Inelastic housing supply: A friction of inter-regional migration

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Abstract

Inter-regional migration is supposed to be driven by income inequality and usually viewed as the primary mechanism by which the U.S. labor market adjusts to the income disparity across regions. However, the migration mechanism has failed to equalize the income disparity in the last thirty-five years. This paper investigates the role of housing supply on inter-regional migration based on MSA level data. The regression results show that the housing supply constraints will stimulate the response in housing price growth but mitigate the response in population growth to employment shock. The slower population growth in lower elastic MSAs could be partially explained by their less responses to labor demand shock in employment. And I find that positive labor demand shocks increase population or employment through mitigating out-migrations, rather than absorb more in-migrations. However, the housing supply constraints accelerate the out-migrations, slow down the income convergence rate across MSAs and even exacerbate the regional income inequality in the last thirty-five years. Further, the friction of inter-regional migration leads to a statistically significant difference in demographic structure between regions with different level of housing constraints. MSAs with higher housing supply elasticities seemed to provide more opportunities to young people. However, housing supply constraints block up the redistribution of developing fruits to outsiders and capitalize more income into local housing values.

Keywords: Migration, Inequality, Income convergence, Housing supply constraints, Employment

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1. Introduction

Americans are known for their ability for moving from low-income to high-income places and migration is the primary mechanism by which the U.S. labor market adjusts to the income disparity across regions. (Barro and Sala-i Martin 1992; Blanchard and Katz 1992; Glaeser and Gottlieb 2014). However, the migration mechanism has failed to equalize the income disparity in the last thirty-five years. As shown in Figure 1 and Figure 2, higher-income regions in 1989 do not experience less income growth and more population growth during this period. During the same period, another data fact is the average housing cost in high-income places has grown faster than other places, as shown in Figure 3. Several researchers have documented that one of the reasons for the large relative increase in housing cost in some regions is the local housing supply constraints. (Mian and Sufi 2010; Saiz 2010; Dalton and Zabel 2011). The motivation of this paper is to investigate the role of housing supply constraints on inter-regional migration and regional income inequality in the last thirty-five years.

The mechanism I propose for explaining the relationship can be understood through the following story. When a region has a technology shock, local firms gain comparative advantages in the nation-wide industries due to the higher productivity, and then are motivated to create more labor demand for more profit. This labor demand shock pushes up wages, and therefore attract more in-migrations coming from lower productivity locations. Finally, the effects of the labor demand shock on wages will be diluted by the increase of labor supply. However, households' decisions to migrate depend not only on job prospects, but also on the relative cost of housing. As a rigid demand of people's living, the housing service's price in the higher productivity location will be stimulated by the increase of immigrants. Therefore, the process of in-migration will be mitigated by the higher cost of living. In particular, when housing supply is inelastic, the high prices of housing service could not be adjusted soon, and therefore act as a friction for inter-regional migration. For more details, I develop a general equilibrium framework about local employment, migration and the housing market in Section 2 to show how employment and the migration response differently to a labor demand shock in regions with different housing supply elasticities.

For finding empirical evidence about the role of housing supply constraints on inter-regional migration, I estimate a Vector Autoregression (VAR) model of population growth, housing price growth, employment growth, and wage growth using annual data from 311 US Metropolitan Statistics Areas (MSA) for the years 1990–2014. By using the calibrations of housing supply elasticities in Saiz (2010), MSAs are divided into two groups: one is less elastic MSAs, and the other is more elastic MSAs. The regression results show that the housing supply constraints will stimulate the response in housing price growth but mitigate the response in population growth due to a labor demand shock. Further, based on another data set containing migration data for years 2009-2015, I find that positive labor demand shocks increase population or employment through mitigating out-migrations, rather than absorbing more in-migrations. However, a lower housing supply elasticity will drive more people out of a region, even though there is a positive labor demand shock.

The paper shows that spatial adjustment frictions in the U.S. labor market can be large. This finding is supposed to inform macro economists to take the supply side of housing market into account when generating simulation models with potential implications for cyclical policy. Further, this finding raises concerns about regional inequality. Based on the regression results, higher income-level MSAs with less elastic housing supply experience relatively faster wage growth, but slower population growth. This indicates the housing supply constraints make the traditional regional income convergence mechanism fail to work and capitalize more income into housing values.

The rest of this paper is organized in the following way. In Section 2, I present literature reviews about relevant research questions. In section 3, I develop a model and use its simulation results to explain how an increase of housing supply elasticity changes migration patterns. In Section 4, I present the construction process of the panel data and the empirical strategy. Section 5 is the analyses of the regression results. Section 6 is the conclusion.

2. Literature review

Saiz (2010) finds that the local housing supply elasticity is an important factor in explaining the evolution of housing values. He finds that the housing supply is severely land-constrained by geography factors, including terrain elevation and presence of water bodies. Using geographic information system (GIS) techniques, he precisely estimates the amount of developable land in U.S. metropolitan areas and finds that it is a very strong predictor for the large variance in housing values across metropolitan statistical areas (MSA) during the period 1970–2000.

Further, he estimates specific housing supply elasticities for each U.S. metropolitan areas. First, he estimates metropolitan specific housing supply functions by taking citywide employment shocks, amenities and immigration shocks into account. At the second stage, he regresses the local average housing price growth on the metropolitan specific housing supply and its interaction terms with the percentage of developable land and Wharton Residential Urban Land Regulation Index created by Gyourko, Saiz, and Summers (2008)[1]. Finally, he argues that the supply elasticities can be well characterized as functions of both natural geography and man-made regulatory constraints,

[1] The index is constructed by Gyourko, Saiz, and Summers (2008) to capture the stringency of residential growth controls.

which in turn are endogenous to prices and demographic growth. And the estimated specific metropolitan housing supply elasticities are one of the main calibrations used in this paper.

Moretti (2011) documents the relationship between college premium and the relative cost of living. He deflates nominal wages using a location-specific CPI and find that at least 22% of the documented increase of the difference between the wage of college graduates and high school graduates is accounted for by spatial differences in the cost of living, which means college graduates are more likely living in expensive cities. Therefore, the college premium is lower in real terms than in nominal terms.

Then he investigates why college graduates are more likely living in expensive cities. He considers two alternative explanations. First, it is possible that college graduates move to expensive cities because of an increase of demand for skilled workers by firms in those cities. Alternatively, one of the reasons could be an increase in the supply of skilled workers in those cities driven by other factors. For example, it is possible that college graduates move into these cities for the local amenities. In this case, the higher cost of housing reflects demands for desirable local amenities, and this may indicate a significant increase in well-being inequality even if the increase in real wage inequality is limited.

Next, he gets into empirical data to test whether the demand-pull or the supply-push explain the change of the geographical location of different skill groups. He follows the ideas of Katz and Murphy (1992) to generate his empirical strategy: there will be positive correlation between college premium and the share of college graduates in local labor force, if under the demand-pull hypothesis. But, if under the supply-push hypothesis, there will be no positive relationship between them. Intuitively, increases in the relative demand of a factor of production in a city should result in increases in its equilibrium relative price there. Increases in the relative supply of factor of production in a city cannot cause an increase in its equilibrium relative price. By finding a positive relationship between the college premium and the share of college graduates, he concludes that changes in the geographical location of different skill groups are mostly driven by changes in their relative demand and the increase in well-being disparities between 1980 and 2000 is smaller than in nominal term.

Zabel (2012) estimates a VAR model of migration, employment, wages, house prices, and new housing supply using annual data from 277 MSAs in the U.S. for years 1990–2006. He gets the data about migrations across MSAs from the Internal Revenue Service (IRS), which provides annual extracts of individual tax returns to the US Census Bureau. He uses the county-to-county migration data based on these extracts, which contains 95% - 98% of all tax returns. To find an exogenous instrument to drive all the above factors, he follows Bartik (1991) in generating an exogenous labor demand variable and interaction terms of this labor demand variable and several housing factors: homeownership rates, the price elasticity of housing supply, and relative housing price levels across MSAs.

Zabel compares responses in migration, employment and wage at the 25th and 75th percentiles of the above housing market factors. The results show that variation in the above housing market factors not only affects cross-city migration but also the housing and labor markets. The house price responses are higher in the MSAs with lower housing supply elasticities in the presence of a labor demand shock. Further, the labor demand shocks can lead to substantial migration responses that depend on the housing market factors: there is more in- and out-migration in the MSAs with higher housing cost in response to a labor demand shock, though net-migration is similar in both cases. Therefore, he concludes that the high cost MSAs will experience more churning responses in migration to labor demand shocks.

