Spatial Equilibrium with Unemployment and Wage Bargaining: Theory and Estimation*

Paul Beaudry†
David A. Green‡
Ben Sand§

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Abstract

In this paper we present a spatial equilibrium model where search frictions hinder the immediate reallocation of workers both within and across local labour markets. Because of the frictions, firms and workers find themselves in bilateral monopoly positions when determining wages. Although workers are not at each instant perfectly mobile across cities, in the baseline model we assume that workers flows are sufficient to equate expected utility across markets. We use the model to explore the joint determination of wages, unemployment, house prices and city size (or migration). A key role of the model is to clarify conditions under this type of spatial equilibrium setup can be estimated. We then use U.S. data over the period 1970-2007 to explore the fit of model and it quantitative properties of the model. Our main goal is to highlight forces that influence spatial equilibria at 10 year intervals.

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†University of British Columbia, and NBER
‡University of British Columbia and Research Fellow, IFS, London
§York University.

Introduction

In most economies, households constantly move between localities in search of better economic conditions. The urban economic literature has emphasized theoretically and empirically the importance of both wages and unemployment in affecting such decisions. However, the canonical spatial equilibrium model – which is at heart of modern urban economics – generally abstracts from unemployment since it builds on a Walrasian setup.[1] In this paper we embed a search and bargaining model of the labour market into a spatial equilibrium setting in order to provide a simple framework where one can discuss the joint determinants of local wages, unemployment rates, house prices and migration. Thus, our goal is to explore the insights to be gained by shifting from a Walrasian framework to one in which unemployment and wage bargaining play a central role.

We begin the paper by presenting a spatial equilibrium model in which search frictions hinder the immediate reallocation of workers within and between local labor markets, which we refer to as cities. The search frictions imply that unemployment arises as an equilibrium phenomenon. Following Pissarides [2000], wages are determined by Nash bargaining between firms and workers. We assume that cities have exogenous differences in terms of productivity, amenities and land availability. Further, we allow cities to be subject to agglomeration externalities and congestion externalities.

An important element of the model is the presence of many industries within each city. Unemployed individuals search for a job across these industries and can also randomly receive an option to search in another city of their choice where the industrial mix will be different. Households will move to cities with either higher wages or lower unemployment, implying increases in the demand for land in those cities. Accordingly, in the spatial equilibrium, house prices will adjust to make households indifferent among cities. Differences in industrial mix across cities will play an important role in helping us identify the effects of wages on housing costs and mobility decisions. In particular, we will be able to examine the sensitivity of household mobility decisions with respect to both wages and unemployment.[2]

The paper builds on our previous work, Beaudry, Green, and Sand [2012, 2011], in which we present a tractable model of search and bargaining with multiple industries and cities. However, in those papers, cities are not assumed to be subject to either agglomeration or congestion externalities. The result is a spatial equilibrium with a particular block recursive system of equations whereby wages and employment rates can be determined independently of house prices and city size, allowing

[1] Two recent references include Glaeser and Gottlieb [2009] and Moretti [2011b]. See Amior [2012] for a recent paper that takes a related but different approach to introducing mobility into a search and bargaining model.

[2] The basic model gives rise to a system of $3 + 2N$ equations where N in the number of industries. The system determines wages for each industry-city pair, the share of employment in each industry in each city, the employment rate in the city, city house prices and the city size (the labor force). However, for most of the analysis, we can focus on a reduced system of 4 equations which determines average city wage, the employment rate, house prices and city size.

us to focus on wage and employment determination without being explicit about the determination of house prices and city size. In contrast, the basic model of this paper is not block recursive and, accordingly, the simultaneous determination of house prices and migration decisions become the central focus.

In order to make the presentation more transparent, we first present a baseline model which abstracts from several features that are then introduced progressively. The baseline model has the advantage of allowing for a clear discussion of the main identification issues.[3] The second main section of the paper focuses on estimating the model using data drawn from the U.S. Census and the ACS over 10 year windows.

Our estimations allow us to address a set of issues central to the intersection of urban and labor economics. These include: (i) the relative importance of wages versus unemployment in affecting migration decisions, (ii) the strength of the housing-cost-wage interaction, (iii) the relevance of agglomeration effects over the medium run and (iv) the nature of the spatial equilibrium process. We find that migration decisions are much more responsive to changes in local employment opportunities than to wages: a one percent increase in a city's employment rate causes an inflow of worker three times greater than a one percent increase in real wages. We also find that the effect of wages on the determination of housing cost is much stronger that the effect of higher house prices on the determination of wage. For these relationships, we find that a 1% increase in housing cost has the direct effect of increasing wages by approximately 0.25%, while an increase in the average citey wage is related to higher housing cost in an approximately 1-to-1 fashion. With respect to the importance of agglomeration effects on productivity, we do not find any significant evidence of such forces over the 10-year periods we focus upon. In fact, our estimates of the wage and employment processes suggest that migration neither increases nor decreases marginal productivity over the medium run. In addition to finding that variation in city size has very little direct effect on wages and employment rates, we also find that for most cities, house prices appear quasi-invariant to migration. More specifically, house prices are invariant to migration in all cities except those with very limited available land, where house prices respond strongly to migration flows. For the land elastic cities, our estimates put into question the equilibrium role of house prices in equating utility across localities. We offer two alternative interpretations of this observation. The first being that some form of congestion externality affects the desirability of different cities, and this plays the key equilibrium force insuring that agents receive equal utility across locations. The second interpretation is that migration frictions are sufficiently prevalent to hinder the equalization of utility over 10 year periods.

The paper is structured as follows. In the next section we present our spatial equilibrium model with multiple industries and wage bargaining. We use the model to derive four estimating equations and to discuss how the parameters of these relationships can be identified. In Section 3 we present the data we use for estimation.

[3] As we are working with observational data, identification will rely on restrictions on unobservables. Given the model is over-identified, the joint validity of the model and the implied restrictions can be evaluated using standard tests.

In Section 4 we report our estimates for the four equation model and discuss their implications for urban-labour issues.

1 Theoretical Framework

In this section, we set out to extend a standard search and bargaining model to include multiple sectors, multiple cities, endogenous migration decisions and endogenous housing costs. Our goal is to derive an empirically tractable spatial equilibrium model with unemployment and wage bargaining. Given that goal, our model is highly stylized, but we will show that this simple model provides a reasonable fit to the data.[4]

Consider an environment where there are C cities and a mass 1 of households, with each household having 1 unit of labour. As we will specify more precisely later, households will have the opportunity to move between cities, and we will be aiming to characterize both the stationary equilibrium, where households are indifferent between living in different cities, and changes in the stationary equilibrium induced by changes in exogenous factors. The mass of households located in city c at time t is denote by L_{ct}, and we will also refer to L_{ct} as the city size. Households have preferences defined over the consumption of a final good, X, the consumption of housing, H, and the consumption of city specific amenities, A_{ct}. The final good is an aggregate of output from I industries. The price of the final good, X, is normalized to 1 and the price of intermediate/industrial good i is given by p_{it}. The $i \in \{1, .., I\}$ industrial goods can be produced in each of the C cities, and employers in a city take the prices, p_{it}, as given.[5]

For now, we will consider all households to be ex-ante identical. Later we will discuss how household skill heterogeneity can be introduced into the model. Cities, in contrast, are heterogeneous ex-ante and ex-post, as they will differ in terms of their productivities, their amenities and the available land. As will be made clear, city-level productivity terms and amenities will have an exogenously given component and an endogenous component which reflects agglomeration and congestion externalities.

