_{j\in\mathcal{I}_n^-}\rho_{ij}^{(2)}=\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(1)}+\sum_{j\in\mathcal{I}_n^-}\rho_{ij}^{(1)}=1.$$

Thus, we have

$$\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(2)}<\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(1)}, \qquad \forall\ i\in\mathcal{I}_n. \tag{A.29}$$

Note that $l_{\cdot j}^{(1)}$ and $l_{\cdot j}^{(2)}$ are given by

$$l_{\cdot j}^{(1)}=\sum_{i\in\mathcal{I}_n}\rho_{ij}^{(1)}l_{\cdot i}^{(1)} \qquad \text{and} \qquad l_{\cdot j}^{(2)}=\sum_{i\in\mathcal{I}_n}\rho_{ij}^{(2)}l_{\cdot i}^{(2)}.$$

Thus, we have

$$\begin{aligned}\sum_{j\in\mathcal{I}_n^+}l_{\cdot j}^{(2)}-\sum_{j\in\mathcal{I}_n^+}l_{\cdot j}^{(1)} &= \sum_{j\in\mathcal{I}_n^+}\sum_{i\in\mathcal{I}_n}\rho_{ij}^{(2)}l_{\cdot i}^{(2)}-\sum_{j\in\mathcal{I}_n^+}\sum_{i\in\mathcal{I}_n}\rho_{ij}^{(1)}l_{\cdot i}^{(1)}\ ,\\ &= \sum_{i\in\mathcal{I}_n}l_{\cdot i}^{(2)}\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(2)}-\sum_{i\in\mathcal{I}_n}l_{\cdot i}^{(1)}\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(1)}\ .\end{aligned}$$

Since $\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(2)}<\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(1)}$ as previously shown in (A.29), then

$$\begin{aligned}\sum_{j\in\mathcal{I}_n^+}l_{\cdot j}^{(2)}-\sum_{j\in\mathcal{I}_n^+}l_{\cdot j}^{(1)} &< \sum_{i\in\mathcal{I}_n}l_{\cdot i}^{(2)}\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(1)}-\sum_{i\in\mathcal{I}_n}l_{\cdot i}^{(1)}\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(1)},\\ &= \sum_{i\in\mathcal{I}_n}\left[\left(l_{\cdot i}^{(2)}-l_{\cdot i}^{(1)}\right)\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(1)}\right].\end{aligned} \tag{A.30}$$

Since by (A.25), $l_{\cdot i}^{(2)}>l_{\cdot i}^{(1)}$, if $i\in\mathcal{I}_n^+$, and $l_{\cdot i}^{(2)}\le l_{\cdot i}^{(1)}$, if $i\in\mathcal{I}_n^-$, and $\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(1)}>0$ by construction, then

$$\begin{aligned}&\sum_{i\in\mathcal{I}_n}\left[\left(l_{\cdot i}^{(2)}-l_{\cdot i}^{(1)}\right)\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(1)}\right]\\ =&\sum_{i\in\mathcal{I}_n^+}\left[\left(l_{\cdot i}^{(2)}-l_{\cdot i}^{(1)}\right)\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(1)}\right]+\sum_{i\in\mathcal{I}_n^-}\left[\left(l_{\cdot i}^{(2)}-l_{\cdot i}^{(1)}\right)\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(1)}\right],\\ <&\sum_{i\in\mathcal{I}_n^+}\left[\left(l_{\cdot i}^{(2)}-l_{\cdot i}^{(1)}\right)\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(1)}\right].\end{aligned}$$

Note that $\rho_{ij}^{(1)}$ are migration probabilities, and $\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(1)} < 1$ by construction, and that $l_{\cdot i}^{(2)} - l_{\cdot i}^{(1)} > 0$, if $i \in \mathcal{I}_n^+$. Then, we have

$$\sum_{i\in\mathcal{I}_n^+}\left[\left(l_{\cdot i}^{(2)} - l_{\cdot i}^{(1)}\right)\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(1)}\right] < \sum_{i\in\mathcal{I}_n^+}\left(l_{\cdot i}^{(2)} - l_{\cdot i}^{(1)}\right),$$

and thus

$$\sum_{i\in\mathcal{I}_n}\left[\left(l_{\cdot i}^{(2)} - l_{\cdot i}^{(1)}\right)\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{(1)}\right] < \sum_{i\in\mathcal{I}_n^+} l_{\cdot i}^{(2)} - \sum_{i\in\mathcal{I}_n^+} l_{\cdot i}^{(1)},$$

which contradicts (A.30). Thus, $\boldsymbol{l} \neq \boldsymbol{l}^*$ cannot hold.■

A1.5 Derivation of new land supplies, κ_{it}

To derive (83), we first note that by using (18) in (24) to eliminate w_{it}, we have

$$h_{i,t-1} = \eta\upsilon_l\left(\frac{y_{it}}{q_{it}}\right). \tag{A.31}$$

By using the above equation in (35) to eliminate $h_{i,t-1}$, we have

$$h_{it} = \beta e^{g_l}\left(1-\theta_i\right)\left[\frac{q_{it}}{p_{it}} + (1-\delta)\right]\eta\upsilon_l\left(\frac{y_{it}}{q_{it}}\right). \tag{A.32}$$

Then, by using (A.31) and (A.32) in (28), we have

$$\begin{aligned} x_{it} &= h_{it} - (1-\delta)h_{i,t-1}, \\ &= \left\{\beta e^{g_l}\left(1-\theta_i\right)\left[\frac{q_{it}}{p_{it}} + (1-\delta)\right] - (1-\delta)\right\}\eta\upsilon_l\left(\frac{y_{it}}{q_{it}}\right). \end{aligned}$$

By combing the above equation with (27) and (26), we have

$$\kappa_{it} = \frac{\gamma_{it}}{\tau_{\kappa,i}},$$

where

$$\gamma_{it} = \frac{\left\{\beta e^{g_l}\left(1-\theta_i\right)\left[\frac{q_{it}}{p_{it}} + (1-\delta)\right] - (1-\delta)\right\}\eta\upsilon_l\left(\frac{y_{it}}{q_{it}}\right)}{p_{it}^{(1-\alpha_{\kappa,i})/\alpha_{\kappa,i}}}.$$

A2 Data sources and measurements

A2.1 Interstate migration and population growth

Between states migration flows are measured using annual data from the Internal Revenue Service (IRS).[A1] The IRS compiles state-to-state migration data using year-to-year address

[A1] For further information on the IRS migration flow data, see `https://www.irs.gov/uac/soi-tax-stats-migration-data`.

changes reported on individual income tax returns filed with the IRS, which are available from 1990 to 2014.[A2] Those who file income tax returns with the IRS in two consecutive years in the same state are considered as non-migrants, and migrants otherwise. We focus on the 48 states and the District of Columbia on the U.S. mainland, and treat Alaska and Hawaii as "foreign countries" in our analysis.

For the years 1990-2014, we compute migration flows and the intrinsic population growth rates of U.S. states using the IRS state-to-state migration flow data. Migrants are considered as the residents of the destination states for the year they migrate.[A3] Thus, the population of State j in year t is measured as the number of tax filers (and their dependents) who report a home address in State j at the start of year $t+1$ as recorded by the IRS for the period from t to $t+1$. We decompose the population changes of U.S. states into an intrinsic component (due to births and deaths) and a net inward migration component. Let

$$l_{i\cdot}(t) \equiv \sum_{j=1}^{n} l_{ij}(t), \text{ and } l_{\cdot j}(t) \equiv \sum_{i=1}^{n} l_{ij}(t), \tag{A.33}$$

where for $i \neq j$, $l_{ij}(t)$ denotes the population flow from State i to State j in year t, measured using the IRS data (see also (1) and (2)). The number that remain in State i is denoted by $l_{ii}(t)$. $l_{i\cdot}(t) - l_{ii}(t)$ measures the outward migration from State i, and $l_{\cdot i}(t) - l_{ii}(t)$, measures the inward migration to State i. The change in population of State i in period t, defined by $l_{\cdot i}(t) - l_{\cdot i}(t-1)$ can now be decomposed as:

$$l_{\cdot i}(t) - l_{\cdot i}(t-1) = [l_{\cdot i}(t) - l_{i\cdot}(t)] + [l_{i\cdot}(t) - l_{\cdot i}(t-1)]\,. \tag{A.34}$$

where the first component $l_{\cdot i}(t) - l_{i\cdot}(t)$ is the net inward migration to State i, and the reminder term, $l_{i\cdot}(t) - l_{\cdot i}(t-1)$, which we refer to as the intrinsic population change of State i. Thus, the actual state level intrinsic population growth rates, $\hat{g}_{l,1t}$, for $i = 1, 2, ..., n$, are measured as

$$\hat{g}_{l,it} = \frac{l_{\cdot i}(t) - l_{\cdot i}(t-1)}{\sum_{i=1}^{n} l_{\cdot i}(t-1)} \tag{A.35}$$

For the period of 1976-1990, state level populations are measured using Census population data, which are scaled such that their 1990 values match those implied by the IRS migration flow data.

A2.2 State level real per capita incomes

The state level per capita annual disposable incomes are obtained from the Bureau of Economic Analysis (BEA).[A4] Real incomes are computed by dividing state level nominal incomes

[A2] The total number of exemptions recorded by the IRS each year is around 80% of the U.S. population.

[A3] For example, suppose a person files income tax returns with the IRS at the starts of year t and year $t+1$, and the two addresses reported are in State i and State j respectively. If $i = j$, this person is considered as a resident in State j in year t. However, if $i \neq j$, the time she migrates to State j can be any point between the starts of year t and year $t+1$. In our analysis, we consider this person as a resident in State j for year t.

[A4] For further information on the BEA state level per capita annual disposable income data (Table SA51), see `https://www.bea.gov/index.htm`.

by state level prices of non-housing consumption goods. The relative prices of non-housing consumption goods across U.S. states for the year 2000 are estimated following the procedure in Holly et al. (2010) (see their Table A.1), where the American Chamber of Commerce Researchers Association (ACCRA) cost of living indices for non-housing items are used at the metropolitan statistical areas.[A5] Similarly, state level non-shelter Consumer Price Index (CPI) series are constructed using the U.S. Bureau of Labor Statistics (BLS) non-shelter CPIs of the cities and areas according to the Holly et al. (2010) procedure.[A6] Then, state level prices of non-housing consumption goods are complied by combining the relative prices of non-housing goods across U.S. states for 2000 and the state level non-shelter (CPI) series over 1976-2014.