Ganong and Shoag (2017) investigate the role of the housing supply constraint on the decline of cross-state income convergence rate in the last three decades. They argue it is the decline of cross-state migration that leads to the smaller income convergence rate and link the decline of migration to housing supply constraints. They construct a new panel measure of land use regulation showing that differences in incomes across states have been increasingly capitalized into housing prices.

3. A Model of Inter-Regional Migration, Housing Cost and Income Convergence

3.1 Labor Market

The description of the labor market corresponds to the version of the Pissarides (1985) model with imperfect mobility of workers across regions.

3.1.1 Household Migration Decision

In my model, the decision to migrate into one region (x) from other regions (o) will be functionally related to three principal variables: (1) the income gap, (2) the probability of obtaining a job in region y, and (3) the rental payments for minimum housing service[2]. They are determined endogenously in the overall framework, but each individual will take them as given.

The discounted present value of working in region x is:

$$W_t^x = w_t^x - a_o R_t^x + \beta E_t\{(1-\rho)W_{t+1}^x + \rho W_{t+1}^o\} \quad (1)$$

The discounted present value of working in other regions is:

$$W_t^o = w_t^o - a_0 R_t^o + \beta E_t\{(1-p_t)W_{t+1}^o + p_t * W_{t+1}^x\} \quad (2)$$

[2] This model does not take the fixed migration cost into account like usual, because the motivation of this model is to explain how variety in housing costs leads to different trends of migration.

where w_t^x is the wage in region x, w_t^o is the real wage in other areas, a_0 is the minimum housing demand of an individual, R_t^x is the rental payment of housing services in region x, R_t^r is the rental payment of housing services in other areas, ρ is the out-migration rate, and p_t is the job finding rate in region x.

3.1.2 Firm's Problem

On the firm's side, the firm's problem in the region x is to

$$\max_{\{n_{t+1}^x, v_t\}} E_0 \sum_{t=0}^{\infty} \beta^t [z_t n_t^x - w_t^x n_t^x - \gamma v_t] \quad (3)$$

$$\text{subject to } n_{t+1}^x = (1-\rho) n_t^x + v_t q_t \quad (4)$$

where γ is the flow cost of vacancies, and the firm takes aggregate productivity, z_t, the wage, w_t^x, and the job-filling probability, q_t, as given.

Then, the value to a firm in region x of having a vacancy is

$$V_t = -\gamma + \beta E_t\{q_t J_{t+1} + (1-q_t) * V_{t+1}\} \quad (5)$$

The value to a firm in region x of having a worker in the firm is:

$$\mathrm{J_t} = z_t - w_t^x + \beta E_t\{(1-\rho) J_{t+1} + \rho V_{t+1}\} \quad (6)$$

I assume free entry for all firms, which implies that in equilibrium:

$$\mathrm{V_t} = 0 \quad (7)$$

Using this condition, we can see that in equilibrium:

$$\frac{\gamma}{q_t} = \beta E_t J_{t+1} \quad (8)$$

The equation is called the job creation condition: it shows that the expected marginal cost from opening a vacancy is equal to the expected marginal benefit (given by the future value of having a productive worker tomorrow). Plug (6) into (8), we make the job creation condition related to the productivity and wage directly:

$$\frac{\gamma}{q_t} = \beta E_t \left[z_{t+1} - w_{t+1}^{x} + \frac{(1-\rho)\gamma}{q_{t+1}} \right] \quad (9)$$

3.1.3 Wage Determination

Then, I use the Nash Bargaining mechanism introduced by Nash (1950) and Rubinstein (1982) to determine wages.

The Nash Bargaining problem is:

$$\max_{w_t^x} \{ (W_t^x - W_t^o)^{\eta} (J_t - V_t)^{1-\eta} \} \quad (10)$$

where η is the bargaining power of the potential migrations. The first order condition (Nash Bargaining solution) is

$$W_t^x - W_t^o = \frac{\eta}{1-\eta} J_t \quad (11)$$

where in equilibrium, $V_t = 0$. Making use of the value functions, we can derive the equilibrium wage:

$$w_t^x = \eta z_t^x + (1-\eta) w_t^o + (1-\eta)(R_t^o - R_t^x) * a_0 + \frac{\gamma * v_t^x}{n_t^o} * \eta \quad (12)$$

3.1.4 Job-finding rate and Job-filling rate

Following ideas of Pissarides (1985), I formalize the idea of matching between workers and firms with a CRS matching function:

$$M_t^x = MN_t^{o\,\xi} * V_t^{x\,1-\xi} \quad (13)$$

where N_t^o is the number of labor force contributed by migrations, V_t^x is the number of vacancies created in region x, and M is an indicator of matching efficiency.

Dividing by the total labor force, I obtain

$$m_t^x = Mn_t^{o\,\xi} * v_t^{x\,1-\xi} \quad (14)$$

Given the CRS properties of $m_t^x(n_t^o, v_t^x)$, the job-finding rate for job searchers is

$$p_t = \frac{m_t^x(n_t^o, v_t^x)}{n_t^o} \quad (15)$$

The firm's job-filling rate can analogously be defined as

$$q_t = \frac{m_t^x(n_t^o, v_t^x)}{v_t^x} \quad (16)$$

3.2 Housing market

Consider a household who owns a_t units of housing at period t. Let $U^x(a_t^x)$ denote its lifetime expected discounted utility. The household's problem can be written recursively as:

$$U^x(a_t^x) = \max_{c_t, d_t, a_{t+1}} E\{c_t^x + v(d_t^x) + \beta U^x(a_{t+1}^x)\} \quad (17)$$

$$\text{s.t. } c_t^x + R_t^x d_t^x + h_t^x a_{t+1}^x = w_t^x + (h_t^x + R_t^x)a_t^x + \pi_t^x \quad (18)$$

The first term between brackets in equation (17) is the utility of consumption; The second term is the utility of housing services; The third term is the continuation value in the next period. Thus, from (17) to (18), the household chooses its consumption, c_t, housing services, d_t, and real estate holdings, a_{t+1}^x, in order to maximize its lifetime utility subject to a budget constraint. The left side of the budget constraint, (18), is composed of the household's consumption, the payment of the rent for housing services, and its end-of-period holdings of housing. The right side is the household's income associated with its employment status, w_t^x, the value of its real estate and augmented for the rental payment, $(h_t^x + R_t^x)a_t^x$, and the profits of the local firms, π_t^x.

The starting point here is a part of the dynamic equilibrium model developed by Branch, Petrosky-Nadeau and Rocheteau (2015). Their model replicates the labor reallocation process between housing and non-housing sectors for last thirty decades in US. The reason why I regard this model as a benchmark is that using consistent methods make it convenient to compare the differences between its results and mine, and then help me state my suggestions for improvements clearer. The household's problem can be solved by following:

At first, substitute c_t^x from (18) into (17) to obtain a bellman equation:

$$U^x(a_t^x) = \max_{d_t^x > 0}\{v(d_t^x) - R_t^x d_t^x\} + \max_{a_{t+1}^x}\{\beta E U^x(a_{t+1}^x) - h_t^x a_{t+1}^x\} + w_t^x + (h_t^x + R_t^x)a_t^x + \pi_t^x \quad (19)$$

From (18), the quantity of housing services rented by the household solves $v'(d_t^x) = R_t^x$, where d_t is independent of the household's housing wealth and the utility of housing services is an increasing concave function of housing services, $v(d_t^x) = \frac{1}{1-\sigma}[d_t^x]^{1-\sigma}$. Therefore, the optimal quantity of housing services is equal to $[R_t^x]^{-\frac{1}{\sigma}}$, when the household is a price taker. Then the total demand for housing services in x sector is

$$D_t^x = N_t^x [R_t^x]^{-\frac{1}{\sigma}} \quad (20)$$

where N_t^x is the total population in region x.