1.1 Search

We assume that search frictions characterize the labor markets in all cities. Each local economy unfolds in continuous time. Note that to simplify notation, and since we are searching for the stationary equilibrium, we will suppress the dependence of variables on time until we focus on changes in stationary equilibria. At each point in time, cities are populated by risk-neutral firms that maximize discounted profits and by worker-households who have per-period indirect utility functions given

[4]Our model exposition shares much with that in Beaudry et al. [2012].

[5]We can model the endogenous determination of prices, but for our purposes this is not necessary. All that is needed is that prices, p_{it}, be subject to an exogenous shifter which can reflect changes in technology or tastes.

by: $y - \gamma_1 p_c^h + \gamma_2 A_c$, where y is the income received by the worker, p_c^h is the price of housing in city c, A_c is the public amenity in city c, and γ_1 and γ_2 are parameters. Households take the the value of amenities as given, but these can affected by congestion externalities such that:

$$A_c = \epsilon_{1c} - \gamma_3 L_c$$

where ϵ_c represents the exogenous amenity draw of city c and γ_3 captures a potential congestion externality.

Both employers and workers discount the future at a rate r. Firms and workers come together in pairs according to a matching technology, and matches end at an exogenous rate, δ. Define E_{ic} and N_{ic} as the number of employed workers (or matches), and the number of available jobs in industry i in city c, respectively. The number of matches produced per unit of time is governed by the matching function:

$$M = M\left((L_c - E_c), (N_c - E_c)\right), \tag{1}$$

where the inputs are the available pool of unemployed workers in the city, $L_c - E_c$, and the number of vacancies, $N_c - E_c$. As is standard in the search and bargaining literature, we assume the matching technology exhibits constant returns to scale and is increasing in both arguments. Given this matching technology, we can write the probability that a worker encounters a vacancy and the probability a firm fills a vacancy as:

$$\psi_c = \frac{M\left((L_c - E_c), (N_c - E_c)\right)}{L_c - E_c} \quad \text{and} \quad \phi_c = \frac{M\left((L_c - E_c), (N_c - E_c)\right)}{N_c - E_c}, \tag{2}$$

respectively. In steady state, the flow of workers leaving unemployment must equal the flow of workers exiting employment, implying the equilibrium condition:

$$\delta \frac{E_c}{L_c} = M\left(1 - \frac{E_c}{L_c}, \frac{N_c}{L_c} - \frac{E_c}{L_c}\right). \tag{3}$$

1.2 Bellman Equations

Firms can open jobs in any industry and city, but once open, a vacancy is industry and city specific. To create a vacancy in industry i in city c, a firm must pay a cost, k_{ic}, the value of which depends on the city and the industry and will be determined by an equilibrium free-entry condition to be specified later. Denote by V_{ic}^v the present-discounted value of a vacancy in industry i and city c. In steady-state, V_{ic}^v must satisfy the Bellman equation:

$$rV_{ic}^v = -h_i + \phi_c\left(V_{ic}^f - V_{ic}^v\right), \tag{4}$$

where h_i is the flow cost of maintaining the vacancy, and with probability ϕ_c the vacancy is converted into a filled job, which has a present-discounted value of V_{ic}^f. In equilibrium, the value to the employer of a filled job value must satisfy

$$rV_{ic}^f = p_i - w_{ic} + \rho_{ic} + \delta\left(V_{ic}^v - V_{ic}^f\right), \tag{5}$$

where w_{ic} is the wage paid to workers in industry i in city c, and ρ_{ic} is an industry-city cost advantage.Thus, once a match occurs, a firm enjoys a profit flow of $p_i - w_{ic} + \rho_{ic}$, and with probability δ the match is broken. Employers take the productivity term ρ_{ic} as given and to allow for agglomeration externalities we allow ρ_{ic} to be determined endogenously according to:

$$\rho_{ic} = \epsilon_{2ic} + \gamma_4 L_c$$

where ϵ_{2ic} represents the exogenous draw of productivity across industries-cities, and $\gamma_4 L_c$ represents the agglomeration effect. We define the ϵ_{2ic}'s such that $\sum_c \epsilon_{2ic} = 0$. For now we assume a very simple form for the agglomeration effect, but in the empirical section we will explore richer formulations.[6]

Workers can either be employed or unemployed. Denote the present-discounted value of employment in industry i in city c as U^e_{ic} and the value of unemployment in city c as U^u_{ic}. The value of being employed U^e_{ic} must satisfy the Bellman relationship:

$$rU^e_{ic} = w_{ic} - \gamma_1 p^h_c + \gamma_2 A_c + \delta(U^u_c - U^e_{ic}). \tag{6}$$

When an individual is unemployed, he receives income from an unemployment benefit, b. Moreover, an unemployed worker is subject to two types of shocks. On the one hand, with a probability ψ_c, the worker is randomly matched with a firm in one of the industries within the city. In addition, the unemployed worker can receive, with probability ψ_0, the possibility of moving to another city. Thus, the value of unemployment must satisfy:

$$rU^u_c = b - \gamma_1 P^h_c + \gamma_2 A_c + \psi_c \left(\cdot \sum_j \eta_{jc} U^e_{jc} - U^u_c \right) + \psi_0 \left(\max_{c'} U^u_{c'} - U^u_c \right), \tag{7}$$

where η_{it} is the ratio of vacant jobs in industry i to the total number of vacancies ($\eta_{ic} = \frac{N_{ic} - E_{ic}}{\sum_i (N_{ic} - E_{ic})}$).[7] Embedded in (7) is the notion that unemployed workers find jobs across industries in proportion to the relative size of that industry.[8] Given this matching assumption for the unemployed, workers flows will need to satisfy

$$\delta E_{ic} = \left(\frac{N_{ic} - E_{ic}}{\sum_i N_{ic} - \sum_i E_{ic}} \right) M \left(L_c - \sum_i E_{ic}, \sum_i N_{ic} - \sum_i E_{ic} \right). \tag{8}$$

The term $\max_{c'} U^u_{c'}$ in (7) represents the fact that unemployed workers are allowed to choose where best to move when they receive the option of moving. We will assume

[6] Combes and Duranton [2012] show that positive agglomeration effects on firm productivity in French data are not related to a Melitz-type selecting out of less productive firms due to increased competition in larger markets. This is partially supportive of our simple specification, though in their model city size has more complex effects on the productivity distribution.

[7] In equilibrium, η_{ic} will equal $\frac{E_{ic}}{\sum_i E_{ic}}$, which allows η_{ic} to be calculated from observed data.