A2.3 State level real house prices and rents

The state level median house prices for 1976-2014 are complied by combining the state level median house prices in 2000 obtained from the Historical Census of Housing Tables, and the state level House Price Index obtained from U.S. Federal Housing Finance Agency (FHFA).[A7] The FHFA House Price Index are available over the period 1976Q1 to 2015Q4. The annual house price index is computed using the simple average of the quarter indices over the year. Real house prices are obtained by dividing nominal house prices by prices of non-housing consumption goods.

The state level annual housing rents are computed for 1976-2014 by combing the state level annual housing rents for 2000 obtained from the Historical Census of Housing Tables, and the state level shelter-CPIs.[A8] We construct the state level shelter-CPI series based on the BLS shelter-CPI data and the procedure followed by Holly et al. (2010) (Table A.1).[A9] Real annual rents are obtained by dividing the nominal annual rents by the prices of non-housing consumption goods.

A2.4 Land-use regulations and supplies

The state level Wharton Residential Land Use Regulatory Index is due to Gyourko et al. (2008), and the state level land share in house value is compiled by Davis and Heathcote (2007).[A10] The state-level data on urban area sizes are from the United States Department

[A5] The Cost of Living Index (COLI), formerly the ACCRA Cost of Living Index is a measure of living cost differences among urban areas in the United States compiled by the Council for Community and Economic Research. For further information, see `http://coli.org/`.

[A6] For further information on the BLS city level CPI data, see `https://www.bls.gov/data/`.

[A7] For further information on the Historical Census of Housing Tables of Home Values, see `https://www.census.gov/hhes/www/housing/census/historic/values.html`. For further information on the FHFA state level house price index, see `http://www.freddiemac.com/finance/fmhpi/archive.html`.

[A8] For further information on the Historical Census of Housing Tables of Housing Rents, see `https://www.census.gov/hhes/www/housing/census/historic/grossrents.html`.

[A9] For further information on the BLS city level CPI data, see `https://www.bls.gov/data/`.

[A10] For further information on the data of state level land share in house value, see `http://datatoolkits.lincolninst.edu/subcenters/land-values/land-prices-by-state.asp`.

of Agriculture (USDA).[A11]

A3 Setting values for the exogenous variables in simulations

A3.1 Simulated productivities and land supplies

For the simulations conducted in Section 6, the state level productivities and land supplies are simulated using the estimated versions of (46) - (50). To do so, we first set the number of replications, R, to 500, and independently draw innovations, i.e., $\varepsilon_{f,t}^{(r)}$, $\varepsilon_{a,it}^{(r)}$ and $\varepsilon_{\kappa,it}^{(r)}$, for $i = 1, 2, ..., n$, $t = T_1 + 1, T_1 + 2, ..., T$ and $r = 1, 2., ..., R$, from the standard normal distribution. Then, we obtain $f_t^{(r)}$, $z_{a,it}^{(r)}$ and $z_{\kappa,it}^{(r)}$ using the estimated versions of (47), (48) and (50), and the simulated innovations, $\varepsilon_{f,t}^{(r)}$, $\varepsilon_{a,it}^{(r)}$ and $\varepsilon_{\kappa,it}^{(r)}$, for $i = 1, 2, ..., n$, $t = T_1+1, T_1+2, ..., T$ and $r = 1, 2., ..., R$, while $f_{T_1}^{(r)}$, $z_{a,iT_1}^{(r)}$ and $z_{\kappa,iT_1}^{(r)}$, for $i = 1, 2, ..., n$, being always set to the realized values in 1999 for all replications $r = 1, 2., ..., R$. Finally, $a_{it}^{(r)}$ and $\kappa_{it}^{(r)}$ are obtained by using the estimated versions of (46) and (49), and the simulated shocks, $f_t^{(r)}$, $z_{a,it}^{(r)}$ and $z_{\kappa,it}^{(r)}$, for $i = 1, 2, ..., n$, $t = T_1 + 1, T_1 + 2, ..., T$ and $r = 1, 2., ..., R$.

A3.2 Realized productivities and land supplies

For the simulations conducted in Sections 7 and 8, the realized state level productivities, a_{it}, for $i = 1, 2, ..., n$, and $t = T_1 + 1, T_1 + 2, ..., T$, are inferred using the estimated version of (76) and realized values of $l_{\cdot i}(t)$ and y_{it}. The realized land supplies, κ_{it}, for $i = 1, 2, ..., n$, and $t = T_1+1, T_1+2, ..., T$, are inferred using the estimated versions of (83) and (84), and realized values of y_{it}, q_{it} and p_{it}. Finally, the realized land supply shocks, $z_{\kappa,it}$, for $i = 1, 2, ..., n$, and $t = T_1 + 1, T_1 + 2, ..., T$, are inferred using the estimated version of (29) and estimates of κ_{it}.

[A11] For further information on the USDA land use data, see `https://www.ers.usda.gov/data-products/major-land-uses`.

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Online Supplement to

"Land Use Regulations, Migration and Rising House Price Dispersion in the U.S."

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S1 Existence and uniqueness of short-run equilibrium

Proposition S1 *Consider the dynamic spatial equilibrium model set up in Sections 2 and 3 by equations (37)-(43), which can be written equivalently in terms of detrended variables by equations (55) to (61). Suppose that the vectors of exogenous processes for labor productivities,* $\boldsymbol{a}_t$*, land supplies,* $\boldsymbol{\kappa}_t$*, and the intrinsic population growth rates,* $\boldsymbol{g}_{lt}$*, for* $t = 1, 2, ...,$ *are given by (51)-(53), condition (54) holds, and the initial values for local population and housing stocks (* $\boldsymbol{l}_0$ *and* $\boldsymbol{h}_0$*) are strictly positive. Then the model has a unique short-run equilibrium in the sense set out in Definition 1.*

Proof: To prove the existence and uniqueness of the short-run equilibrium, we show that given $\boldsymbol{l}_{t-1}^*$ and $\boldsymbol{h}_{t-1}^*$, then $\boldsymbol{w}_t^*, \boldsymbol{q}_t^*, \boldsymbol{p}_t^*, \boldsymbol{l}_t^*, \boldsymbol{x}_t^*, \boldsymbol{h}_t^*$ and $\mathbf{R}_t^*$ are uniquely determined by equations (55) to (61). We first show that $l_{\cdot i}^*(t) > 0$, and hence $1 > \rho_{ij}^*(t) > 0$, for all i and $j \in \mathcal{I}_n$. Consider a population vector $\boldsymbol{l}_t^*$ that solves (55) to (61). Note that $\sum_{i=1}^n l_{\cdot i}^*(t) > 0$, and $l_{\cdot i}^*(t)$ is non-negative for any $i \in \mathcal{I}_n$. Thus, $l_{\cdot i}^*(t) > 0$ has to hold for at least one i. Without loss of generality, we assume

$$l_{\cdot 1}^*(t) > 0. \tag{S.1}$$

Note also that since $l_{\cdot 1}^*(t)$ is the first element in $\boldsymbol{l}_t^*$, then from (55) we have

$$l_{\cdot 1}^*(t) = \sum_{i=1}^n \rho_{i1}^*(t) l_{\cdot i}^*(t-1), \tag{S.2}$$

where, upon using (56), (58) and (57), $\rho_{i1}^*(t)$ is given by

$$\rho_{i1}^*(t) = \frac{\alpha_{i1}^{-\psi} \left(\tau_{w,1} a_1^{\lambda_a}\right)^{1-\eta} \left(h_{1,t-1}^*\right)^{\eta} \left(l_{\cdot 1}^*(t)\right)^{-[\eta+\lambda_l(1-\eta)]}}{\sum_{s=1}^n \alpha_{is}^{-\psi} \left(\tau_{w,s} a_s^{\lambda_a}\right)^{1-\eta} \left(h_{s,t-1}^*\right)^{\eta} \left(l_{\cdot s}^*(t)\right)^{-[\eta+\lambda_l(1-\eta)]}} \tag{S.3}$$

which implies

$$\rho^*_{i1}(t) = \frac{1}{1 + \sum_{s \neq i} \left(\frac{\alpha_{is}^{-\psi} \left(\tau_{w,s} a_s^{\lambda_a}\right)^{1-\eta} \left(h^*_{s,t-1}\right)^{\eta}}{\alpha_{i1}^{-\psi} \left(\tau_{w,1} a_1^{\lambda_a}\right)^{1-\eta} \left(h^*_{1,t-1}\right)^{\eta}} \right) \left(\frac{l^*_{\cdot 1}(t)}{l^*_{\cdot s}(t)} \right)^{\eta + \lambda_l(1-\eta)}}, \text{ for } i = 1, 2, ..., n. \tag{S.4}$$

Note that since $\eta \in (0,1)$ and $\lambda_l, \tau_{w,s}, \alpha_{is}$ and $a_s > 0$ by assumption, and that also $h^*_{s,t-1} > 0$, for $t = 1, 2, ...,$ since $h_{s0} > 0$ and the depreciation rate of housing stock δ is less than one. Thus, $\alpha_{is}^{-\psi} \left(\tau_{w,s} a_s^{\lambda_a}\right)^{1-\eta} \left(h^*_{s,t-1}\right)^{\eta} > 0$. In addition, it is supposed that $l^*_{\cdot 1}(t) > 0$. Hence, if $l^*_{\cdot s}(t) = 0$, for any $s \in \{2, 3, ..., n\}$, then $\rho^*_{i1}(t) = 0$, for all $i \in \mathcal{I}_n$, and using (S.4) it follows that $l^*_{\cdot 1}(t) = 0$, which contradicts our supposition. The same line of reasoning can be applied to any other elements of $\boldsymbol{l}^*_t$, and we must have $l^*_{\cdot 1}(t) > 0$, for any $i \in \mathcal{I}_n$.