When it comes to supply side, the total supply of housing services in x sector is the sum of the housing stock at the beginning of the period, A_0^x, and new supply, S_t^x, where S_t^x is a function of the rent payment:

$$S_t^x = A_0^x * \varepsilon^x * \frac{R_t^x - R_0^x}{R_0^x} \quad (21)$$

The second term on the right side of the equation is the housing supply elasticity with respect to price change in sector x. Note the initial housing stock is A_0^x, rather than A_{t-1}^x. The reason is that the housing supply elasticity estimated by Saiz (2010) is a measure of the long-run change of housing stock. Then the supply function of housing services in region x is:

$$A_t^x = A_0^x * (1 + \varepsilon^x * \frac{R_t^x - R_0^x}{R_0^x}) \quad (22)$$

Finally, the rental payment is determined by the market equilibrium, which means set total demand, D_t^x, equal to total supply, A_t^x. I get:

$$R_t^x = \left\{\frac{a_0^x n_0^x}{n_t^x}[1 - \varepsilon + \varepsilon * R_t^x * (a_0^x)^\sigma]\right\}^{-\sigma} \quad (23)$$

Further, by deriving Bellman and Black-Scholes equations based on (18), the price of housing is determined by a liquidity-augmented asset pricing equation:

$$h_t^x = E_t[\sum_{j=1}^{\infty} \beta^j R_{t+j}^x] \quad (24)$$

The above equation indicates that the price of one unit of housing service is equal to its future discounted rental payments.

3.3 Equilibrium dynamics

To provide a definition of dynamic equilibrium for the model, I assume the economy is driven by productivity improvement, which is formulized in the following way:

$$\log(z_t) = \rho_z * \log(z_{t-1}) + \varepsilon_z \quad (25)$$

where ε_z represents the shock to productivity and $\mathrm{Var}(\varepsilon_z) = \sigma_z^2$.

Therefore, the equilibrium of the model is a bounded sequence, $\{n_t^x, R_t^x, h_t^x, n_t^o, w_t^x, p_t, q_t\}_{t=0}^{\infty}$, which solves (9), (12), (15), (16), (23), (24) and (25).

3.4 Calibration

I calibrate the discount factor β, the risk aversion parameter in the CRRA utility function of housing service σ, the out-migration rate ρ, the original bargaining power of workers η, the matching elasticity ξ, productivity shock σ_z, productivity auto-correlation coefficient ρ_z, steady-state productivity z_{ss}, vacancy cost γ, matching efficiency M, housing supply elasticity ε_s, and wage in other regions w_t^o. Table A1 in Appendix A summarizes the calibration and related sources or targets.

Note the key point about the calibrations is to keep all other parameters the same when processing simulations for different housing supply elasticities. Because the objective of this model is to test if there will be different migration outcomes of regions with different housing supply elasticities, rather than replicate the differences in real world, some parameter values are not calibrated based on data.

3.5 Simulation results and propositions

By setting different calibrations to housing supply elasticity when processing simulations, I get different results of migration responses to the same productivity shock. The impulse response figures based on different simulation calibrations are showed later in the article (Figure 5 – 6). By comparing Figure 5 and Figure 6, I get the following propositions:

Proposition 1. regions with higher wages will experience more responses in in-migration, to the same productivity shock and ceteris paribus.

Proposition 2. regions with larger housing supply elasticities will experience more responses in in-migration, to the same productivity shock and ceteris paribus.

Proposition 3. regions with smaller housing supply elasticities will experience more responses in housing price growth and wage growth, to the same productivity shock and ceteris paribus.

4. Empirical evidence

In the following section, I collect data and construct regression models to find empirical evidence for the three propositions based on the theoretical model.

4.1 Data description

The data used in this analysis consists of information on population, in- and out-migration, rental payments, house prices, employment, and wages at the MSA-level (across the United States) for the years 1990–2014 (Note the labor demand shock is not calculated for the year 1998, because the industry identification is changed from SIC to NAICS in 1998). Since MSA definitions change over time, I collect data at the county level and aggregate to the MSA level using the November 2007 MSA definitions.

I calculate the housing price growth rate based on the Housing Price Index (HPI) data supplied by Federal Housing Finance Agency (FHFA). The HPI is a weighted, repeat-sales index, meaning that it measures average price changes in repeat sales or refinancings on the same properties. This information is obtained by reviewing repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac since January 1975. Note HPIs are not comparable across MSAs, because all the MSAs' housing prices are indexed to be 100 in 1990. Therefore, I only analyze the differences in annual growth rate of housing price within MSAs.

Further, I collect data about median rental payments to capture renters' housing costs. The data is called the Zillow Rent Index (ZRI): A smoothed, seasonally adjusted measure of the median estimated market rate rent across a given region and housing type. ZRI is a dollar-denominated alternative to repeat-rent indices. A historical quarterly data set about ZRI at the county-level is available on Zillow. In the data set, rents are chained back in time using annual U.S. Census Bureau American Community Survey data from 2006 until the start of the Zillow Rent Index. Before 2006, rents are chained back using Decennial Census data.

The migration data comes from IPUMS National Historical Geographic Information System (NHGIS). The migration data offers data about geographic mobility for current residents at the county level for the years 2009-2015. Based on 5-year PUMS data from the American Community Survey (ACS), NHGIS group collect data of total population, current residents who are living in the same MSA one year ago and who are not[3]. Therefore, the number of in-migration is the head count of current residence who are not living in the same MSA one year ago. The head count of out-migration equals to the total population one year ago minus the number of people who are

[3] It is not a fluctuation happening in a specific year, but a 5-year average treating this year as an end of the period.

living in the same MSA this year[4]. And the net-migration is the difference between in-migration and out-migration. Further, I divide them by the total population one year ago to calculate the in-migration rate, out-migration rate and net-migration rate.

I have another data set, which contains population growth rate for the years 1990-2014 to capture the change of migration patterns. The data comes from the NATIONAL BUREAU of ECONOMIC RESEARCH (NBER). The Census Bureau's Population Estimates Program publishes population estimates each year from 1970 to 2014. For checking if population growth is a good replacement of migration rate, I will use the two data sets to run the regressions in sector 4.2 separately.

The employment data comes from the County Business Patterns (CBP). CBP is an annual series that provides subnational economic data by industry. This series includes the number of establishments, employment during the week of March 12, first quarter payroll, and annual payroll. I use the category introduced by Mian and Sufi (2012) to divide total employment into three sectors based on 4-digit NAICS code: local service sector, construction sector and non-local service sector.

To find an exogenous labor demand shock, I follow the method introduced by Bartik (1991). The predicted change in labor demand is a weighted average of national industry growth rates, where the weights are equal to the share of an industry's employment relative to total metropolitan area employment. To be specific, the formula I use is:

$$\mathrm{shock_{it}} = \sum_{j=1}^{J} \frac{e_{ij,t-1}}{e_{i,t-1}} \left(\frac{\overline{e_{ijt}} - \overline{e_{ij,t-1}}}{\overline{e_{ij,t-1}}} - \frac{e_t - e_{t-1}}{e_{t-1}}\right) \quad (26)$$

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[4] The estimated out-migration will be violated by natural population growth rate. However, based on Hill et al (2012), migration is the main driver of population growth in U.S. cities. Therefore, the violation will be too small to affect the overall fluctuations of population growth.

Where j indexes industry and J is the total number of industries, e is the total employment. Therefore, e_t is national employment in year t, $e_{ij,t-1}$ is employment in industry j in MSA i in year t-1, and $\overline{e_{ijt}} = \mathrm{e_{jt}} - e_{ijt}$. The formula above shows that the industry employment growth rates are adjusted to exclude local employment growth when calculating industry employment growth rates and express industry employment growth relative to national employment growth. For the years 1990–1997, employment in each metropolitan area is defined at the 2-digit SIC level using data from the County Business Patterns and aggregated to the metropolitan level. For the years 1999–2014, I define industries using 3-digit NAICS. I omit the construction sector and local service sector because changes in construction industry employment are likely to be related to housing supply regulation and employment changes in local service sector in one MSA cannot indicate labor demand shocks in other regions.

4.2 Empirical strategy

The approach I use to test how the housing supply constraint affects migration responses to a labor demand shock is a Vector autoregression model, because most of factors are endogenously affected by others like I have talked in the introduction section. I use the PVAR Stata package introduced by Love (2016) to run this model and treat the labor demand shock as an exogenous variable. Further, the MSAs are divided into two groups based on their housing supply elasticities[5]:

$$\mathrm{e_i} = 1 \; if \; elasticity_i \leq the \; median \; of \; the \; elasticities$$

$$\mathrm{e_i} = 0 \; if \; elasticity_i > the \; median \; of \; the \; elasticities$$

[5] This kind of grouping allows me to generate different IRFs by running the model separately for two groups later, but it is not consistent to the previous researches (Zabel 2012; Mian and Sufi 2012). To eliminate possible concerns, the results using same method of grouping to the previous researches are attached in Appendix C.