[8] We assume that workers only search while unemployed, which is clearly a strong assumption. This assumption is very useful for clarifying how we identify the wage effect on different outcomes. Moreover, it fits with findings in Pissarides and Wadsworth [1989] that the unemployed are much more likely to undertake regional migration than the employed. Amior [2012] presents a model of search and bargaining with migration in which the migration decision is modeled as actively searching for jobs in other cities. He uses this framework to study the relationship between variation in local housing costs and earnings inequality.

mobility shocks are sufficiently frequent such that, in equilibrium, utility will be equalized across cities. That is,

$$U_c^u = U_{c'}^u, \text{ for all } \{c, c'\}. \tag{9}$$

Therefore, the term $\max_c' U_{c'}^u - U_c^u$ will be zero in equilibrium and the value of unemployment in city c will satisfy

$$rU_c^u = b - \gamma_1 P_c^h + \gamma_2 A_c + \psi_c \cdot \left(\sum_j \eta_{jc} U_{jc}^e - U_c^u \right). \tag{10}$$

In writing the above equations, note that we have assumed that there are always gains from trade between workers and firms in all jobs created in equilibrium. Once a match is made, workers and firms bargain a wage, which is set according to the bargaining rule

$$\left(V_{ic}^f - V_{ic}^v \right) = \left(U_{ic}^e - U_c^u \right) \cdot \kappa, \tag{11}$$

where κ is a parameter governing the relative bargaining power of workers and firms.

Finally, the number of jobs created in industry i in city c, denoted N_{ic}, is determined by a free-entry condition. In much of the search and bargaining literature, the entry cost is treated as a fixed factor, which is a very restrictive assumption. Instead, we want to allow for the possibility of the entry cost increasing as the industry grows in order to capture the scarcity of some hidden factor, such as entrepreneurial talent.[9] Accordingly, we specify the entry cost in industry i in c, k_{ic} as

$$k_{ic} = \left(\frac{N_{ic}}{L_c} \right)^{\gamma_5} \epsilon_{3ic}.$$

If γ_5 equals zero, we have the exogenously fixed-entry formulation, where ϵ_{3ic} represents a city-industry specific exogenous draw in the cost of creating jobs. However, by allowing γ_5 to differ from zero, we allow the entry cost to increase with an increase in job creation. We view the most likely scarce factor to be entrepreneurial talent and believe that such talent is likely proportional to the population of a city.[10] Based on this, we allow the entry cost to increase with the ratio $\frac{N_{ic}}{L_c}$.

The free entry condition implies that

$$k_{ic} = V_{ic}^v. \tag{12}$$

1.3 Housing market

So far, we have set out a model where wages are determined by Nash bargaining, jobs are created until there are zero expected profits at the margin, employment is determined by the matching function and households migrate across cities until

[9] Our formulation is similar to that adopted in Fonseca, Lopez-garcia, and Pissarides [2001] which views potential job creators as being drawn from the population and differing in terms of their capacity to manage many jobs.

[10] Behrens, Durnanton, and Robert-Nicoud [2012]) show that variation in the proportion of workers who are self-employed across U.S. cities is invariant to city size.

expected utility is equalized. The only remaining element that needs to be specified is the determination of the cost of housing. Given the indirect utility function of households, the implicit demand for housing is proportional to the city population. This allows us to focus on the supply of housing services in determining the cost of housing. We will begin with the case where housing relates only to the use of land, so that we can focus on the supply function for land. There is now a substantial literature indicating that cities differ greatly in the extent to which the local supply of land can respond to changes in demand, and we want to allow for such heterogeneity [Saiz, 2010]. Accordingly, we will let $\frac{1}{1+e_c}$ represent the city-specific elasticity of land supply with respect to the price of housing, denoted p_c^h, and we let the supply of land services $Land_c^s$ be given by:

$$Land_c^s = (P_c^h)^{\frac{1}{1+e_c}} \cdot \epsilon_{4c}, \tag{13}$$

where ϵ_{4c} is an exogenous shifter of the supply of land, which, for example, could represent local regulation or geographic constraints. In this formulation, the supply function for land services is exogenously given without being specific about the owners of the land. Equilibrium in the land market implies that the price of housing is given by

$$P_c^h = \left(\frac{L_c}{\epsilon_{4c}}\right)^{1+e_c}. \tag{14}$$

This formulation of the housing price equations is quite restrictive as it does not allow for wage costs to have any direct effects on housing costs. In particular, it would be reasonable have wages affect the equilibrium price of housing through either supply effects or demand effects. For example, if land is not the only input into housing, when wages increase this likely increases the cost of building housing and, therefore, the price of housing. Alternatively, wages can affect the demand for housing. For both these reasons, it appears desirable to consider the following, slightly extended, equilibrium house price equation:

$$p_c^h = w_c^{e_w} \left(\frac{L_c}{\epsilon_{4c}}\right)^{1+e_c}, \tag{15}$$

where e_w is the elasticity of house prices to wages and w_c could be either the average wage in the city (to capture demand effects) or the wage paid in the construction industry (to capture supply effects).

This completes the model specification. Note that the main exogenous driving forces of the model which govern the city-level outcomes are the city-industry productivity terms ϵ_{2ic} and ϵ_{3ic}, the amenity term ϵ_{1c}, the land supply term ϵ_{4c} and the land elasticity e_c.

1.4 Model Solution

A stationary spatial equilibrium for this economy is a set of prices $\{w_{ic}, p_c^h\}$, a set of quantities $\{N_{ic}, E_{ic}, L_c\}$ and a set of value functions $\{U_{ic}^e, U_c^u, V_{ic}^v, V_{ic}^f\}$ such that[11]

[11] To be complete, we should add intermediate goods prices p_i to the definition of equilibrium. However, since these prices are common across cities, we can disregard their determination.

1. $U^e_{ic}, U^u_c, V^v_{ic}, V^f_{ic}$ satisfy the Bellman equations.
2. The wages w_{ic} satisfy the bargaining rule $\left(V^f_{ic} - V^v_{ic}\right) = (U^e_{ic} - U^u_c) \cdot \kappa$.
3. The number of jobs N_{ic} satisfy the free entry condition $V^v_{ic} = \left(\frac{N_{ic}}{L_c}\right)^{\gamma_5} \epsilon_{3ic}$.
4. The city size L_c is such that U^u_c is equalised across cities.
5. The cost of housing satisfies $P^h_c = w_c^{e_w} (\frac{L_c}{\epsilon_{4c}})^{\frac{1}{e_c}}$.
6. The worker flows satisfy $\delta E_{ic} = \left(\frac{N_{ic} - Eic}{\sum_i N_{ic} - \sum_i E_{ic}}\right) M\left(L_c - \sum_i E_{ic}, \sum_i N_{ic} - \sum_i E_i\right)$.

While we could focus on all the elements of this spatial equilibrium, our goal will be more limited as we will direct our attention mainly to the determination of city aggregates. In particular, we will focus on the determination of city size L_c, the local cost of housing p^h_c, the city-level employment rate $\frac{\sum_i E_i}{L_c}$ and the average city wage $\sum_i \frac{E_i}{\sum_j E_j} w_{ic}$. Since the worker-flow condition implies that $\eta_i = \frac{E_i}{\sum_i E_i}$, we will now refer to η_{ic} as the employment share in industry i in city c, and $\sum_i \eta_{ic} w_{ic}$ as the average wage.