Second, let $\mathcal{L}_t(\epsilon)$ with $\epsilon > 0$, be a set of population vector:

$$\mathcal{L}_t(\epsilon) \equiv \left\{ \left(l^*_{\cdot 1}(t), ..., l^*_{\cdot n}(t)\right) \middle| L_0 \geq l^*_{\cdot i}(t) \geq \epsilon \text{ for any } i, \text{ where } \epsilon > 0, \sum_{i=1}^{n} l^*_{\cdot i}(t) = L_0 \right\}$$

Consider a mapping F, define

$$F(\boldsymbol{l}^*_t) = \boldsymbol{l}^*_{t-1} \mathbf{R}(\boldsymbol{l}^*_t; \boldsymbol{h}^*_{t-1}),$$

where $\boldsymbol{l}^*_{t-1}$ and $\boldsymbol{h}^*_{t-1}$ are given, and $\mathbf{R}(\boldsymbol{l}^*_t, \boldsymbol{h}^*_{t-1})$ is the migration probability matrix with typical element $\rho^*_{ij}(t)$, which is given by (S.3). Thus, for (55) to hold, the above mapping should have a fixed point. Consider a $\boldsymbol{l}^*_t \in \mathcal{L}_t(\epsilon)$. Note that $l^*_{\cdot i}(t)$ is the ith element of $\boldsymbol{l}^*_t$ and satisfies $L_0 \geq l^*_{\cdot i}(t) \geq \epsilon$, for $i = 1, 2, ..., n$. Then, by using (S.3), we have

$$\begin{aligned}
\rho^*_{ij}(t) &= \frac{\alpha_{ij}^{-\psi} \left(\tau_{w,j} a_j^{\lambda_a}\right)^{1-\eta} \left(h^*_{j,t-1}\right)^{\eta} \left(l^*_{\cdot j}(t)\right)^{-[\eta + \lambda_l(1-\eta)]}}{\sum_{s=1}^{n} \alpha_{is}^{-\psi} \left(\tau_{w,s} a_s^{\lambda_a}\right)^{1-\eta} \left(h^*_{s,t-1}\right)^{\eta} \left(l^*_{\cdot s}(t)\right)^{-[\eta + \lambda_l(1-\eta)]}} \\
&> \frac{\alpha_{ij}^{-\psi} \left(\tau_{w,j} a_j^{\lambda_a}\right)^{1-\eta} \left(h^*_{j,t-1}\right)^{\eta} (L_0)^{-[\eta + \lambda_l(1-\eta)]}}{\sum_{s=1}^{n} \alpha_{is}^{-\psi} \left(\tau_{w,s} a_s^{\lambda_a}\right)^{1-\eta} \left(h^*_{s,t-1}\right)^{\eta} (\epsilon)^{-[\eta + \lambda_l(1-\eta)]}} = \frac{\alpha_{ij}^{-\psi} \left(\tau_{w,j} a_j^{\lambda_a}\right)^{1-\eta} \left(h^*_{j,t-1}\right)^{\eta} (L_0)^{(1-\eta)(1-\lambda_l)}}{\sum_{s=1}^{n} \alpha_{is}^{-\psi} \left(\tau_{w,s} a_s^{\lambda_a}\right)^{1-\eta} \left(h^*_{s,t-1}\right)^{\eta} (\epsilon)^{(1-\eta)(1-\lambda_l)}} \frac{\epsilon}{L_0}.
\end{aligned}$$

Since η and $\lambda_l \in (0,1)$, then $(1-\eta)(1-\lambda_l) > 0$. Suppose ϵ is small enough such that

$$\rho^*_{ij}(t) > \frac{\epsilon}{L_0}, \text{ for } i \text{ and } j \in \mathcal{I}_n.$$

Define $\boldsymbol{l}^{*'}_t = F(\boldsymbol{l}^*_t) = \boldsymbol{l}^*_{t-1} \mathbf{R}(\boldsymbol{l}^*_t; \boldsymbol{h}^*_{t-1})$. Thus we have

$$l^{*'}_{\cdot j}(t) = \sum_{i=1}^{n} \rho^*_{ij}(t) l^*_{\cdot i}(t-1) > \sum_{i=1}^{n} \left(\frac{\epsilon}{L_0}\right) L_0 = \epsilon \qquad \text{for any } j \in \mathcal{I}_n.$$

In addition,

$$\sum_{j=1}^{n} l^{*'}_{\cdot j}(t) = \sum_{j=1}^{n} \sum_{i=1}^{n} \rho^*_{ij}(t) l^*_{\cdot i}(t-1) = \sum_{i=1}^{n} l^*_{\cdot i}(t-1) \sum_{j=1}^{n} \rho^*_{ij}(t) = \sum_{i=1}^{n} l^*_{\cdot i}(t-1) = L_0.$$

Therefore, when ϵ is small enough such that $\rho^*_{ij}(t) > \epsilon/L_0$ for any $i, j \in \mathcal{I}_n$, then $\boldsymbol{l}^*_t \in \mathcal{L}_t(\epsilon) \Rightarrow \boldsymbol{l}^{*'}_t = F(\boldsymbol{l}^*_t) \in \mathcal{L}_t(\epsilon)$. Thus, F is a continuous mapping from $\mathcal{L}_t(\epsilon)$ to itself, where $\mathcal{L}_t(\epsilon)$ is a compact convex set. Thus, Brouwer Fix Point Theorem is applicable to ensure the existence of fixed point. Then, using the solution of $\boldsymbol{l}^*_t$, the other variables of the model, namely, $\boldsymbol{p}^*_t, \boldsymbol{q}^*_t, \boldsymbol{x}^*_t, \boldsymbol{h}^*_t$and $\mathbf{R}^*_t$, can be solved for using equations (56) to (61).

Third, to show the uniqueness, suppose there are $\boldsymbol{l}^{*(1)}_t, \boldsymbol{l}^{*(2)}_t \in \mathcal{L}_t(\epsilon)$, with $\boldsymbol{l}^{*(1)}_t \neq \boldsymbol{l}^{*(2)}_t$, and $\boldsymbol{l}^{*(1)}_t = F(\boldsymbol{l}^{*(1)}_t)$, $\boldsymbol{l}^{*(2)}_t = F(\boldsymbol{l}^{*(2)}_t)$. Define $\mathcal{I}^+_n \equiv \{j|\ l^{*^{(2)}}_{\cdot j}(t) > l^{*^{(1)}}_{\cdot j}(t),\ j \in \mathcal{I}_n\}$ and $\mathcal{I}^-_n \equiv \{j|\ l^{*^{(2)}}_{\cdot j}(t) \leq l^{*^{(1)}}_{\cdot j}(t),\ j \in \mathcal{I}_n\}$. Thus, neither $\mathcal{I}^+_n$ nor $\mathcal{I}^-_n$ is empty, and we have

$$\sum_{j\in\mathcal{I}^+_n} l^{*^{(2)}}_{\cdot j}(t) > \sum_{j\in\mathcal{I}^+_n} l^{*^{(1)}}_{\cdot j}(t). \tag{S.5}$$

Note that by using (S.3), we have

$$\begin{aligned}
\frac{\sum_{j\in\mathcal{I}^+_n} \rho^{*(2)}_{ij}(t)}{\sum_{j\in\mathcal{I}^-_n} \rho^{*(2)}_{ij}(t)} &= \frac{\sum_{j\in\mathcal{I}^+_n} \alpha^{-\psi}_{ij}\left(\tau_{w,j}a^{\lambda_a}_j\right)^{1-\eta}\left(h^*_{j,t-1}\right)^{\eta}\left(l^{*(2)}_{\cdot j}(t)\right)^{-[\eta+\lambda_l(1-\eta)]}}{\sum_{j\in\mathcal{I}^+_n} \alpha^{-\psi}_{ij}\left(\tau_{w,j}a^{\lambda_a}_j\right)^{1-\eta}\left(h^*_{j,t-1}\right)^{\eta}\left(l^{*(2)}_{\cdot j}(t)\right)^{-[\eta+\lambda_l(1-\eta)]}}, \\
&< \frac{\sum_{j\in\mathcal{I}^+_n} \alpha^{-\psi}_{ij}\left(\tau_{w,j}a^{\lambda_a}_j\right)^{1-\eta}\left(h^*_{j,t-1}\right)^{\eta}\left(l^{*(1)}_{\cdot j}(t)\right)^{-[\eta+\lambda_l(1-\eta)]}}{\sum_{j\in\mathcal{I}^+_n} \alpha^{-\psi}_{ij}\left(\tau_{w,j}a^{\lambda_a}_j\right)^{1-\eta}\left(h^*_{j,t-1}\right)^{\eta}\left(l^{*(1)}_{\cdot j}(t)\right)^{-[\eta+\lambda_l(1-\eta)]}}, \\
&= \frac{\sum_{j\in\mathcal{I}^+_n} \rho^{*(1)}_{ij}(t)}{\sum_{j\in\mathcal{I}^-_n} \rho^{*(1)}_{ij}(t)}.
\end{aligned}$$

Note also that

$$\sum_{j\in\mathcal{I}^+_n} \rho^{*(2)}_{ij}(t) + \sum_{j\in\mathcal{I}^-_n} \rho^{*(2)}_{ij}(t) = \sum_{j\in\mathcal{I}^+_n} \rho^{*(1)}_{ij}(t) + \sum_{j\in\mathcal{I}^-_n} \rho^{*(1)}_{ij}(t) = 1.$$

Thus,

$$\sum_{j\in\mathcal{I}^+_n} \rho^{*(2)}_{ij}(t) < \sum_{j\in\mathcal{I}^+_n} \rho^{*(1)}_{ij}(t) \qquad \text{for any } i \in \mathcal{I}_n. \tag{S.6}$$

Since $\boldsymbol{l}^{*(1)}_t = F(\boldsymbol{l}^{*(1)}_t)$, $\boldsymbol{l}^{*(2)}_t = F(\boldsymbol{l}^{*(2)}_t)$, thus for any $j \in I$

$$l^{*(2)}_{\cdot j}(t) = \sum_{i\in I} \rho^{*(2)}_{ij}(t) l^*_{\cdot i}(t-1) \qquad \text{and} \qquad l^{*(1)}_{\cdot j}(t) = \sum_{i\in I} \rho^{*(1)}_{ij}(t) l^*_{\cdot i}(t-1)$$