Then I add an interaction term of the treatment indicator and the labor demand shock into this model to capture the influence of the housing supply elasticity on the dependent variables. The specific model is:

$$Y_{\text{it}} = \begin{bmatrix} eog_{it} \\ wog_{it} \\ elg_{it} \\ wlg_{it} \\ ecg_{it} \\ wcg_{it} \\ hg_{it} \\ pg_{it} \end{bmatrix} = \beta_0 + \sum_{j=1}^{4} \alpha_j Y_{i,t-j} + \beta_1 shock_{it} + \beta_2 e * shock_{it} + \beta_3 lw_{t-1} * shock_{it} + \beta_4 lr_{t-1}$$

$$* shock_{it} + \beta_5 lg_{t-1} + u_i + v_t + \varepsilon_{it} \quad (27)$$ [6]

where i indexes MSAs and t year, and u_i is an MSA fixed effect. The MSA fixed effects capture unobserved, time invariant MSA-specific factors that affect the dependent variables in the model. The dependent variable set Y_{it} contains annual employment growth rate in the non-local service sector, eog_{it}, annual employment growth rate in the local service sector, elg_{it}, annual employment growth rate in the construction sector, ecg_{it}, annual wage growth rate in the non-local service sector, wog_{it}, annual wage growth rate in the local service sector, wlg_{it}, annual wage growth rate in the construction sector, wcg_{it}, annual housing price growth rate, hg_{it}, and annual population growth rate, pg_{it}. Other control variables (lw_{t-1}, lr_{t-1} and lg_{t-1}) are the level of incomes, the level of medium rental payments for housing service and the level of difference between wages and housing costs at t-1.

Moreover, I generate another regression model to test if there are consistent results based on the migration data from 2009 to 2015:

[6] The labor demand shock is standardized into 0-1 scaling: each variable in the data set is recalculated as (shock – min(shock))/(max(shock) – min(shock)). By doing that, all shocks are positive, but relative intensities are different.

$$inmigr_{\mathrm{it}} = \gamma_0 + \sum_{j=1}^{2} \alpha_j inmigr_{i,t-j} + \sum_{j=0}^{1} \gamma_{1j} shock_{i,t-j} + \sum_{j=0}^{1} \gamma_{2j} e_i * shock_{i,t-j} + \sum_{j=0}^{1} \gamma_{3j}\, lg08_i * shock_{i,t-j} + u_i + v_t + \varepsilon_{it} \quad (28)$$

where $inmigr_{\mathrm{it}}$ is the in-migration rate in year t at MSA i. Another control variable ($lg08_i$) is the difference between wages and housing costs in 2008 (one year before the period of the migration data).

This VAR model here is similar to the one developed by Zabel (2012), which I have mentioned in the section of literature review. The model I have developed makes the following differences: First, the dependent variable in my paper is population growth rate and migration rate, rather than the head count. The reason I take the rate for population and migration is that I want to control for the different endowments of regions. For example, 1000 increase of in-migration may indicate different relative changes of economic factors for Houston (population: 2.3m) and Lawrence, KS (population: 0.1m). Further, given the bartik labor demand shock also capture relative changes within specific regions, it is better to keep all factors consistently. Second, I use different data sets. I use population growth rate as a replacement of migration for the years 1990-2014, and another data set containing migration data is from IPUMS for years 2009-2015. Third, the employment is divided into three sectors based on Main and Sufi (2012): local-service sectors, construction sectors, and non-local service sectors, which makes it possible to analyze different responses to labor demand shock by industries.

4.3 results analyses

Comparing figure 7 to figure 8, the less elastic MSAs will experience faster and more growth in housing price response to labor demand shock. But they do not experience faster and more growth in population growth. According to the first column in Table 3, MSAs with higher housing cost will experience less population growth response to labor demand shock. Further, MSAs with lower housing supply elasticities will experience 0.1008 standard deviation less population growth response to labor demand shock. This indicates that the housing supply constraints will stimulate the response in housing price growth but mitigate the response in population growth to labor demand shock.

The differences of population responses to labor demand shocks can be partially explained by different employment responses. Based on Table 3, MSAs with lower housing supply elasticities will experience 0.0836 standard deviation less employment growth response to labor demand shock in the non-local service sector. The difference in the local service sector is 0.0148. The results of the local sector's employment are consistent to my findings of population responses, because the employment in this sector is highly related to local populations. MSAs with higher housing supply elasticities will experience a faster and more population growth, which indicates more demands for local service. ((More details about calculation procedure are in Appendix B).

The findings based on the other data set makes the migration responses to labor demand shock clearer. According to Table 4, less elastic MSAs will experience more out-migration and less in-migration responses to a standard deviation increase of labor demand shock, where the results of net-migration responses are consistent to the findings based on the population data set. The difference in the standard deviation changes in net-migration, in-migration and out-migration responses between two groups are economically significant, which are 0.63, 0.15 and 1.41 to one standard deviation increase of labor demand shock (More details about calculation procedure are in Appendix). Further, another interesting finding is that the effect on out-migration rate is much larger than on in-migration rate. This indicates that positive labor demand shocks increase population or employment through mitigating out-migrations, rather than absorb more in-migrations.

To test the concerns on the income convergence, I calculate the average annual wage growth rate, population growth rate, net-migration rate, in-migration rate and out-migration rate for each MSA. Then I regress them on their initial wage levels, controlling for the average annual labor demand shock and mean temperature on January (instruments for local amenity). According to Table 5, I find that higher income-level MSAs experience less wage growth during this period if they are in the more elastic group, which means a normal pattern of income convergence happens in these MSAs for the time 1990-2015. However, for less elastic MSAs, higher income-level MSAs even have faster wage growth, which means the housing supply constraints capitalize the increase of incomes into housing values, rather than more beneficiaries. The results showed in Table 6 are consistent to this statement, less elastic MSAs extrude more out-migrations, and finally make less people taste the economic developing fruits. Finally, according to Table 7, the friction of inter-regional migration leads to a statistically significant difference in demographic structure between two groups: MSAs with higher housing supply elasticities have higher rates of young people (age from 19 to 35) and higher rates of infants (age from 0 to 5). Given the average rate of young people and children in each MSA is 0.2 and 0.06 in 2016, the semi-elasticities of the differences are both about 5%. Although it is not economically significant right now, the different rates of both young people and infants should draw a concern of the potential significant change of demographic structure in the future.

5. Conclusion

This paper investigates the role of housing supply on inter-regional migration based on MSA level data. By using the calibrations of housing supply elasticities in Saiz (2010), MSAs are divided into two groups: one is less elastic MSAs, and the other is more elastic MSAs. The regression results show that the housing supply constraints will stimulate the response in housing price growth but mitigate the response in population growth to employment shock. MSAs with lower housing supply elasticities will experience 0.1008 standard deviation less population growth response to labor demand shock. Further, based on another data set, the difference in the standard deviation changes of in-migration and out-migration responses between two groups are 0.15 and 1.41 to one standard deviation increase of labor demand shock. And I find that positive labor demand shocks increase population or employment through mitigating out-migrations, rather than absorb more in-migrations. However, less housing supply elasticity will drive more people out of a region, even though there is a positive labor demand shock. It is interesting to find valid instruments to test whether the increase of housing price will cause the increase of out-migration in the future.

The slower population growth in less elastic MSAs could be partially explained by their less responses to labor demand shock in employment. MSAs with lower housing supply elasticities will experience 0.0836 standard deviation less employment growth response to labor demand shock in the non-local service sector and 0.0148 standard deviation less in the local service sector. This finding is supposed to inform macro economists to take the across-regional variations of housing supply into account when generating simulation models containing housing sector.

About the income convergence concerns, the housing supply constraints slow down the income convergence rate across MSAs and even exacerbate the regional income inequality in the last thirty-five years. Further, the friction of inter-regional migration leads to a significant difference in demographic structure between two groups. MSAs with higher housing supply elasticities seemed to provide more opportunities to young people. However, housing supply constraints block up the redistribution of developing fruits to outsiders and capitalize more income into housing values. Several researchers have pointed out the positive relationship between housing values and residents welfares (like education spending (Zabel 2014) and city infrastructure (Zhang 2015)). This may indicate that the housing supply constraints make the regional inequality begin at birth and harder to be broken by migration. It is interesting to analyze in the future why local firms choose to pay more wages to local workers, rather than move away.