1.5 Deriving the City Size Equation

A central element of the spatial equilibrium concept is the idea that labour will move across localities until expected utility is equalized. Although, in our setup, there are frictions to mobility, as long as these frictions are small enough, the distribution of labor across localities will be determined by the indifference condition, $U^u_c = \bar{U}^u$ for all c, where $\bar{U^u}$ is the common level of utility. We can use this condition to derive an expression for equilibrium city sizes, L_c. This first requires using the Bellman equations for U^u_c and U^e_{ic} to get the following explicit expression for U^u_c

$$U^u_c = \frac{b - \gamma_1 P^h_c + \gamma_2 \epsilon_{1c} - \gamma_2 \gamma_3 L_c}{r} + \frac{\psi_c(\sum_i \eta_{ic} w_{ic} - b)}{r(r + \delta + \psi_c)}.$$

Note that, in the above expression, the expected utility associated with a city is increasing in the average city wage, decreasing in the price of housing, increasing in the amenity, ϵ_{1c}, and decreasing in the city size due to congestion. Furthermore, it can be verified that through ψ_c, expected utility is increasing in the city-employment rate $\frac{E}{L}_c$. Using the equilibrium condition $U^u_c = \bar{U^u}$, we can solve for the city size, L_c, to recover

$$L_c = \frac{1}{\gamma_2 \gamma_3} \left((b - \bar{U^u} r) + \frac{\psi_c(\sum_i \eta_{ic} w_{ic} - b)}{(r + \delta + \psi_c)} - \gamma_1 P^h_c + \gamma_2 \epsilon_{1c} \right).$$

This city size equation captures the notion that cities will tend to be larger when the average wage is high relative to the price of housing, with the error term of the equation reflecting unmeasured amenities. However, this equation only gives implicit recognition of the dependence of city size on unemployment through ψ_c. In order to get an explicit expression of this link, we take a log-linear approximation to the equation, where the linearization is taken around a point where cities are identical (that is, all the ϵs are set to 1, and the land elasticity is the same) and we use the worker flow relationships to link ψ_c to the employment rate. Furthermore, we express the equations as a difference between two steady states which differ in terms of the ϵs. This leads to the following baseline city-size equation we use in our empirical investigation:

$$\Delta \ln L_c = \alpha_{10} + \alpha_{11} \Delta \ln \sum_i \eta_{ic} w_{ic} + \alpha_{12} \Delta \frac{E}{L}_c - \alpha_{13} \Delta \ln p_c^h + \alpha_{14} + \Delta \epsilon_{1c}, \tag{16}$$

where the parameters α can be expressed as functions of the more fundamental parameters of the model. However, since we will not try to recover these more fundamental parameters, this link is omitted. Equation (16) now explicitly captures the potential effects of all three of the aggregate variables on city size. Moreover, the error in this equation has a structural interpretation since it changes with city-amenity values. Hence, to estimate this equation it will be necessary to find instruments for the different regressors which are uncorrelated with changes in amenities.

1.6 The Housing Cost Equation

The housing cost equation is the easiest to derive among our four basic equations as it follows directly from equation (15). In our baseline specification, we include the the possibility that the average wage in a city may directly affect the cost of housing. To make the equation comparable to the others, we log-linearize and take first differences to express changes over time in stationary outcomes induced by changes in the ϵs. This leads to a housing cost equation of the form:

$$\Delta \ln p_c^h = \alpha_{20} + \alpha_{21} \Delta \ln \sum_i \eta_{ic} w_{ic} + \alpha_{22} \Delta \ln L_c + \alpha_{23} e_c \Delta \ln L_c + \Delta \epsilon_{4c}. \tag{17}$$

In the above equation, we see that housing costs increase with the population of the city and city wages. Note that the assumption that the elasticity of land is potentially different across cities leads to us to express the link between housing cost and city size as depending on the elasticity e_c. In our empirical work, we will use measurable proxies for this elasticity. In this equation, the error term reflects changes in the local cost of housing supply. To estimate the housing cost equation we will need to identify data variation that affects wages and city size which are independent of local changes in construction costs.

1.7 The Employment Rate Equation

The third equation we want to derive is an employment rate equation. In order to derive this equation we need to proceed in steps. We can first derive an equation for job creation by using the equilibrium condition $V_{ic}^v = k_{ic}$ which states that jobs in a city-industry will be created until the value of a vacant job equals the cost of creating the marginal job. Then we can use the worker flow equations to map job creation to employment. Using the Bellman equations for V_{ic}^v and V_{ic}^e, we can express the value of a vacancy as

$$rV_{ic}^v = -\frac{(r+\delta)}{r+\delta+\phi_c} \cdot h_i + \frac{\phi_c}{r+\delta+\phi_c} \cdot (p_i - w_{ic} + \epsilon_{3ic} + \gamma_4 L_c),$$

where the value of a vacancy is higher if the price of the good is high relative to wages, and if the city is large (because of agglomeration effects). This relationship also leaves the link between the value of a vacancy and the employment rate within a city implicit as the effect runs through ϕ_c.

To get to our employment rate equation, we now use the free-entry relationship $V^v_{ic} = \left(\frac{N_{ic}}{L_c}\right)^{\gamma_5} \epsilon_{3ic}$, where we have replaced the cost of job creation k_{ic} by its determinants, and we use the equilibrium worker-flow relationship to replace N_{ic} by E_{ic}. This gives an equilibrium relationship between a city's employment rate within an industry, the wage paid in the industry, the employment rate in the city (because of search frictions), the size of the city (because of agglomeration) and the productivity in the industry-city cell. Taking a log-linear approximation of the resulting equation, and taking a first difference to emphasize changes in equilibrium outcomes, we obtain an equation of the form

$$\Delta \ln \frac{E_{ic}}{L_c} = \varphi_{0i} - \varphi_1 \Delta \ln w_{ic} + \varphi_2 \Delta \ln \frac{E_c}{L_c} + \varphi_3 \Delta \ln L_c + \varphi_4 \epsilon_{2ic} - \varphi_5 \epsilon_{3ic},$$

where the φ parameters can be linked to the fundamental parameters. Since we are interested in deriving an equation for the employment rate for a city, we can sum over the different industry employment rates and use the association between changes in industry prices and industry growth to obtain an equation for the change in the employment rate for a city:[12]

$$\Delta \ln \frac{E}{L}_c = \alpha_{30} + \alpha_{31} \sum_i \eta_{ic} \cdot g_i - \alpha_{32} \sum_i \eta_{ic} \left(\Delta \ln w_{ic} - \Delta \ln w_i\right) + \alpha_{33} \Delta \ln L_c + \alpha_{34} \Delta \epsilon_{5c}, \tag{18}$$

where ϵ_{5c} corresponds to a share weighted sum of ϵ_{2ic} and ϵ_{3ic}, and g_{it} is the rate of growth of employment in industry i at the national level, w_i in the average wage in industry i across all cities.