Then, we have

$$\sum_{j\in\mathcal{I}_n^+}(l_{\cdot j}^{*(2)}(t)-l_{\cdot j}^{*(1)}(t)) = \sum_{j\in\mathcal{I}_n^+}\sum_{i\in I}\rho_{ij}^{*(2)}(t)l_{\cdot i}^{*}(t-1)-\sum_{j\in\mathcal{I}_n^+}\sum_{i\in I}\rho_{ij}^{*(1)}(t)l_{\cdot i}^{*}(t-1)$$
$$= \sum_{i\in I}\sum_{j\in\mathcal{I}_n^+}\left(\rho_{ij}^{*(2)}(t)-\rho_{ij}^{*(1)}(t)\right)l_{\cdot i}^{*}(t-1)$$
$$= \sum_{i\in I}\left(\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{*(2)}(t)-\sum_{j\in\mathcal{I}_n^+}\rho_{ij}^{*(1)}(t)\right)l_{\cdot i}^{*}(t-1)$$
$$< 0$$

Thus, the above contradicts with (S.5), which implies that $\boldsymbol{l}_t^{*(1)} \neq \boldsymbol{l}_t^{*(2)}$ cannot be true. ■

S2 Computation of the impulse responses

The impulse responses reported in the paper are computed using the Monte Carlo techniques developed by Koop et al. (1996). As discussed in Section 4.1, the model economy set out in Sections 2 and 3 can be written in a compact form as:

$$\boldsymbol{\zeta}_t = \boldsymbol{f}\left(\boldsymbol{\zeta}_{t-1}, \boldsymbol{a}_t, \boldsymbol{a}_{t-1}, \boldsymbol{\kappa}_{t-1}, \boldsymbol{g}_{l,t}; \Theta\right), \tag{S.7}$$

where Θ is a row vector that contains all the parameters, $\boldsymbol{\zeta}_t = [\boldsymbol{l}(t), \boldsymbol{q}_t]$ is a $1\times 2n$ vector, and

$$\boldsymbol{\chi}_t = \boldsymbol{g}\left(\boldsymbol{\zeta}_t, \boldsymbol{a}_t, \boldsymbol{\kappa}_t; \Theta\right), \tag{S.8}$$

where $\boldsymbol{\chi}_t = [\boldsymbol{p}_t, \boldsymbol{h}_t]$ is a $1\times 2n$ vector.

Define $\boldsymbol{\xi}_t = [\boldsymbol{\zeta}_t, \boldsymbol{\chi}_t]$, which is a $1\times 4n$ vector. Then, the (S.7) and (S.8) can be combined and written as

$$\boldsymbol{\xi}_t = \boldsymbol{\psi}\left(\boldsymbol{\xi}_{t-1}, \boldsymbol{a}_t, \boldsymbol{a}_{t-1}, \boldsymbol{\kappa}_t, \boldsymbol{\kappa}_{t-1}, \boldsymbol{g}_{l,t}; \Theta\right). \tag{S.9}$$

The stochastic processes of $\boldsymbol{a}_t$ and $\boldsymbol{\kappa}_t$, are given by

$$\ln \boldsymbol{a}_t = \ln \boldsymbol{a} + \boldsymbol{g}_a t + \boldsymbol{\lambda} f_t + \boldsymbol{z}_{a,t}, \tag{S.10}$$
$$f_t = \rho_f f_{t-1} + \sigma_f \varepsilon_{f,t}, \tag{S.11}$$
$$\boldsymbol{z}_{a,t} = \boldsymbol{z}_{a,t-1}\mathbf{diag}(\rho_{a,1}, \rho_{a,2}, ...\rho_{a,n}) + \boldsymbol{\varepsilon}_{a,t}\mathbf{diag}(\sigma_{a,1}, \sigma_{a,2}, ...\sigma_{a,n}), \tag{S.12}$$

and

$$\ln \boldsymbol{\kappa}_t = \ln \boldsymbol{\kappa} + \boldsymbol{g}_\kappa t + \boldsymbol{z}_{\kappa,t}, \tag{S.13}$$
$$\boldsymbol{z}_{\kappa,t} = \boldsymbol{z}_{\kappa,t-1}\mathbf{diag}(\rho_{\kappa,1}, \rho_{\kappa,2}, ...\rho_{\kappa,n}) + \boldsymbol{\varepsilon}_{\kappa,t}\mathbf{diag}(\sigma_{\kappa,1}, \sigma_{\kappa,2}, ...\sigma_{\kappa,n}), \tag{S.14}$$

and the values of state level intrinsic population growth rates, $\boldsymbol{g}_{l,t}$, for $t = 0, 1, 2, ...,$ are exogenously given.

Impulse response function: To illustrate the computation algorithm, we take the computation of the impulse responses to a standard deviation negative productivity shock to State i^* as an example. Note that the model is Markovian. Thus, the relevant history is only the period before the start of simulation. Let the shock hits the economy in period 1. Then, the impulse response function is given by

$$\begin{aligned} GI_\xi(t, \varepsilon_{a,i^*1}, \boldsymbol{\xi}_0, \boldsymbol{a}_0, \boldsymbol{\kappa}_0) &= E(\boldsymbol{\xi}_t|\varepsilon_{a,i^*1}, \boldsymbol{\xi}_0, \boldsymbol{a}_0, \boldsymbol{\kappa}_0) - E(\boldsymbol{\xi}_t|\boldsymbol{\xi}_0, \boldsymbol{a}_0, \boldsymbol{\kappa}_0) \\ \text{for } t &= 1, 2, ..., T, \end{aligned}$$

where T is the horizon of the impulse response analyses, $E(\boldsymbol{\xi}_t|\boldsymbol{\xi}_0, \boldsymbol{a}_0, \boldsymbol{\kappa}_0)$ is the expectation of $\boldsymbol{\xi}_t$ conditional only on $\boldsymbol{\xi}_0$, $\boldsymbol{a}_0$ and $\boldsymbol{\kappa}_0$, and $E(\boldsymbol{\xi}_t|\varepsilon_{a,i^*1}, \boldsymbol{\xi}_0, \boldsymbol{a}_0, \boldsymbol{\kappa}_0)$ is the expectation of $\boldsymbol{\xi}_t$ conditional on both $\boldsymbol{\xi}_0, \boldsymbol{a}_0, \boldsymbol{\kappa}_0$ and ε_{a,i^*1}. Recall that ε_{a,i^*1} is the innovation to the local productivity shock in State i^* in period 1.

Initial values: In our impulse response simulations, we assume that the economy is on the balanced growth path when $t = 0$. Recall that in Section 4.2, we established the uniqueness of the balanced growth path by showing that for given values of $L_0, \boldsymbol{\kappa}$ and $\boldsymbol{a}$, the steady states of the detrended variables are uniquely determined by the equation system (64)-(71). Note that detrended variables equal non-detrended variables when $t = 0$. Thus, we use the steady state values of the detrended variables as the initial values for the corresponding non-detrended variable in the impulse response simulations, which implies that the economy is on the balanced growth path when $t = 0$.

Deterministic variables: The intrinsic population growth rates of all states are set equal to the balanced growth path level given by (52):

$$\boldsymbol{g}_{l,t} = [\hat{g}_l, \hat{g}_l, ..., \hat{g}_l], \text{ for } t = 1, 2, ..., T,$$

where g_l is the balanced growth path intrinsic population growth rate, which is assumed to be common to all states, and estimated as the average growth rate of the national population over the period 1976-2014.

Stochastic processes: The state level productivities and land supplies, $\boldsymbol{a}_t$ and $\boldsymbol{\kappa}_t$, are simulated using the estimated (S.10) - (S.14), where f_0, $\boldsymbol{z}_{a0}$ and $\boldsymbol{z}_{\kappa 0}$ are set to 0.

We set the numbers of replications and horizons to R and T, and independently draw innovations from the standard normal distribution. Let $\varepsilon_{f,t}^{(r)}$, $\boldsymbol{\varepsilon}_{a,t}^{(r)}$ and $\boldsymbol{\varepsilon}_{\kappa,t}^{(r)}$ denote the simulated $\varepsilon_{f,t}$, $\boldsymbol{\varepsilon}_{a,t}$ and $\boldsymbol{\varepsilon}_{\kappa,t}$, for replication r, where $\boldsymbol{\varepsilon}_{a,t}^{(r)} = \left[\varepsilon_{a,1t}^{(r)}, \varepsilon_{a,2t}^{(r)}, ..., \varepsilon_{a,nt}^{(r)}\right]$ and $\boldsymbol{\varepsilon}_{\kappa,t}^{(r)} = \left[\varepsilon_{\kappa,1t}^{(r)}, \varepsilon_{\kappa,2t}^{(r)}, ..., \varepsilon_{\kappa,nt}^{(r)}\right]$. The innovations, $\varepsilon_{f,t}^{(r)}$, $\varepsilon_{a,it}^{(r)}$ and $\varepsilon_{\kappa,it}^{(r)}$, for $i = 1, 2, ..., n$, $t = 1, 2., ..., T$ and $r = 1, 2., ..., R$, are independently drawn from the standard normal distribution.

Productivity processes without shock: When there is no shock, for each replication r, we plug the simulated innovations, $\varepsilon_{f,t}^{(r)}$ and $\boldsymbol{\varepsilon}_{a,t}^{(r)}$, into (S.10) - (S.12), and obtain a series of simulated productivities, $\boldsymbol{a}_t^{(r)}$, for $t = 1, 2., ..., T$.

Productivity processes with shock: When there is shock, for each replication r, we plug the simulated innovations, $\varepsilon_{f,t}^{(r)}$ and $\boldsymbol{\varepsilon}_{a,t}^{(r)}$, with the i^*th element of $\boldsymbol{\varepsilon}_{a,1}^{(r)}$, i.e., $\varepsilon_{a,i^*1}^{(r)}$, being replaced by -1 (a negative shock), into (S.10) - (S.12), and obtain another series of simulated productivities, $\breve{\boldsymbol{a}}_t^{(r)}$, for $t = 1, 2., ..., T$.

Land supply processes: For both the cases with and without shock, for each replication r, we plug the simulated innovations, $\boldsymbol{\varepsilon}_{\kappa,t}^{(r)}$, into (S.13) - (S.14), and obtain a series of simulated productivities, $\boldsymbol{\kappa}_t^{(r)}$, for $t = 1, 2., ..., T$.

Computation: To compute $E(\boldsymbol{\xi}_t | \boldsymbol{\xi}_0, \boldsymbol{a}_0, \boldsymbol{\kappa}_0)$ and $E(\boldsymbol{\xi}_t | \varepsilon_{a,i^*1}, \boldsymbol{\xi}_0, \boldsymbol{a}_0, \boldsymbol{\kappa}_0)$ numerically, we conduct the following two simulations.