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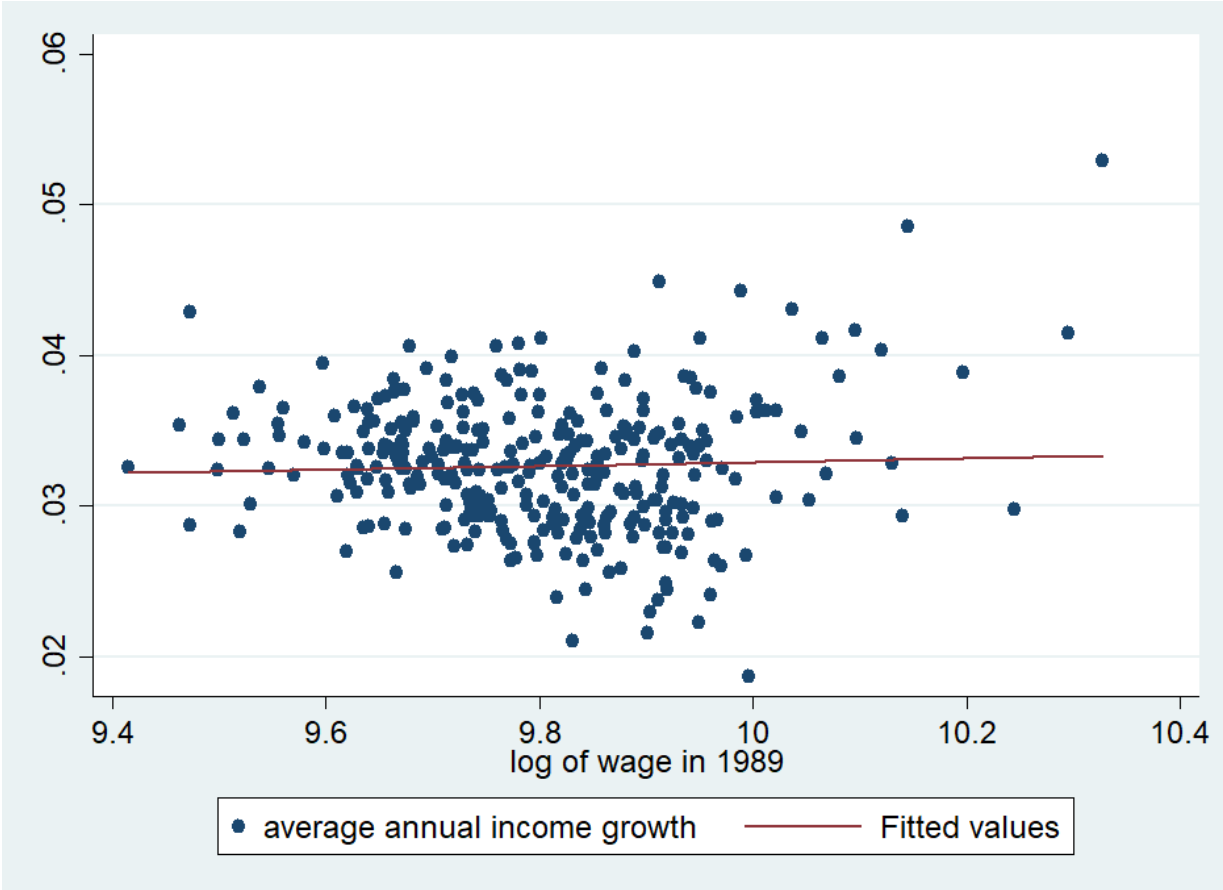
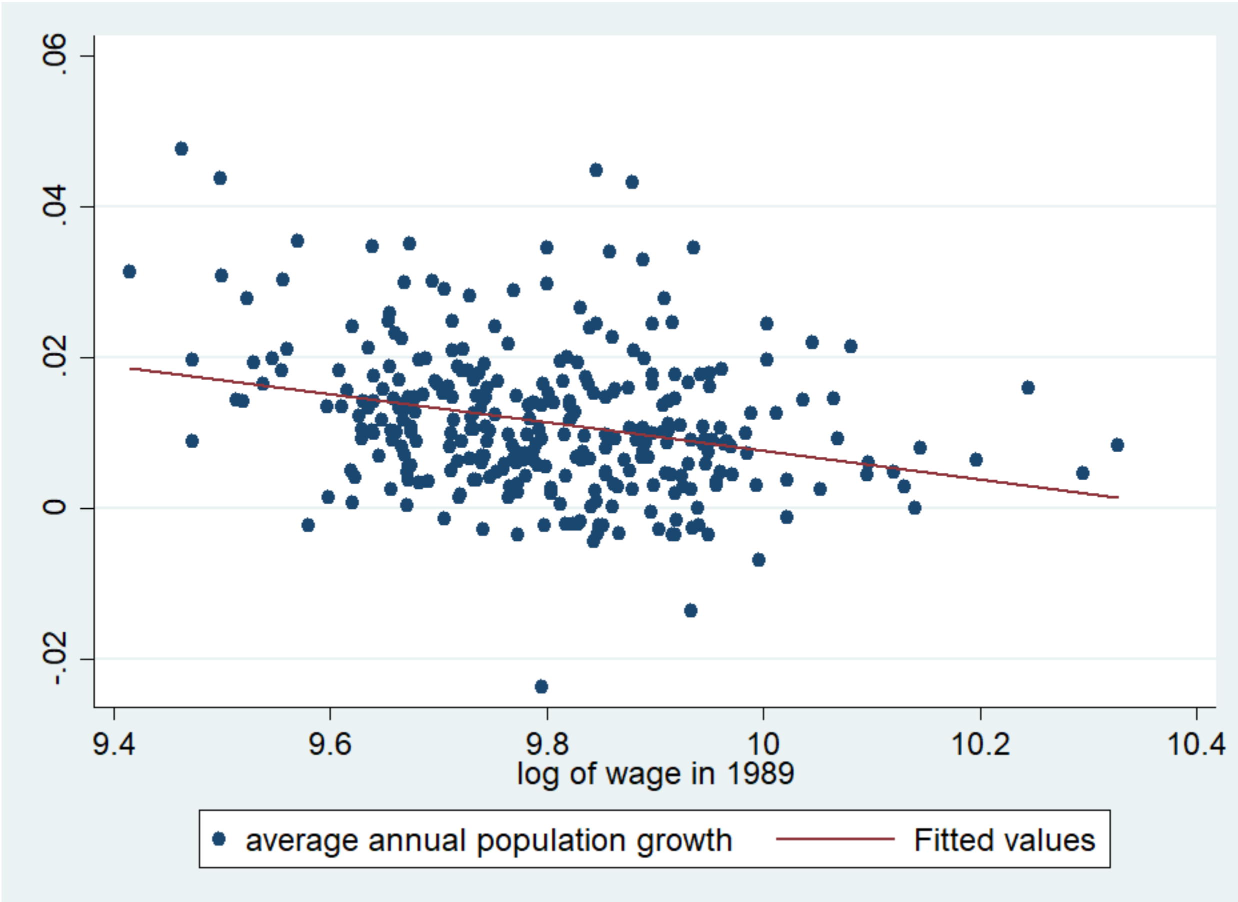
Figure 1 Average income growth across MSAs from 1990-2015