From Equation (18) we see that the employment rate in an city is negatively affected by the local cost of labor and positively affected by city size. However, these two effects are obtained conditioning on the $\sum_i \eta_{ic} \cdot g_i$ term. The easiest interpretation of the latter term is as a local aggregate demand shifter; it reflects the effect on local employment from an industrial mix that is concentrated in industries that grow well at the national level. This term corresponds to a variable that is often used in the regional economics literature [Bartik, 1991, Blanchard and Katz, 1992, for example] to capture demand shifts. Interestingly, the term arises naturally in our setting and, we argue, this justifies it as an instrument for the employment rate when estimating other equations in the model. Note that the error term in Equation (18) is composed of changes in productivity terms that affect variable and fixed costs. Accordingly, to estimate (18), we need to isolate data variation which is unrelated to such local productivity changes.

[12] See Beaudry et al. [2011] for details of this derivation. In deriving this equation we also used the approximation $\sum_i \eta_{ic} \Delta \ln \frac{E_{ic}}{L_c} \approx \Delta \ln \frac{E_c}{L_c}$.

1.8 The Wage Equation

The last equation we derive is an equation for the average wage within a city.[13] Recall that wages are set to split the surplus between the employer and the worker. Using the Bellman equations to calculate the surplus, one obtains the following equation for industry-specific wages:

$$w_{ic} = \gamma_{c0} + \gamma_{c1} p_i + \gamma_{c2} \sum_j \eta_{jc} w_{jc} + \gamma_{c1}(\epsilon_{2ic} + \gamma_4 L_c). \tag{19}$$

Equation (19) links wages in industry i in city c to the national price of the industrial good, p_i, the average level of wages in city c, and the city size. The coefficients in (19) are $\gamma_{c0} = \frac{(r+\delta)(r+\delta+\phi_c)\kappa}{[(r+\delta)+\kappa(r+\delta+\phi_c)](r+\delta+\psi_c)}(b + \tau_c)$, $\gamma_{c1} = \frac{r+\delta}{(r+\delta+\phi_c)\kappa+(r+\delta)}$ and $\gamma_{c2} = \frac{(r+\delta+\phi_c)\kappa}{[(r+\delta)+\kappa(r+\delta+\phi_c)]} \frac{\psi_c}{(r+\delta+\psi_c)}$. Equation (19) captures the notion that, in a multi-sector search and bargaining model, sectoral wages act as strategic complements; that is, within a city, high wages in one sector are associated with high wages in other sectors. This follows directly from a combination of equations (6) and (7), which show that a worker's outside option in bargaining depends on the wages he could get at other jobs in the city, weighted by the probabilities of getting those jobs.

The wage equation, given by (19), contains a classic reflection problem in that the sectoral wage depends on the average of such wages in the city. One can respond to this, in part, by using the model to show that the average wage can be replaced by a function of national-level wage premia. In particular, through a series of simple derivations, we can rewrite the wage equation (19) as

$$w_{ic} = \tilde{d}_{ic} + \left(\frac{\gamma_{c2}}{1-\gamma_{c2}}\right)\left(\frac{\gamma_{c1}}{\gamma_1}\right) \sum_j \eta_{jc}(w_i - w_1) + \gamma_{c1}\gamma_4 L_c + \gamma_{c1}\epsilon_{2ic} + \gamma_{c1}\left(\frac{\gamma_{c2}}{1-\gamma_{c2}}\right) \sum_j \eta_{2jc}\epsilon_{jc}, \tag{20}$$

where $w_i - w_1$ is the wage premium relative to an arbitrary, baseline industry at the national level, and $\tilde{d}_{ic}$ is a function of p_i and of $\gamma_{c0}, \gamma_{c1}, \gamma_{c2}$ from equation (19). Equation (20) states that wages within an industry-city cell depend on the industrial composition of a city as captured by the index $\sum_j \eta_{jc}(w_i - w_1)$. We denote this index by R_c and refer to it as average city rent. A high value of this index indicates that a city's employment is concentrated in high-paying industries. Thus, the specific composition effect captured in (20) is one related to the proportion of "good jobs" in a city, where, by good jobs we mean jobs in industries that pay a relative wage premium.

As with previous equations, it is useful to make the dependence of wages on the city's employment rate explicit by taking a log-linear approximation of (20), then taking the first difference to look at changes over time, and finally aggregating over industries in order to get a specification for the change in the average city wage. This is given by equation (21):

$$\Delta \ln \sum_i \eta_{ic} w_{ic} = \alpha_{40} + \alpha_{41}\Delta R_c - \alpha_{42}\Delta \frac{E}{L}_c + \alpha_{43}\Delta \ln L_c + \alpha_{44}\Delta \ln \sum \epsilon_{i2c}. \tag{21}$$

[13] This equation is the central focus of Beaudry et al. [2012], and the reader interested in a detailed derivation should consult that paper.

Equation (21) indicates that average wages within a city will be higher if the industrial composition of a city is weighted toward high-paying industries and will be lower if the city has a low employment rate. Both of these effects are due to the fact that wages are bargained, as both of these factors affect the bargaining position of workers. City size can also affect wages through an agglomeration externality which affects productivity. One element that may appear as missing from Equation (21) is housing costs, which one might also expect to affect the bargaining position of workers. While this would be true if expected utility was different across cities, when utility is equalized across cities workers can't use local housing costs to push up wages since, in equilibrium, high housing costs reflect a compensating differential. In our baseline specification we maintain this assumption, but we also report robustness results where we add housing prices to Equation (21). Finally, note that the error term in Equation (21) reflects changes in local productivity effects and, accordingly, estimation of this equation requires isolating variation in the data that is unrelated to such changes.

1.9 Endogeneity Considerations

The main advantage of spelling out the theoretical model is that we specify the contents of the error terms in each equation and, from that, can be precise about the nature of any endogeneity concerns. Fortunately, the model also provides potential suggestions for instrumental variables and the conditions under which they will be valid. We term this approach "structural-IV" estimation since it combines positive features of both full structural and standard IV estimation. From the structure, we obtain a clear notion of what we are estimating and the required identification conditions but, by using first-order approximations to key structural equations, we also follow the standard IV estimation literature in being clear on the nature of our identifying variation.

1.9.1 Wage Equation

We begin by discussing the nature of potential endogeneity in the wage equation. Once the main issues are described for this equation, the others follow easily. The error term in the city-aggregate wage equation, (21), consists of the change in the log of the city-specific sum of local productivity shocks.[14] To understand the relationship of this error term with the first right-hand side variable in (21), ΔR_c, it is useful to decompose the changes in ΔR_c as:

$$\Delta R_{ct} = \sum_i (\eta_{ict} - \eta_{ict-1}) \cdot \nu_{it-1} + \sum_i \eta_{ict} \cdot (\nu_{it} - \nu_{ict-1}), \tag{22}$$

where $\nu_{ict} = w_{it} - w_{1t}$ is the wage premium and we have introduced t subscripts to make the timing clear.

From (22), ΔR_c is a function of levels and changes in ν_{it} and η_{ict}. The former are national-level variables and, as such, do not vary across cities. Endogeneity issues,

[14] Recall that we assume that $\sum_c \epsilon_{2ic} = 0$, since any national-level component of productivity shocks in an industry will be reflected in the industry price, p_i.

though, are concerned with cross-city correlations between ΔR_c and the error term, which is a city-level average of local productivity shocks. Thus, the ν_{it} elements in (22) do not raise identification problems. On the other hand, the first term on the right-hand side of (22) shows that changes in the city-level rent variable depend on changes in the city's industrial composition. Not surprisingly, one can write the η_{ict} terms as functions of the city-industry productivity shocks, ϵ_{2ict}, that are aggregated together in the error term. This raises potential endogeneity concerns to the extent that cities that undergo specific composition shifts also tend to be cities with improving productivity overall.