- *Simulation 1 (no shock):* For each replication r, given the initial values, $\boldsymbol{\xi}_0$, $\boldsymbol{a}_0$ and $\boldsymbol{\kappa}_0$, and the deterministic processes of $\boldsymbol{g}_{l,t}$, we simulate the model (S.9) using the simulated productivity processes, $\boldsymbol{a}_t^{(r)}$ and $\boldsymbol{\kappa}_t^{(r)}$, for $t = 1, 2, ..., T$, and obtain a series of realized $\boldsymbol{\xi}_t$, i.e., $\boldsymbol{\xi}_t^{(r)}$, for $t = 1, 2, ..., T$:

$$\boldsymbol{\xi}_t^{(r)} = \boldsymbol{\psi}\left(\boldsymbol{\xi}_{t-1}^{(r)}, \boldsymbol{a}_t^{(r)}, \boldsymbol{a}_{t-1}^{(r)}, \boldsymbol{\kappa}_t^{(r)}, \boldsymbol{\kappa}_{t-1}^{(r)}, \boldsymbol{g}_{l,t}; \Theta\right).$$

- *Simulation 2 (with shock):* For each replication r, given the initial values, $\boldsymbol{\xi}_0$, $\boldsymbol{a}_0$ and $\boldsymbol{\kappa}_0$, and the deterministic processes of $\boldsymbol{g}_{l,t}$, we simulate the model (S.9) using the simulated productivity processes, $\breve{\boldsymbol{a}}_t^{(r)}$ and $\boldsymbol{\kappa}_t^{(r)}$, for $t = 1, 2, ..., T$, and obtain a series of realized $\boldsymbol{\xi}_t$, i.e., $\breve{\boldsymbol{\xi}}_t^{(r)}$, for $t = 1, 2, ..., T$:

$$\breve{\boldsymbol{\xi}}_t^{(r)} = \boldsymbol{\psi}\left(\breve{\boldsymbol{\xi}}_{t-1}^{(r)}, \breve{\boldsymbol{a}}_t^{(r)}, \breve{\boldsymbol{a}}_{t-1}^{(r)}, \boldsymbol{\kappa}_t^{(r)}, \boldsymbol{\kappa}_{t-1}^{(r)}, \boldsymbol{g}_{l,t}; \Theta\right).$$

Here, $\boldsymbol{\xi}_t^{(r)}$ and $\breve{\boldsymbol{\xi}}_t^{(r)}$ are the simulated $\boldsymbol{\zeta}_t$ in replication r in Simulation 1 and Simulation 2, respectively. Then, the two expectations, $E(\boldsymbol{\xi}_t | \boldsymbol{\xi}_0, \boldsymbol{a}_0, \boldsymbol{\kappa}_0)$ and $E(\boldsymbol{\xi}_t | \varepsilon_{a,i^*1}, \boldsymbol{\xi}_0, \boldsymbol{a}_0, \boldsymbol{\kappa}_0)$, are approximated as the averages across replications:

$$\hat{E}(\boldsymbol{\xi}_t | \boldsymbol{\xi}_0, \boldsymbol{a}_0, \boldsymbol{\kappa}_0) = \frac{1}{R} \sum_{r=1}^{R} \boldsymbol{\xi}_t^{(r)} \quad \text{and} \quad \hat{E}(\boldsymbol{\xi}_t | \varepsilon_{a,i^*1}, \boldsymbol{\xi}_0, \boldsymbol{a}_0, \boldsymbol{\kappa}_0) = \frac{1}{R} \sum_{r=1}^{R} \breve{\boldsymbol{\xi}}_t^{(r)}.$$

Thus, the approximated impulse response in period t is given as

$$GI_{\boldsymbol{\xi}}(t, \varepsilon_{a,i^*1}, \boldsymbol{\xi}_0, \boldsymbol{a}_0, \boldsymbol{\kappa}_0) = \frac{1}{R} \sum_{r=1}^{R} \breve{\boldsymbol{\xi}}_t^{(r)} - \frac{1}{R} \sum_{r=1}^{R} \boldsymbol{\xi}_t^{(r)}.$$

S3 Calibration and estimation of parameters

Table S1: Benchmark calibration and estimation of parameters

		Value	Description
I. Preference			
η	Calibrated	0.24	Share of housing in consumption; Davis and Ortalo-Magné (2011).
β	Calibrated	0.98	Discount factor of landlords; Match the risk-free interest rate of 2%.
II. Migration and intrinsic population growth rates			
ψ	-	1.00	Weight of migration costs in utility function; Set to one.
α_{ij}	Estimated	See text	Route-specific migration costs.
g_l	Estimated	0.01	Intrinsic population growth rate; Match the U.S. average population growth rate over the period 1977-1999.
III. Housing supplies and investment			
$\alpha_{\kappa,i}$	Estimated	See text	Location-specific shares of land in house values; Set to the state level average land values relative to total value of housing stocks over the period 1977-1999.
θ_i	Estimated	See text	Location-specific housing investment costs; Match the state level average rent-to-price ratios over the period 1977-1999.
δ	Estimated	0.02	Depreciation rate of housing stocks; Set to the national housing stock depreciation rate over the period 1977-1999.
IV. Labor productivity processes			
v_l	Calibrated	0.67	Share of labor cost in output; Valentinyi and Herrendorf (2008).
v_ϕ	Calibrated	0.06	Effects of agglomeration on TFP; Davis et al. (2014).
$\bar{\phi}_i$	-	1.00	Location-specific intercepts in the functions for agglomeration effects; Set to one.
a_i	Estimated	See text	Location-specific intercepts in the labor productivity processes.
g_a	Calibrated	0.02	Growth rate of labor productivities. Match the average annual growth rate of the U.S. real per capita income during the period 1977-1999.
ρ_f	Estimated	0.92	AR(1) autoregressive coefficient for f_t.
σ_f	Estimated	0.03	Standard deviation of the innovation to f_t.
λ_i	Estimated	See text	Location-specific loading coefficients for f_t.
$\rho_{a,i}$	Estimated	See text	AR(1) autoregressive coefficients for $z_{a,it}$.
$\sigma_{a,i}$	Estimated	See text	Standard deviations of the innovations to $z_{a,it}$.
V. Land supply processes			
$\tau_{\kappa,i}$	Estimated	See text	Location-specific scalars in the housing supply functions.
κ_i	Estimated	See text	Location-specific intercepts in the land supply processes.
$g_{\kappa,i}$	Estimated	See text	Location-specific land supply growth rates.
$\rho_{\kappa,i}$	Estimated	See text	AR(1) autoregressive coefficients for $z_{\kappa,it}$.
$\sigma_{\kappa,i}$	Estimated	See text	Standard deviations of the innovations to $z_{\kappa,it}$.

Table S2: Location-specific parameters related to housing supplies and investment

State		$\hat{\alpha}_{\kappa,i}$	$\hat{\theta}_i$			$\hat{\alpha}_{\kappa,i}$	$\hat{\theta}_i$
AL	Alabama	0.0707	0.0175	NE	Nebraska	0.0598	0.0278
AZ	Arizona	0.1362	0.0155	NV	Nevada	0.2070	0.0071
AR	Arkansas	0.0571	0.0279	NH	New Hampshire	0.2394	0.0183
CA	California	0.5176	0.0092	NJ	New Jersey	0.4045	0.0130
CO	Colorado	0.2785	0.0138	NM	New Mexico	0.1067	0.0066
CT	Connecticut	0.4770	0.0056	NY	New York	0.2328	0.0160
DE	Delaware	0.1508	0.0178	NC	North Carolina	0.1390	0.0228
DC	District of Columbia	0.5312	0.0130	ND	North Dakota	0.0971	0.0184
FL	Florida	0.1442	0.0304	OH	Ohio	0.1109	0.0191
GA	Georgia	0.1210	0.0249	OK	Oklahoma	0.0857	0.0264
ID	Idaho	0.1058	0.0126	OR	Oregon	0.1665	0.0167
IL	Illinois	0.1854	0.0137	PA	Pennsylvania	0.1034	0.0233
IN	Indiana	0.0780	0.0200	RI	Rhode Island	0.2331	0.0097
IA	Iowa	0.1037	0.0283	SC	South Carolina	0.1062	0.0225
KS	Kansas	0.0687	0.0286	SD	South Dakota	0.0857	0.0248
KY	Kentucky	0.0654	0.0242	TN	Tennessee	0.0792	0.0247
LA	Louisiana	0.0826	0.0186	TX	Texas	0.0602	0.0343
ME	Maine	0.1330	0.0188	UT	Utah	0.2039	0.0102
MD	Maryland	0.3666	0.0179	VT	Vermont	0.2351	0.0158
MA	Massachusetts	0.3138	0.0137	VA	Virginia	0.3216	0.0218
MI	Michigan	0.0955	0.0286	WA	Washington	0.2029	0.0129
MN	Minnesota	0.0712	0.0217	WV	West Virginia	0.0975	0.0190
MS	Mississippi	0.0628	0.0258	WI	Wisconsin	0.1116	0.0206
MO	Missouri	0.0704	0.0258	WY	Wyoming	0.1678	0.0062
MT	Montana	0.0947	0.0121				
Average across the U.S. states		0.1682	0.0189				