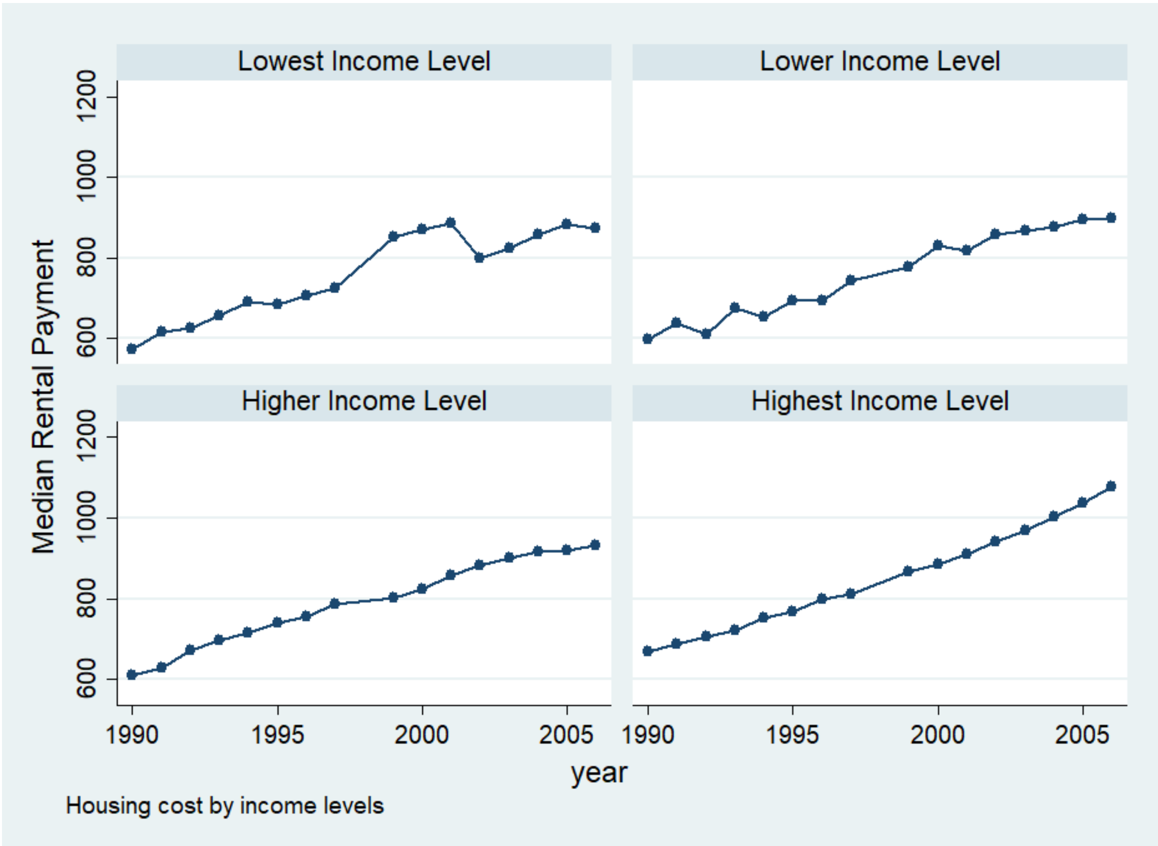
Source: County Business Patterns

Figure 2 Average population growth across MSAs from 1990-2015



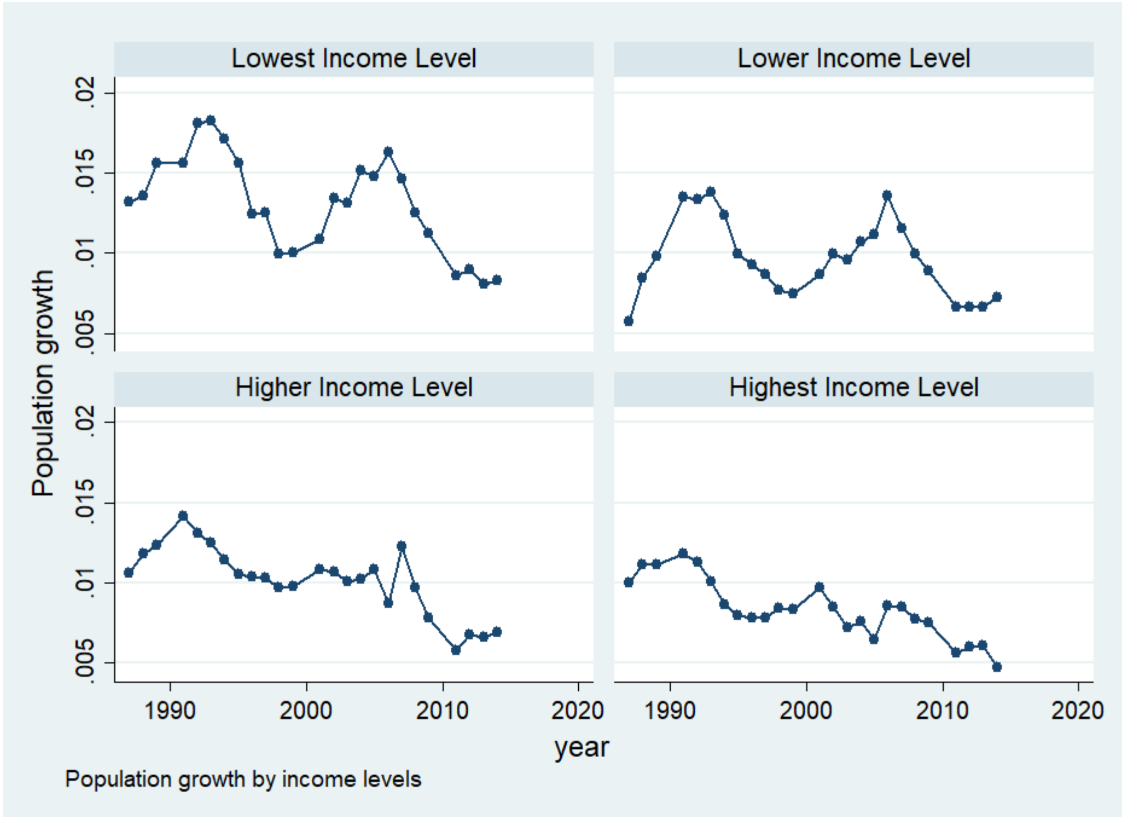
Source: County Business Patterns and Census U.S. Intercensal County Population Data

Figure 3 Time trend of medium rental payment by different wage-level groups



Source: County Business Patterns and Zillow research

Figure 4 Time trend of population growth by different wage-level groups



Notes: This figure shows that lower income level regions experience more fluctuations in population growth in the last thirty-five years. However, higher income level regions experience cyclical decline during this period. Further, the population growth in higher income level regions tends to be slower than lower income level regions, which does not account with the hypothesis of migration mechanism. Source: County Business Patterns and Census U.S. Intercensal County Population Data