We address this potential concern using instrumental variables based on the two components in (22). The idea underlying the instruments is to break any contemporaneous link between changes in city average productivity and changes in city-level industrial composition by using cross-city differences in initial industrial composition combined with national-level growth by industry. More specifically, following Bartik [1991] and Blanchard and Katz [1992], we form predicted values for employment in industry i, in city c, in period t as:

$$\hat{E}_{ict} = E_{ict-1}\left(\frac{E_{it}}{E_{it-1}}\right).$$

In other words, we predict period t employment using employment in the industry-city cell in period $t-1$ multiplied by the national-level growth rate for the industry. Using these predicted values, we can then form predicted industry-specific employment shares, $\hat{\eta}_{ict} = \frac{\hat{E}_{ict}}{\sum_i \hat{E}_{ict}}$, for the city in period t and, finally, form our first instrument as:

$$IV1_{ct} = \sum_i \nu_{it-1}\cdot(\hat{\eta}_{ict} - \eta_{ict-1}) = \sum_i \eta_{ict-1}\cdot(g^*_{it} - 1)\cdot\nu_{it-1}, \tag{23}$$

where $g^*_{it} = \frac{1+g_{it}}{\sum_k \eta_{kct}(1+g_{kt})}$ and g_{it} is the growth rate in employment in industry i at the national level. $IV1$ is very similar to the first component in the decomposition of ΔR_{ct} except that we break the direct link to the growth in local productivity by using national-level changes. The intuition from the model is that in cities with an initial concentration in industries that grow well at the national level, workers in all industries will have better outside options and will be able to bargain better wages.

$IV1$ is a function of start-of-period industrial composition, η_{ict-1}, and national-level wage premia and industrial growth rates. As argued earlier, the latter do not vary across city and so are not a source of potential correlation with the error term. Thus, for $IV1$ to be a valid instrument, we require start-of-period local productivity shocks to be uncorrelated with changes in those shocks.[15]

We can also form an instrument based on the second component in the decomposition of ΔR_{ct}:

$$IV2_{ct} = \sum_i \hat{\eta}_{ict}\cdot(\nu_{it} - \nu_{it-1}). \tag{24}$$

[15] This is actually somewhat stronger than the minimal condition needed for $IV1$ to provide consistent estimates. For a complete derivation of the conditions see Beaudry et al. [2012].

This instrument is generated using start-of-period industry-city shares multiplying national-level industrial premia and growth rates. As before, the national-level variables are not relevant in establishing consistency since the variation being used is cross-city variation. This means that the same condition for consistency applies for $IV2$ as for $IV1$. In Beaudry et al. [2012], we argue that this provides an overidentifying restriction from the model that can be tested, and we show that this restriction cannot be rejected at any conventional significance level.[16] We also show that the two instruments are not strongly correlated across cities. One is built on changes in ΔR_{ct} arising because of shifts in industrial composition while the other emphasizes shifts in wage premia. Under the model, these two forces should provide the same estimated effects: it doesn't matter in bargaining whether the average-city wage changes because a high-paying industry leaves the city or because that industry stops paying a premium. We argue that the fact that this implication is confirmed in the data is strongly supportive of this model, providing a rationale for our building our discussion in this paper around it.

The employment rate variable, $\Delta \frac{E}{L}_c$ on the right side of (21) raises similar endogeneity concerns because it is clearly related to the productivity changes in the error term. We respond to this by using an instrument that we call $IV3$, constructed as $\sum_i \eta_{ict-1} \cdot g_{it}$. This is what that we called the local aggregate demand shifter in equation (18). It is similar in nature to $IV1$ in that it consists of start-of-period city-level industrial shares multiplied by national-level growth rates, but in this case the wage premia do not play a role. A city that has a strong weight on an industry that turns out to grow well at the national level will have a high value for this instrument. Once again, the consistency condition for the instrument is that start-of-period local productivity shocks are not correlated with growth in those shocks.

Finally, we also need to consider endogeneity issues related to $\Delta \ln L_c$ since we would expect labor inflows and outflows (and, thus, city size) to be related to the aggregate productivity shocks in the wage equation error term. To obtain potential instruments within the context of the model, consider substituting the equations for wages (21), the employment rate (18), and the housing price (17) into the city-size equation (16) to obtain a reduced form equation. The resulting reduced form has the potential instruments we have discussed so far (instruments related to ΔR_{ct} and $IV3$) on the right-hand side, but we clearly need additional instruments to satisfy both rank and order conditions. The reduced form also has on the right-hand side the interaction between $IV3$ and a measure of the elasticity of land supply. As we discuss in our Data section, we use a measure of the fraction of land available for residential development to form this interaction and use it as an additional instrument. As we will see, issues of collinearity between this constructed variable and $IV3$ result in poorly defined estimates. For that reason, we will also present specifications in which we use variables related to climate conditions as additional in-

[16] Note that the two instruments consist of different weightings of the start-of-period industrial composition and, therefore, of the start-of-period values for the productivity shocks. If the identifying assumption that those start of period values are uncorrelated with growth in the shocks were violated then we would expect the two instruments, with their different weightings on the resulting non-zero correlation, to provide very different estimates.

struments. These conditions (average temperature and precipitation) can be seen as components of the amenity shifter, ϵ_{1c}, for a city. The direct implication of the model is that it is changes in these amenities that matter for the change in city size, but qualities such as climate conditions tend to change very little over time. Instead, we use levels in the climate conditions variables, which are valid if the amenities have changed in their value over time. Given, as we will see, that the climate variables are significant predictors of city size, this does seem to be the case. This fits with Dahl [2002]'s findings in an examination of the return to education and worker mobility across U.S. States. For the climate variables to be valid instruments, it must be the case that city changes in average productivity and climate level are uncorrelated.

1.9.2 Employment Rate, Housing Cost, and City Size Equations

The identification considerations for the employment rate equation are very similar to those of the wage equation, since the error term in (18) also includes the change in the city-aggregate productivity along with changes in the city-level cost of creating jobs. Equation (18) has what we call $IV3$ on the right-hand side and, therefore, does not imply any issues as long as initial values for the productivity shocks are not correlated with changes in the productivity and job creation cost shocks. For the right-hand side wage terms, we have $IV1$ and $IV2$ as instruments; these require the same type of identification assumptions as previously discussed. Finally, the considerations for $\Delta \ln L_c$ are similar to those in the wage equation and we again use the elasticity of land supply and, in some specifications, the climate variables as instruments.