Table S3: Location-specific parameters of the labor productivity processes

State		$\hat{\lambda}_i$	SE	p-value	$\hat{\rho}_{a,i}$	SE	p-value	$\hat{\sigma}_{a,i}$
AL	Alabama	1.3500	0.0830	0.0000	0.8589	0.1086	0.0000	0.0133
AZ	Arizona	0.9067	0.1355	0.0000	0.8089	0.1153	0.0000	0.0228
AR	Arkansas	0.9156	0.0932	0.0000	0.7286	0.1414	0.0000	0.0194
CA	California	0.3449	0.1533	0.0343	0.8694	0.1057	0.0000	0.0239
CO	Colorado	1.1385	0.1041	0.0000	0.8507	0.1390	0.0000	0.0191
CT	Connecticut	1.6242	0.1737	0.0000	0.8270	0.1132	0.0000	0.0280
DE	Delaware	1.3316	0.1136	0.0000	0.7059	0.1565	0.0002	0.0252
DC	District of Columbia	0.5195	0.1849	0.0099	0.7746	0.0992	0.0000	0.0269
FL	Florida	1.5818	0.1475	0.0000	0.7405	0.1315	0.0000	0.0276
GA	Georgia	2.1065	0.1119	0.0000	0.7394	0.1463	0.0000	0.0240
ID	Idaho	0.6251	0.1496	0.0004	0.7247	0.1147	0.0000	0.0252
IL	Illinois	0.9811	0.0533	0.0000	0.3842	0.1758	0.0398	0.0138
IN	Indiana	1.1175	0.0826	0.0000	0.8134	0.1025	0.0000	0.0123
IA	Iowa	0.2285	0.1354	0.1051	0.4526	0.1889	0.0255	0.0378
KS	Kansas	0.6216	0.0567	0.0000	0.3714	0.1929	0.0672	0.0159
KY	Kentucky	0.9512	0.0836	0.0000	0.7206	0.1464	0.0001	0.0178
LA	Louisiana	0.2497	0.1011	0.0214	0.6956	0.1178	0.0000	0.0173
ME	Maine	1.1732	0.1084	0.0000	0.8417	0.1267	0.0000	0.0196
MD	Maryland	1.3749	0.0959	0.0000	0.7012	0.1505	0.0001	0.0211
MA	Massachusetts	1.6583	0.1668	0.0000	0.8216	0.1227	0.0000	0.0294
MI	Michigan	1.0009	0.0898	0.0000	0.7040	0.1369	0.0000	0.0180
MN	Minnesota	1.2649	0.0570	0.0000	0.0955	0.2094	0.6527	0.0176
MS	Mississippi	1.0084	0.1246	0.0000	0.8873	0.1014	0.0000	0.0185
MO	Missouri	1.2509	0.0597	0.0000	0.5434	0.1879	0.0085	0.0159
MT	Montana	-0.3493	0.1437	0.0233	0.3939	0.1899	0.0500	0.0403
NE	Nebraska	0.8859	0.0708	0.0000	-0.1827	0.1980	0.3663	0.0206
NV	Nevada	1.4794	0.1905	0.0000	0.9022	0.0993	0.0000	0.0275
NH	New Hampshire	1.9806	0.2323	0.0000	0.7920	0.1068	0.0000	0.0358
NJ	New Jersey	1.4646	0.1077	0.0000	0.7568	0.1439	0.0000	0.0219
NM	New Mexico	0.5373	0.0585	0.0000	0.7661	0.1673	0.0001	0.0130
NY	New York	1.2613	0.1260	0.0000	0.8292	0.1375	0.0000	0.0243
NC	North Carolina	1.9992	0.1169	0.0000	0.6985	0.1519	0.0001	0.0263
ND	North Dakota	-0.1182	0.2531	0.6448	0.0022	0.2127	0.9917	0.0796
OH	Ohio	0.8190	0.0685	0.0000	0.6346	0.1530	0.0004	0.0155
OK	Oklahoma	-0.3802	0.1414	0.0131	0.6517	0.1587	0.0005	0.0325
OR	Oregon	0.7045	0.1365	0.0000	0.7930	0.1063	0.0000	0.0213
PA	Pennsylvania	1.0008	0.0845	0.0000	0.7710	0.1288	0.0000	0.0157
RI	Rhode Island	0.9745	0.1682	0.0000	0.8807	0.1042	0.0000	0.0252
SC	South Carolina	1.5644	0.0742	0.0000	0.6996	0.1511	0.0001	0.0164
SD	South Dakota	0.8927	0.1288	0.0000	0.2804	0.2052	0.1857	0.0388
TN	Tennessee	2.1752	0.1451	0.0000	0.7874	0.1265	0.0000	0.0271
TX	Texas	1.1899	0.1242	0.0000	0.9746	0.1236	0.0000	0.0195
UT	Utah	1.0823	0.1101	0.0000	0.9438	0.0994	0.0000	0.0149
VT	Vermont	1.4196	0.1048	0.0000	0.7451	0.1277	0.0000	0.0195
VA	Virginia	1.3727	0.1008	0.0000	0.7820	0.1264	0.0000	0.0186
WA	Washington	1.0695	0.0763	0.0000	0.7613	0.1380	0.0000	0.0154
WV	West Virginia	0.1421	0.0726	0.0624	0.4836	0.1887	0.0178	0.0201
WI	Wisconsin	1.2697	0.0689	0.0000	0.6330	0.1633	0.0008	0.0166
WY	Wyoming	-0.7628	0.1712	0.0002	0.5032	0.1872	0.0134	0.0446
Average across the U.S. states		1.0000			0.6723			0.0237

Table S4: Location-specific parameters of the land supply processes

State		WRI	$\hat{g}_{\kappa,i}$	SE	p-value	$\hat{\rho}_{\kappa,i}$	SE	p-value	$\hat{\sigma}_{\kappa,i}$
AL	Alabama	-1.1401	0.0879	0.0273	0.0040	0.9017	0.1206	0.0000	0.4879
AZ	Arizona	0.9917	0.1009	0.0171	0.0000	0.8163	0.1307	0.0000	0.3275
AR	Arkansas	-1.0279	0.2017	0.0334	0.0000	0.8833	0.1299	0.0000	0.6364
CA	California	1.0057	-0.0081	0.0077	0.3003	0.7490	0.1143	0.0000	0.1377
CO	Colorado	0.8514	0.0225	0.0114	0.0614	0.9233	0.1082	0.0000	0.1785
CT	Connecticut	0.7112	-0.0067	0.0127	0.6033	0.8830	0.0994	0.0000	0.1981
DE	Delaware	0.8514	-0.0566	0.0198	0.0092	0.8576	0.1024	0.0000	0.3137
DC	District of Columbia		-0.0161	0.0070	0.0321	0.7467	0.1231	0.0000	0.1366
FL	Florida	0.6972	0.0782	0.0052	0.0000	0.5419	0.2119	0.0180	0.1508
GA	Georgia	-0.1163	0.0375	0.0109	0.0023	0.8757	0.1464	0.0000	0.2193
ID	Idaho	-0.7053	0.0724	0.0264	0.0120	0.9174	0.0965	0.0000	0.3950
IL	Illinois	-0.0882	-0.0141	0.0170	0.4156	0.8445	0.1159	0.0000	0.3115
IN	Indiana	-1.2383	0.0132	0.0266	0.6242	0.8812	0.1208	0.0000	0.4837
IA	Iowa	-1.2102	0.1207	0.0392	0.0055	0.9313	0.0960	0.0000	0.5719
KS	Kansas	-1.4066	0.1999	0.0341	0.0000	0.9754	0.1184	0.0000	0.5596
KY	Kentucky	-0.6212	-0.0064	0.0301	0.8329	0.9128	0.1144	0.0000	0.5116
LA	Louisiana	-1.3084	0.2236	0.0422	0.0000	0.8887	0.1041	0.0000	0.6419
ME	Maine	1.1319	-0.0676	0.0293	0.0312	0.8537	0.1052	0.0000	0.4875
MD	Maryland	1.2862	-0.0060	0.0066	0.3766	0.8722	0.1118	0.0000	0.1155
MA	Massachusetts	2.3661	-0.0731	0.0213	0.0024	0.9124	0.0852	0.0000	0.2864
MI	Michigan	0.2063	-0.0969	0.0340	0.0093	0.9010	0.1105	0.0000	0.5697
MN	Minnesota	0.2904	0.0285	0.0250	0.2671	0.8120	0.1543	0.0000	0.5412
MS	Mississippi	-0.9718	0.2309	0.0341	0.0000	0.9083	0.1348	0.0000	0.6544
MO	Missouri	-1.2663	0.0443	0.0269	0.1140	0.8103	0.1424	0.0000	0.5783
MT	Montana	-0.3267	0.0411	0.0346	0.2477	0.8736	0.1145	0.0000	0.6103
NE	Nebraska	-0.7755	0.0995	0.0418	0.0265	0.9879	0.0989	0.0000	0.5934
NV	Nevada	-0.4529	0.0711	0.0091	0.0000	0.6113	0.1325	0.0001	0.1877
NH	New Hampshire	2.0856	0.0053	0.0244	0.8313	0.8596	0.1003	0.0000	0.3874
NJ	New Jersey	1.4124	-0.0286	0.0137	0.0491	0.8934	0.0976	0.0000	0.2096
NM	New Mexico	0.0240	0.0382	0.0159	0.0249	0.7506	0.1249	0.0000	0.3071
NY	New York	0.1642	-0.0855	0.0225	0.0010	0.9254	0.0870	0.0000	0.3060
NC	North Carolina	-0.3126	0.0033	0.0100	0.7425	0.8698	0.1344	0.0000	0.1983
ND	North Dakota	-0.5791	0.1953	0.0321	0.0000	0.6902	0.1663	0.0004	0.8126
OH	Ohio	-0.3267	0.0090	0.0262	0.7357	0.9157	0.0980	0.0000	0.3951
OK	Oklahoma	-0.8035	0.2954	0.0414	0.0000	0.8535	0.1097	0.0000	0.6672
OR	Oregon	0.2904	-0.0435	0.0298	0.1583	0.9397	0.0863	0.0000	0.3977
PA	Pennsylvania	0.6972	-0.0828	0.0297	0.0107	0.8690	0.0988	0.0000	0.4594
RI	Rhode Island	2.3942	-0.0643	0.0230	0.0107	0.8991	0.1019	0.0000	0.3656
SC	South Carolina	-0.8877	0.0277	0.0113	0.0227	1.0186	0.1315	0.0000	0.1939
SD	South Dakota	-1.2804	0.0545	0.0292	0.0759	0.8546	0.1260	0.0000	0.5606
TN	Tennessee	-0.7755	0.0051	0.0220	0.8190	0.8618	0.1263	0.0000	0.4200
TX	Texas	-0.4529	0.2911	0.0401	0.0000	0.8064	0.1141	0.0000	0.6618
UT	Utah	0.0801	0.0169	0.0212	0.4323	0.9599	0.0847	0.0000	0.2717
VT	Vermont	0.6691	-0.0108	0.0134	0.4264	0.7502	0.1447	0.0000	0.3043
VA	Virginia	-0.0882	0.0135	0.0059	0.0327	0.8146	0.1240	0.0000	0.1171
WA	Washington	1.2161	-0.0574	0.0148	0.0008	0.8107	0.1222	0.0000	0.2866
WV	West Virginia	-1.0840	0.1989	0.0341	0.0000	0.9383	0.1046	0.0000	0.5298
WI	Wisconsin	0.2764	-0.0002	0.0313	0.9955	0.8987	0.1082	0.0000	0.5181
WY	Wyoming	-0.4529	0.1273	0.0266	0.0001	0.9425	0.0920	0.0000	0.3673
Average across the U.S. states		0.0000	0.0455			0.8611			0.4005

Notes: The average WRI is computed across the 48 states on the U.S. mainland, since Alaska and Hawaii are excluded from our analyses. The WRIs of the states we included are re-scaled such that the mean and the standard deviation of the sub-sample are zero and one, respectively.