Figure 5 IRFs with lower housing supply elasticity based on simulation model

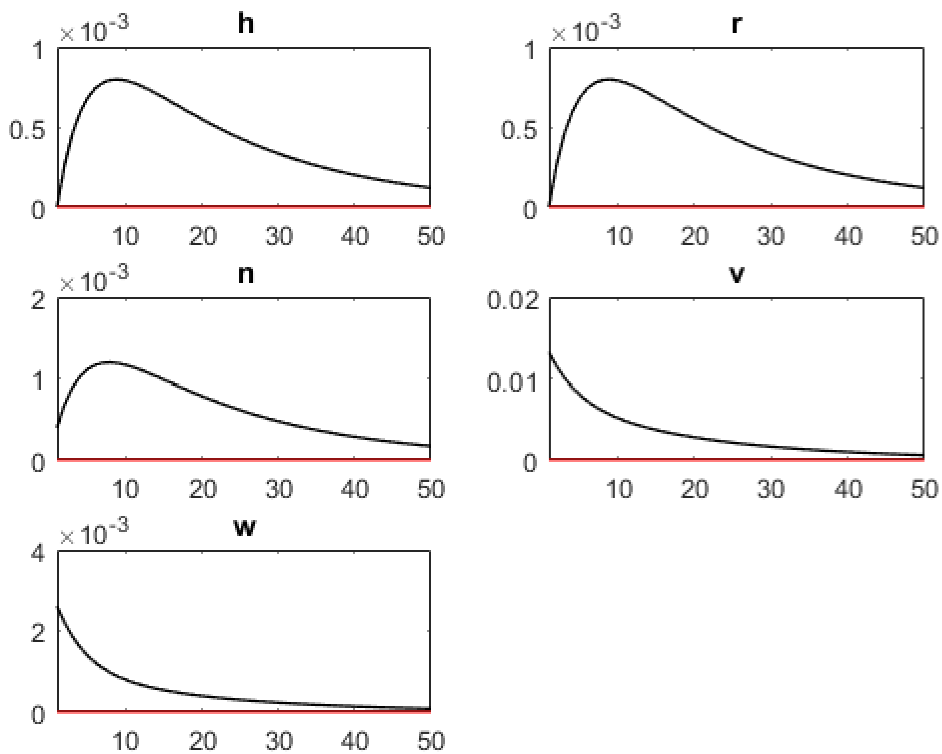


Figure 6 IRFs with higher housing supply elasticity based on simulation model

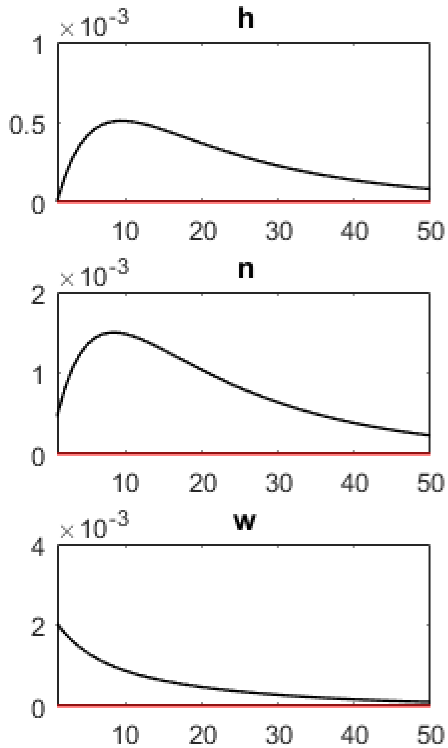


Figure 7 IRFs with lower housing supply elasticity based on panel data

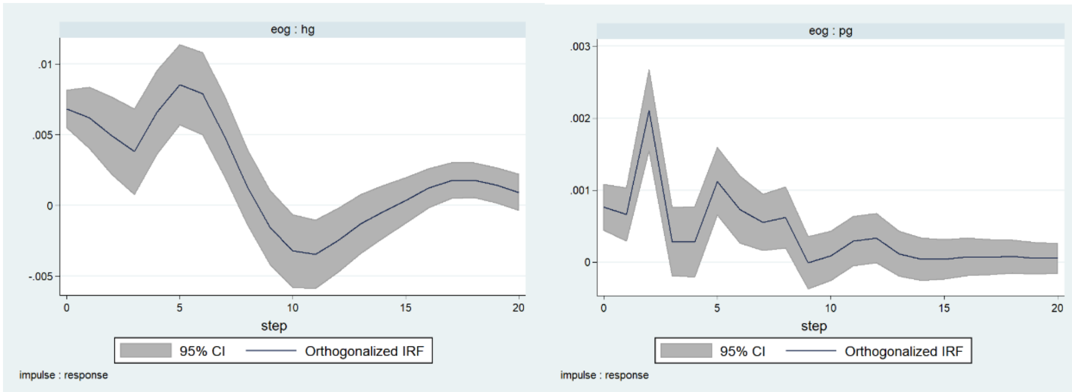
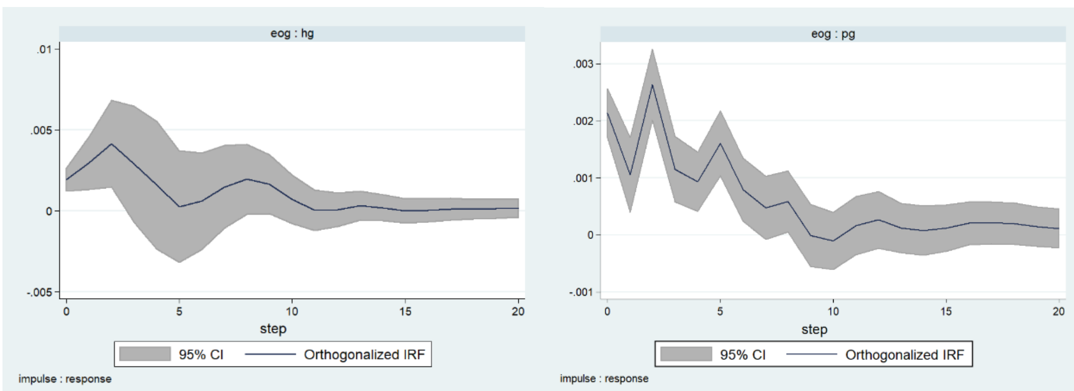
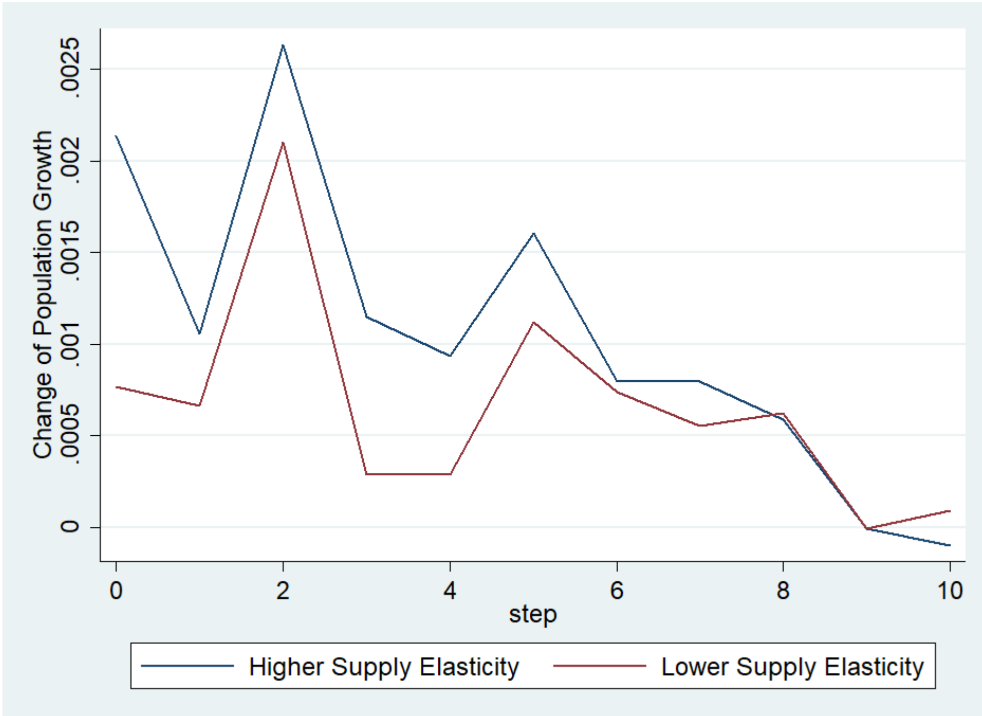


Figure 8 IRFs with higher housing supply elasticity based on panel data



Notes: I estimate the VAR model (equation 27) without time dummies for two groups and generate impulse response diagrams separately, by assuming the impulse coming from the annual employment growth rate in non-local service sector, eog_{it}. (The difference in standard deviation of eog_{it} for two groups is small (sd = 0.0531 if $\mathrm{e_i} = 1$ and 0.0503 if $\mathrm{e_i} = 0$), which means the impulse strength will be similar.) Comparing the pictures on the right of Figure 7 and Figure 8, there is at least a significant difference in the sense of contemporaneous responses (at step 0). Comparing the pictures on the left of Figure 7 and Figure 8, there is at least two significant differences: one is at step 0, the other is at step 5.

Figure 9 IRFs of population growth based on panel data



Notes: Figure 9 is a combination of population growth responses in two groups (pictures on the right of Figure 7 and Figure 8). The relative strait line allows me to replicate the pictures by pining down the corresponding values. This figure shows that the long-run population growth is more responsive to the labor demand shock in higher supply elasticity regions, without testing the differences are whether significant or not.