The endogeneity considerations are somewhat different for the housing cost and city-size equations. In these equations, the error terms do not contain average productivity shocks, since these shocks affect city size and house prices entirely through their impacts on wages and employment rates. Taking advantage of this identifying restriction from the model and assuming that shocks to the supply of land, ϵ_4, are independent of shocks to productivity, the cost of creating jobs, and amenities, the housing price equation (17) can be consistently estimated by OLS. If ϵ_4 reflects local political decisions about building roads or zoning regulations, however, the independence assumption may not be valid; development decisions may be related to perceived industrial growth. Given this possibility, we also estimate (17) using the same instruments that we use for wages in other equations. For $\Delta \ln L_c$, the local aggregate demand shifter, $IV3$, is now available as an instrument, since it enters the reduced form equation for $\Delta \ln L_c$ but not the housing cost equation. For all of these instruments, we require that start-of-period productivity and job creation costs are uncorrelated with changes in shocks to land supply – even if the *changes* in all of these variables are correlated. Of course, we can run a Hausman-type test, comparing the OLS and IV estimates, as a test of whether $\Delta\epsilon_4$ is uncorrelated with $\Delta\epsilon_1$, $\Delta\epsilon_2$, and $\Delta\epsilon_3$ and, therefore, of whether OLS provides consistent estimates.

1.10 Worker Heterogeneity

In the model presented earlier, all workers are homogeneous. To relate this model to actual data, we need to consider both observed and unobserved heterogeneity among workers. In Beaudry et al. [2011], we describe an approach to introducing heterogeneity in observable skills in which individual workers are thought of as bundles of efficiency units. If efficiency units are perfect substitutes in production, we show that, within the context of our model, one can write the wage of any skill type in reference to an arbitrarily chosen skill type. This justifies the use of regression adjusted wages in our empirical specifications, and we describe in detail how we make those adjustments when we discuss our data in section 2. Further, when search is random, the probability that a vacancy meets a worker of a given skill type is just the product of the probability of meeting any worker and the proportion of workers of that skill type. This allows us to separate the probability of meeting a worker from worker-skill types and implies that (apart from a second order adjustment) it is appropriate to use the overall (i.e., not conditional on education) employment rate in our specifications.

The other key issue that arises once we introduce heterogeneity is potential worker self-selection across cities. In particular, one might be concerned that variation in wages across cities reflects selection of workers of different skill types to the extent, say, that more skilled workers are better able to leave under-performing cities and move to more productive ones. If this is the case, that would affect our interpretation of estimated patterns. If the selection is in terms of observable characteristics such as education and experience, then the regression adjustment to wages that we describe in the Data section will allow us to focus on other sources of variation. For unobservable characteristics of workers, however, we need some other response.

We address potential selection based on unobserved ability across cities using a methodology that follows Dahl [2002] in his study of differences in returns to education across U.S. states. To make the issues involved clear, consider a version of (20) where we explicitly introduce individual heterogeneity:

$$E(w_{kic}|d_{kic}=1) = \alpha_{0ic} + \alpha_1 R_c + \alpha_2 L_c + E(e_{kic}|d_{kc}=1), \tag{25}$$

where k indexes individuals, the αs are parameters that amalgamate the relevant parameters in (20), e_{kic} corresponds to the error term from that equation, and d_{kc} is an indicator variable that equals 1 if person k is observed in city c. As is standard in selection problems, (25) implies that estimation of the wage regression yields biased estimates of the αs if the non-zero error mean term is correlated with the right hand side variables. Dahl [2002] shows that one can solve the selection problem in the context of individuals choosing among multiple locations by forming an estimate of the selection probabilities and including these probabilities in the wage regression. More specifically, he argues (under an index sufficiency condition) that one can represent the error mean as a function of the probability that people born in a given state choose location k and the probability that they choose not to move. He then proposes introducing a flexible function of these probabilities in regressions.

We follow this procedure with some modifications based on the fact that we are using cities rather than states and that we have immigrants in our wage sample. Once we have formed the probabilities that people either stay in their state of birth or move to a specific city, we introduce quadratics in these probabilities into an individual wage regression along with education, experience, gender, and race variables.[17] We then use the residuals from this regression (which is run separately by year, thereby allowing for changes in returns to education, etc. over time) as the corrected wage variable in the rest of our estimations. This is the wage removing observable skill effects and effects from selection on unobservables.[18]

2 Data

The data we use comes from the U.S. decennial Censuses from the years 1970 to 2000 and from the American Community Survey (ACS) for 2007. Since the Census definitions of cities and industries change over time, we construct definitions of cities and industries that attempt to maximize consistency between Census years. Our sample includes individuals aged 20-65 residing in one of 142 cities that are based on the U.S. Census Bureau's 1990 definition of Primary Metropolitan Statistical Areas. Details on how we construct the industry and city definitions are left to Appendix A.

Our approach to dealing with worker heterogeneity is to control for observed characteristics via a regression framework. Since our analysis takes place at the city level, rather than the individual level, we use a common two-step procedure. Specifically, we run regressions separately by year of log weekly wage on a vector of individual characteristics and a full set of city dummy variables.[19] We then take the estimated coefficients on the city dummies as our measure of city average wages, eliminating all cells with fewer than 20 observations.

Similarly, we construct the ΔR_{ct} variable, which is a function of the national-industrial wage premia and the proportion of workers in each industry in a city, by estimating analogous regressions at the national level. We control for the same set of individual characteristics and a full set of industry indicators. We extract the coefficients on the industry dummy variables as our measure of the industrial premia, denoted by ν_i in the model.

Finally, following Moretti [2011a], we measure housing prices as the city average

[17]The locational probability variables enter strongly significantly in the wage regressions, implying that selection on unobservables is present. However, estimates of our main regressions in which we use a wage variable that is corrected for observable characteristics but not selection on unobservables yields substantively similar results to those presented here.

[18]Skill composition of mobility could, in principle, also affect the employment rate equation. We have generated results using employment rates adjusted for composition in much the same way as we did for wages but have chosen to follow common convention in the estimation of employment and unemployment regressions by presenting non-composition adjusted results here. Using composition adjusted employment rates does not alter our key findings.

[19]In our first-stage regression, we include indicators for education (4 categories), a quadratic in experience, interactions of the experience and education variables, a gender dummy, black, hispanic and immigrant dummy variables, and the complete set of interactions of the gender, race and immigrant dummies with all the education and experience variables.

of the gross monthly rent of 2 or 3 bedroom units[20] and measure city-level housing supply elasticity using estimates developed by Saiz [2010]. In his paper, Saiz uses satellite generated data on the availability of land that is suitable for development and local regulatory restrictions to estimate housing supply elasticities. Saiz [2010] concludes that geography is a key factor in explaining urban development and housing prices across U.S. metro areas. In our empirical work, we make use of two variables generated by Saiz. The first is the 'elasticity of housing supply', that we denote with e in our empirical work. This variable, which is estimated by Saiz, depends on the geographical features of the city as well as potentially endogenous regulations and zoning laws. The second variable that we use is the land 'unavailable for development', which we denote u below. This variable depends only a city's predetermined geographical features, such as the amount of land forgone to bodies of water or steep inclines.

3 Results

3.1 City Size

We start our discussion of our results with the estimates of the city-size equation (16) and its related first-stage regressions. Recall that our key right-hand side variables are changes in the average-city wage, the employment rate, and the price of housing. In the first column of Table 1, we present OLS estimates of the coefficients on these variables. The estimated coefficients are all of the expected signs, with higher wages and employment rates being associated with larger cities (and thus net in migration) while higher housing prices have a negative relationship with city size. However, none of the estimated coefficients are significant at 5% or better levels.