S4 Supplementary results

S4.1 House price dispersion between U.S. states

We divide the District of the Columbia and the 48 states on the U.S. main land (referred to as 49 U.S. states for short) into five regions following the regional categorization by National Geographic Society. The time series plots of log house price-to-income ratios during 1976-2014 for the 49 U.S. states separately are displayed in Figure S1. As can be seen the house price-to-income ratios of states within the same region share similar dynamic patterns. Figure S2 shows the log house price-to-income ratios aggregated at the five U.S. regions. Regional-level house price-to-income ratio is measured as the population weighted average of state level house price-to-income ratios, where the population weights are computed based on state level population data over the period 1976-2014. This figure shows that house price-to-income ratio has significantly increased in the West, and considerably dropped in the Southwest and the Southeast. The difference in house price-to-income ratio between the Southwest and the West is increasing overtime. In addition, a dispersion decomposition shows that around 70% of the between-state variance is due to the between-region differences (Figure S3).

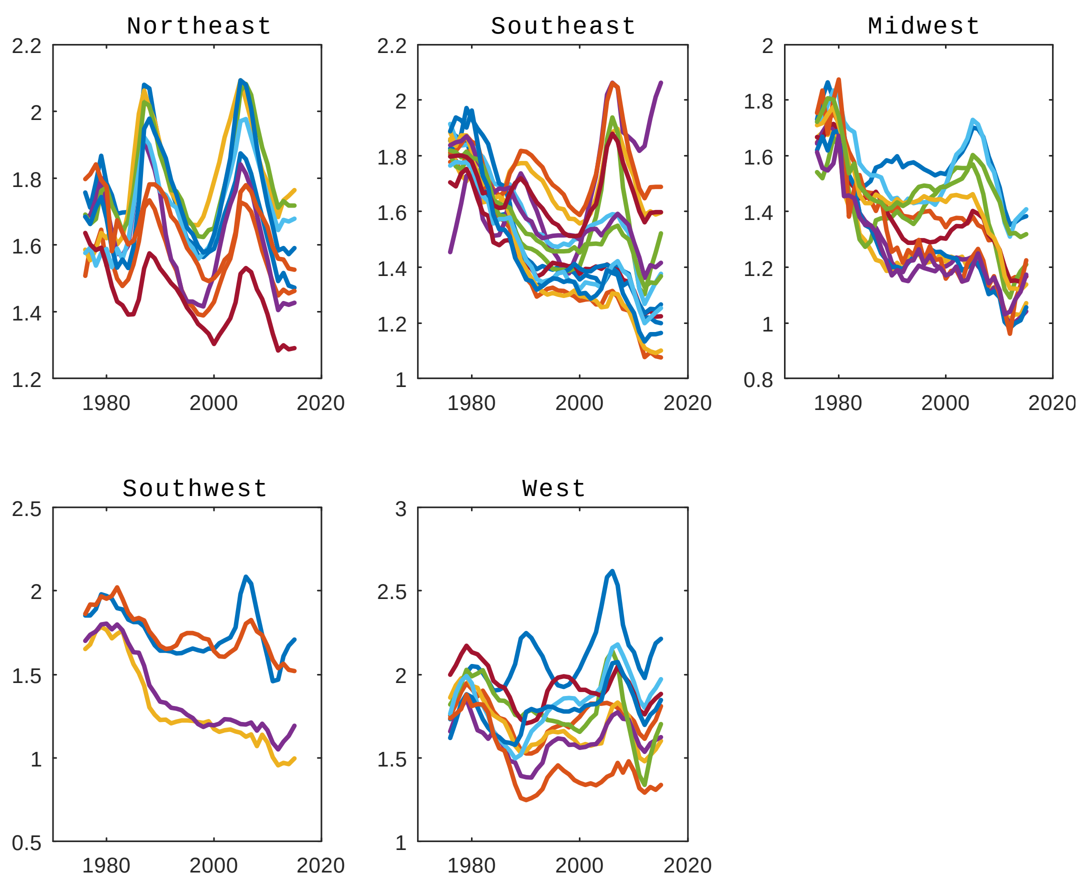

Figure S1: State level log house price-to-income ratios (grouped in to five U.S. regions)

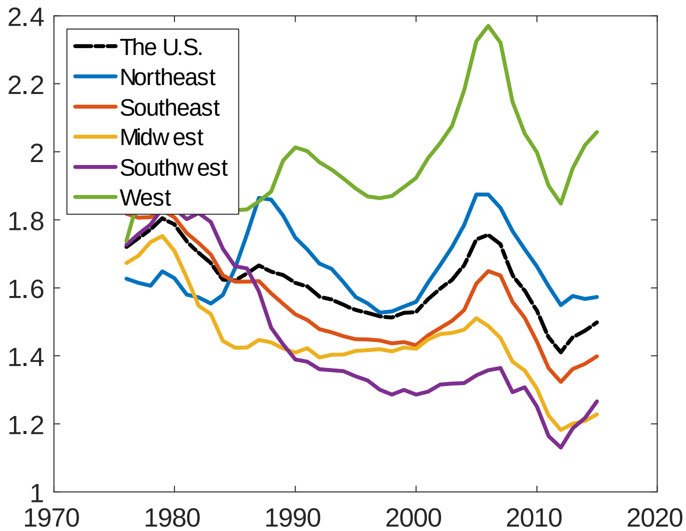

Figure S2: Log house price-to-income ratios of U.S. regions

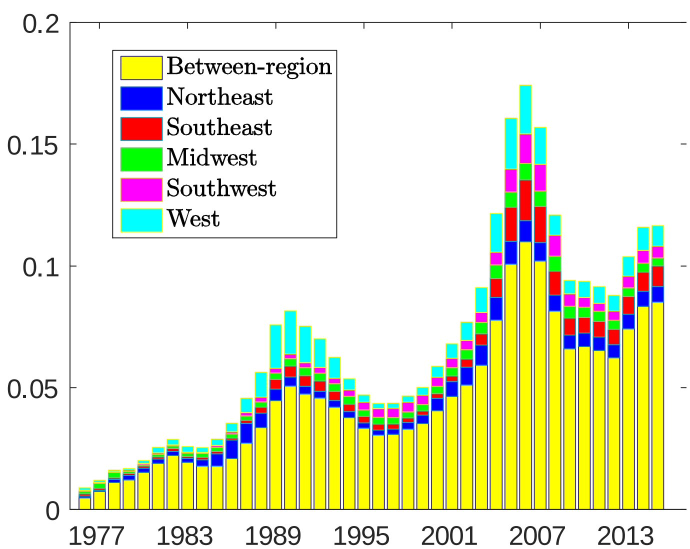

Figure S3: Regional decomposition of log house price-to-income ratio dispersion

Notes: This figure shows the decomposition of the variance of log house price-to-income ratio across U.S. states. The between-state variance is decomposed into between-region variance (yellow) and weighted within-region variances (blue, green, red, pink, cyan).

S4.2 House price dispersion between MSAs

We investigate the patterns of house price dispersions between Metropolitan Statistical Areas (MSAs) using data from Van Nieuwerburgh and Weill (2010). As shown in Figure S4, the dispersion of log house price-to-income ratios across MSAs has significantly increased during 1975-2007. We then decomposed the house price-to-income ratio dispersion between MSAs into within- and between- state dispersion. In doing so, we group the MSAs in the U.S. mainland by state. A multi-state MSA is equally split across the states shared by the MSA in question.[S1] For instance, Kansas city, which is on the Kansas-Missouri boarder, is equally divided between Kansas and Missouri. A "state" is considered as a group of MSAs,[S2] and the dispersion across these groups is referred to as *between-state dispersion* and the dispersion across MSAs within a group is referred to as *within-state dispersion*. Figure S4 shows the decomposition of between-MSA dispersion of log house price-to-income ratios. It is clear that increases in within-state dispersions contributed very little to the increases in the between-MSA dispersions during 1975-2007.

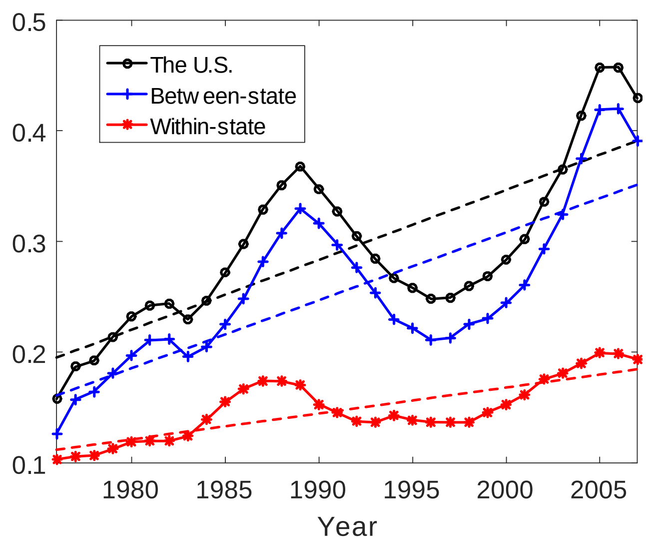

Figure S4: Dispersion of log house price-to-income ratios between- and within- U.S. states

Notes: The line designated with 'o' shows the dispersion of log house price-to-income ratio across all MSAs. The line designated with '+' shows the dispersion of log house price-to-income ratio across the U.S. states. The line designated with '*' shows the average of within-state dispersions, where within-state dispersion is the standard deviation of log house price-to-income ratio across the MSAs that are within a given state.

[S1] In the sample, around 10% of the MSAs are multi-state MSAs.

[S2] In the US, around 86% of its population live in MSAs. In the most populated states, such as, California, New York, Texas, Illinois, and Florida, more than 95% of their population live in MSAs.