Table 1 Data Source

Variable	year	Source
Annual average income per worker	1990-2015	County Business Patterns
Median rental payments	1990-2015	Zillow research
Housing price index	1990-2015	Federal Housing Finance Agency
Labor demand shock	1990-2015	Bartik Methods (1991)
Migration	2009-2016	IPUMS NHGIS
Housing supply elasticity	-	Saiz (2010)
Population	1990-2014	Census U.S. Intercensal County Population Data

Table 2 Summary Statistics

Variable	Mean	Median	Std.Dev.	Min	Max
Population growth rate	1.14	0.93	1.61	-28.52	67.48
Housing price growth rate	2.70	2.79	5.61	-52.23	28.97
Employment growth rate in non-local service sector	2.07	1.88	5.14	-29.99	54.90
Employment growth rate in construction sector	13.18	2.03	51.76	-216.17	351.70
Employment growth rate in local service sector	6.00	1.15	58.98	-241.64	303.00
wage growth rate in non-local service sector	3.19	3.22	3.17	-17.47	24.74
wage growth rate in local service sector	4.52	3.02	18.88	-104.56	105.14
wage growth rate in construction sector	3.87	3.69	12.19	-79.16	128.25
Net-migration rate	0.99	0.76	3.11	-42.90	72.04
In-migration rate	6.17	5.49	2.55	2.09	19.90
Out-migration rate	5.42	4.77	3.75	0.18	45.03

Table 3 The impact of labor demand shock on employment growth rate (1990-2014)

	(1)	(2)	(3)	(4)
VARIABLES	Population growth	Employment growth in the non-local sector	Employment growth in the local-service sector	Employment growth in the construction sector
$shock$	-0.9972***	-6.6073***	-5.3397*	-3.1658
	(0.3771)	(1.3394)	(3.0993)	(6.0433)
$e_i * shock$	-0.0634***	-0.1688**	-0.3402*	-0.3708
	(0.0200)	(0.0698)	(0.1907)	(0.3533)
$lw_{t-1} * shock$	0.1225***	0.6786***	0.5983*	0.3202
	(0.0371)	(0.1309)	(0.3211)	(0.5900)
$lr_{t-1} * shock$	-0.0410***	-0.0628***	-0.0573	-0.0100
	(0.0069)	(0.0233)	(0.0678)	(0.1156)
Constant	0.7732***	4.1926***	2.4260	0.3126
	(0.2399)	(0.8419)	(1.8543)	(3.6625)
Observations	5,032	5,032	5,032	5,032
Number of smsa	295	295	295	295

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4 The impact of low housing supply elasticity on migration rate (2009-2015)

	(1)	(2)	(3)
VARIABLES	Net-migration rate	In-migration rate	Out-migration rate
shock	2.227	-0.553	-2.445
	(6.670)	(0.468)	(7.757)
L.shock	-60.882	-5.330*	66.932
	(38.935)	(2.750)	(45.617)
e*shock	0.154	-0.027	-0.117
	(0.254)	(0.018)	(0.293)
L.e*shock	-2.603**	-0.118	3.546**
	(1.135)	(0.076)	(1.403)
lg08*shock	-0.218	0.054	0.239
	(0.640)	(0.045)	(0.744)
L.lg08*shock	5.894	0.518**	-6.506
	(3.736)	(0.264)	(4.379)
L.Dep Var	-0.378**	0.303***	-0.009
	(0.149)	(0.105)	(0.249)
L2.Dep Var	-0.367**	0.117***	-0.006
	(0.146)	(0.041)	(0.238)
Constant	0.018***	0.034***	0.052**
	(0.006)	(0.006)	(0.022)
Observations	642	642	642
Number of smsa	214	214	214

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5 Income convergences in different wage-level MSAs (1989-2014)

	(1)	(3)
VARIABLES	Average wage growth rate	Average wage growth rate (adjusted by housing cost)
lw89	-0.0085***	-0.0089***
	(0.0024)	(0.0024)
e*lw89	0.0157***	0.0157***
	(0.0039)	(0.0041)
Constant	0.1146***	0.1178***
	(0.0240)	(0.0239)
Observations	298	290
R-squared	0.0952	0.0939

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6 Migration in different wage-level MSAs (2009-2016)

	(1)	(2)	(3)
VARIABLES	Average in-migration rate	Average out-migration rate	Average net-migration rate
lw08	-0.0505***	-0.0716***	0.0218***
	(0.0127)	(0.0129)	(0.0078)
e*lw08	0.0287	0.0638***	-0.0361***
	(0.0196)	(0.0199)	(0.0121)
Constant	0.5830***	0.8018***	-0.2264***
	(0.1325)	(0.1342)	(0.0814)
Observations	298	298	298
R-squared	0.1123	0.1338	0.0952

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7 Difference in demographic structure between two groups

	(1)	(2)	(3)	(4)
VARIABLES	babyrate1990	babyrate2016	youngrate1990	youngrate2016
e	0.0010	0.0036***	0.0025	0.0097**
	(0.0013)	(0.0011)	(0.0039)	(0.0038)
Constant	0.0884***	0.0600***	0.2483***	0.2049***
	(0.0010)	(0.0008)	(0.0030)	(0.0030)
Observations	322	322	322	322
R-squared	0.0021	0.0319	0.0013	0.0197

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix A Simulation Calibrations

Table A1 Calibration of the theoretical model

Description	Parameter	Value	Source/target
Out-migration rate	ρ	0.05	IPUMS
Discount factor	β	0.95	-
Risk aversion parameter in the CRRA utility function of housing service	σ	2	-
Original bargaining power of workers	η	0.05	Petrongolo and Pissarides (2001)
Matching elasticity	ξ	0.5	Branch, Petrosky-Nadeau and Rocheteau (2015)
Productivity auto-correlation coefficient	ρ_z	0.95	Petrongolo and Pissarides (2001)
Productivity shock	σ_z	0.007	Petrongolo and Pissarides (2001)
Initial housing stock	A_0	1	Indexation
High housing supply elasticity	ε_x^h	3	Saiz (2010)
Low housing supply elasticity	ε_x^l	1	Saiz (2010)
In-migration rate	n_t^o	0.06	IPUMS
Vacancy cost	γ	-	$0.03 * w_t^x$
Matching efficiency	M	-	$n_t^o = 0.06$
Steady-state productivity	z_{ss}	1	Indexation
Income gap	w_t^o / w_t^x	0.9	-

Appendix B: Calculation procedures of the semi-standardized coefficients

Based on Table 3,

Semi-standardized coefficient in short-term is:

$$\mathrm{D}_{\mathrm{pg}} = -0.0634 * \frac{sd(shock)}{sd(pg)} = -0.1008$$
$$\mathrm{D}_{\mathrm{eog}} = -0.1688 * \frac{sd(shock)}{sd(eog)} = -0.0836$$
$$\mathrm{D}_{\mathrm{e1g}} = -0.3402 * \frac{sd(shock)}{sd(e1g)} = -0.0148$$

Based on Table 4,

Semi-standardized coefficient in long-term is:

$$_{migr}\eta_{long-term} = \frac{(2.227 - 60.882 + \mathrm{lg} * (-0.072 + 5.894) - (2.603 - 0.427) * e_i}{1 + 0.367 + 0.378} * \frac{sd(shock_{it})}{sd(migr_{it})}$$

The difference of semi-standardized coefficient is:

$$_{migr}D_{long-term} = \frac{-(2.603 - 0.427) * e_i}{1 + 0.367 + 0.378} * \frac{sd(shock_{it})}{sd(migr_{it})} = -0.63$$

$$_{inmigr}D_{long-term} = \frac{-(0.118 - 0.054) * e_i}{1 - 0.303 - 0.117} * \frac{sd(shock_{it})}{sd(migr_{it})} = -0.15$$

$$_{outmigr}D_{long-term} = \frac{(3.546 - 0.117) * e_i}{1 + 0.006 + 0.009} * \frac{sd(shock_{it})}{sd(migr_{it})} = 1.41$$

Appendix C: Regression Results of Equation 27 using same grouping method of Zabel (2012)

Table C1 The impact of labor demand shock on employment growth rate (1990-2014)

	(1)	(2)	(3)	(4)
VARIABLES	Population growth	Employment growth in the non-local service sector	Employment growth in the local service sector	Employment growth in the construction sector
shock	-1.0058*	-4.7264**	-8.9933**	-12.0749
	(0.5450)	(1.8607)	(3.9169)	(9.4128)
$\varepsilon_i * \text{shock}$	0.0254**	0.0840**	0.0477	0.1906
	(0.0106)	(0.0348)	(0.0965)	(0.1622)
$lw_{t-1} * \text{shock}$	0.1172**	0.4730***	0.9213**	1.6342
	(0.0531)	(0.1809)	(0.4063)	(0.8997)
$lr_{t-1} * \text{shock}$	-0.0422***	-0.0580**	-0.0136	-0.0647
	(0.0075)	(0.0249)	(0.0679)	(0.1136)
Constant	0.8164**	2.8767***	0.9708	-7.1088
	(0.3285)	(1.1049)	(2.2930)	(5.4762)
Observations	4,268	4,268	4,268	4,268
Number of smsa	242	242	242	242

Note: Standard errors are in parentheses. The table shows the coefficient of PVAR estimation showed in equation 27. Demand shocks are interacted with the specific metropolitan housing supply elasticity ε_i directly. This table shows that I can get consistent results using the same grouping method to previous researches (Zabel 2012). ∗significant at 10%; ∗∗significant at 5%; ∗∗∗significant at 1%.