S4.3 Land-use regulations in California and Texas

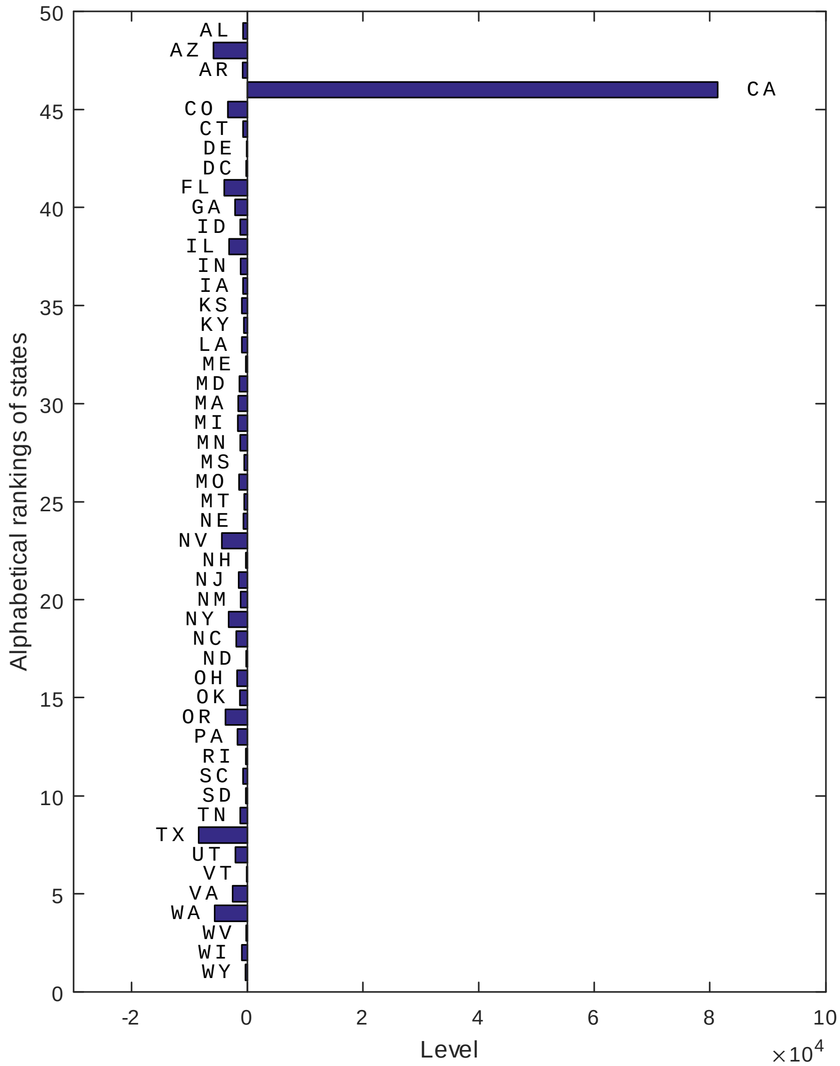

Figure S5: Effects of loosening of land-use regulations in California on population by states

Notes: This figure shows the counterfactual changes in U.S. population by states in 2014 in response to an exogenous increase in land supply growth rate of California to the national average.

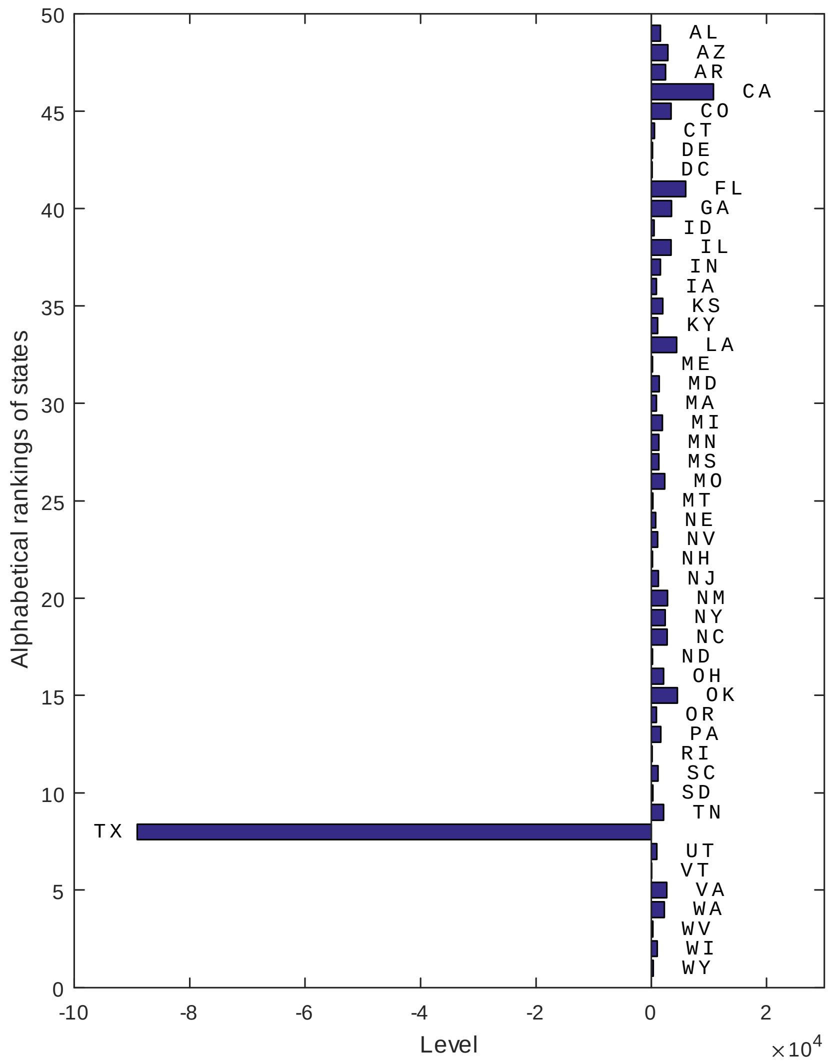

Figure S6: Effects of tightening of land-use regulations in Texas on population by states

Notes: This figure shows the counterfactual changes in U.S. population by states in 2014 in response to an exogenous decrease in land supply growth rate of Texas to the national average.

S5 Derivation of dispersion decomposition formula

Let U.S. states be indexed by i, and denote the collection of all states by $\mathcal{I}$, where $i \in \mathcal{I}$, and $\mathcal{I} = \{1, 2, ..., 49\}$. Let j denote the index for regions and $\mathcal{J}$ be the collection of all regions, where $j \in \mathcal{J}$ and $\mathcal{J} = \{1, 2, ..., 5\}$. Let $\mathcal{I}_j$ be the collection of the indices of the states in region j, with $\mathcal{I} = \cup_{j\in\mathcal{J}}\mathcal{I}_j$, and $\mathcal{I}_{j_1} \cap \mathcal{I}_{j_2} = \emptyset$, if $j_1 \neq j_2$. Further, let ω_i be the population share of State i. Define $\nu_j \equiv \sum_{i\in\mathcal{I}_j} \omega_i$ to be the weight of region j in the U.S. mainland, with $\sum_{j\in\mathcal{J}} \nu_j = 1$. It is now easily seen that the weight of State i in region j is ω_i/ν_j, with $i \in \mathcal{I}_j$, and $\sum_{i\in\mathcal{I}_j} \omega_i/\nu_j = 1$.

The dispersion of log house price-to-income ratios across all states is given by

$$\hat{\sigma}^2_{xt} \equiv \sum_{i\in\mathcal{I}} \omega_i(x_{it} - \bar{x}_t)^2, \qquad \text{where} \qquad \bar{x}_t \equiv \sum_{i\in\mathcal{I}} \omega_i x_{it}.$$

The dispersion of log house price-to-income ratios within region j is given by

$$\hat{\sigma}^2_{xjt} \equiv \sum_{i\in\mathcal{I}_j} \frac{\omega_i}{\nu_j}(x_{it} - \bar{x}_{jt})^2, \qquad \text{where} \qquad \bar{x}_{jt} \equiv \sum_{i\in\mathcal{I}_j} \frac{\omega_i}{\nu_j} x_{it},$$

and the dispersion of log house price-to-income ratios across regions is given by

$$\hat{\sigma}^2_{xrt} \equiv \sum_{j\in\mathcal{J}} \nu_j(\bar{x}_{jt} - \bar{x}_t)^2.$$

It is easy to see that the following decomposition of variance holds:

$$\begin{aligned}
\hat{\sigma}^2_{xt} &= \sum_{j\in\mathcal{J}}\sum_{i\in\mathcal{I}_j} \omega_i(x_{it} - \bar{x}_{jt} + \bar{x}_{jt} - \bar{x}_t)^2 \\
&= \sum_{j\in\mathcal{J}}\sum_{i\in\mathcal{I}_j} \omega_i \left[(x_{it} - \bar{x}_{jt})^2 + (\bar{x}_{jt} - \bar{x}_t)^2 + 2\,(x_{it} - \bar{x}_{jt})\,(\bar{x}_{jt} - \bar{x}_t)\right] \\
&= \sum_{j\in\mathcal{J}}\sum_{i\in\mathcal{I}_j} \omega_i\,(\bar{x}_{jt} - \bar{x}_t)^2 + \sum_{j\in\mathcal{J}} \nu_j \sum_{i\in\mathcal{I}_j} \frac{\omega_i}{\nu_j}\,(x_{it} - \bar{x}_{jt})^2 \\
&\quad +2\sum_{j\in\mathcal{J}} (\bar{x}_{jt} - \bar{x}_t) \sum_{i\in\mathcal{I}_j} \omega_i\,(x_{it} - \bar{x}_{jt})\,(\bar{x}_{jt} - \bar{x}_t) \\
&= \sum_{j\in\mathcal{J}} \nu_j\,(\bar{x}_{jt} - \bar{x}_t)^2 + \sum_{j\in\mathcal{J}} \nu_j \hat{\sigma}^2_{xjt} \\
&= \hat{\sigma}^2_{xrt} + \sum_{j\in\mathcal{J}} \nu_j \hat{\sigma}^2_{xjt}.
\end{aligned}$$

Finally, the average within-region dispersion, $\hat{\sigma}_{xwt}$, is given by

$$\hat{\sigma}_{xwt} \equiv \left(\sum_{j\in\mathcal{J}} \nu_j \hat{\sigma}^2_{xjt}\right)^{0.5},$$

where $\hat{\sigma}_{xjt}$ is the standard deviation of log house price-to-income ratios across states within region j, and ν_j is the population weight of region j.

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