As discussed earlier, our model implies that OLS is unlikely to provide consistent estimates of the coefficients in this regression equation. For that reason, we turn to estimates using combinations of the instruments described in section 1.9. Before doing so, we need to establish the strength of the instruments in the first stage. Table 2 contains estimates of the first-stage regressions for each of the three right-hand side endogenous variables. The first set of three columns include as regressors $IV1$ (the instrument based on changes in the city's industrial composition), $IV3$ (the Blanchard-Katz style instrument that captures general local-demand shifts), and the interaction of $IV3$ with Saiz [2010]'s measure of the fraction of land that is unavailable for development, denoted as u. $IV1$ has a strong positive effect on wages, a negative effect on the employment rate and a positive effect on house prices. This fits with a model under which a shift in composition toward industries that tend to pay higher wages leads to higher wages in all industries through bargaining spillover effects. Those wage increases would then imply reductions in the employment rate as potential entrepreneurs see the profitability of opening a vacancy reduced, and increases in house prices because of in-migration. The general demand measure has a positive effect on the employment rate, as predicted, but little impact on the

[20] See Moretti [2011a] for a detailed discussion of this measure for city housing costs.

other two outcomes. Finally, the interaction of $IV3$ with land unavailability has a strong effect on the change in housing prices but not on the other two variables. The F-statistics associated with a test for weak instruments are reported at the bottom of the relevant column in Table 1. These show that the instruments are strong predictors for the city wage and the house price but less so for the employment rate (where the associated F-Statistic is 7.15). But the Angrist-Pischke statistic, which takes account of multiple instruments, soundly rejects the hypothesis that the instruments do not enter the first stage for all three endogenous variables [Angrist and Pichke, 2009].

The second set of three columns in Table 2 contain the first-stage estimates for specifications using $IV2$ (the instrument constructed based on changes in national-level industrial wage premia) instead of $IV1$. The results are similar to those in the first set of columns, with the main exception being that $IV3$ now has stronger impacts on all three outcomes. The positive coefficients in all three equations fit with theoretical predictions since higher local demand should imply higher wages and (through attracting more people to the city) higher house prices. Finally, in the third set of columns, we include both $IV1$ and $IV2$ along with the other instruments. The results are similar to those in the other sets of columns and the F-statistics and Angrist-Pischke tests at the bottom of the last column in Table 1 imply that we do not have a weak instrument problem.

Returning to Table 1, columns (2)-(5) contain coefficient estimates using the different combinations of instruments listed in the row labelled "IV Set". The effects in the three columns are very similar and, in fact, the test statistic related to the over-identification restriction that $IV1$ and $IV2$ generate the same results (reported in the last row of the table) implies that the null hypothesis of no difference cannot be rejected at any standard significance level (the p-value is 0.19). Again, this fits with the model's implication that these very different forms of variation should generate the same results. Focusing on column (4) – where all the instruments are used – the key result is that changes in the employment rate have strong effects on city size while the effects of changes in average wages and housing prices are not statistically significant. In fact, the point estimates indicate that the impact on city size is twice as large for a percentage change in employment rates compared to wages. The implication is that households have strong migration responses to changes in employment rates but much less strong responses to wages and house price changes. The greater importance of employment rates relative to wages fits with results in Blanchard and Katz [1992] that indicate that migration across U.S. states is very responsive to employment shocks. The result makes some intuitive sense as not being able to find employment is a shock that is discrete in nature and potentially large in its impact on incomes. It seems more reasonable to expect a large and discrete response to this (i.e., relocation) than to a change in a wage. To reiterate our point from the introduction, considering the migration and the labor market problem in a search and bargaining framework provides us with a consistent way to think about both employment rate and wage effects on migration. This, in turn, allows us to characterize endogeneity problems and solutions to them, which leads to the estimated causal effects showing the importance of employment rate shifts.

To investigate this result further, in Table 3 we present results where we combine the wage and housing cost variables. This is effectively a constraint on the specification from Table 1 in which we assume that potential migrants care about real wages net-of-house price differences. To the extent that wages and house price movements are collinear, this allows the real wage to have its fullest effect. We form the change in the real wage by subtracting from the change in the nominal wage, the change in the house price multiplied by an assumed valued for the proportionate importance of house prices in household budgets. Using $IV1$, $IV2$ and $IV3$ as instruments, we find that the real wage has a well identified, statistically significant effect on migration, compared to the specification in Table 1 where wages and housing costs had separate effects. However, this has little impact on the employment rate coefficient, which has an impact on migration that is still twice as large as wage effects. The results are largely unchanged when we vary the proportion of the budget dedicated to housing from 0.35 up to 0.45. These results imply that agents tend to respond three times more to employment rate changes than to wage changes. It is interesting to think of these results in the context of standard models of the labor market and city size where the labor market is assumed Walrasian. In those models, changes in the local economy are modelled as affecting wages which then generate a migration response. Our results echo those of Blanchard and Katz [1992] by suggesting that is not the main channel affecting migration adjustments.

3.2 House Costs

We turn next to our results from estimating equation (17), which we present in Table 4. The first column contains OLS estimates of the regression of changes in the log of housing prices on changes in average city wages, changes in city size, and the latter variable interacted with the measure of the elasticity of the supply of land. [21] We present these for interest sake but given our arguments about endogeneity, we prefer to focus our discussion on the IV specification. A Hausman test of the restriction that the coefficients in the IV and OLS specifications are the same (and, therefore, that amenity and land-supply shocks are independent of productivity shocks) rejects the restriction at any standard significance level.

Column 2 of the Table contains estimates when we use our full set of instruments ($IV1$, $IV2$, $IV3$ and $u \cdot IV3$). The signs on the coefficients fit with increased wages generating higher house prices. Note that this effect does not occur through a migration response to higher wages, since we control for changes in city size in the regression. Instead, it fits with increased labor costs leading to increased building costs. Interestingly, the size of the wage coefficient is close to 1 and we cannot reject the restriction that it equals 1. The coefficient on the change in city size variable is positive, as we would expect, and is statistically significant. Thus, the key adjustment mechanism in the model (and in more standard models) in which increases in

[21] Our estimated coefficient on city size, 0.059, is quite similar to the estimate of 0.085 obtained (and interpreted within a structural model) in Behrens et al. [2012]'s regression of house rents on city size using U.S. Census data in 2000. However, our specification includes the interaction with land supply elasticity while theirs does not.

migration push up house prices is present in the data. The coefficient on the interaction of city size with the elasticity of land supply indicates, however, that that effect is weakened the more elastic is the supply of labor, which fits with expectations.

It seems plausible that effects of the elasticity of the supply of land could be very non-linear, with changes in city size having particularly substantial effects on house prices when the elasticity is very low and having zero effects for a wide range of large elasticity values. To investigate this, in the third column we present a specification in which we interact the change in city size with a set of indicator variables corresponding to different ranges of the elasticity of the elasticity of housing supply (where the range is given by elasticity quintiles in our sample).[22] The wage effect remains very similar to that in the more restrictive specification but the interactions do indicate a strong non-linearity. Effectively, the positive effect of increased city size on house prices is only present for cities with very inelastic housing supplies (cities like San Francisco and Boston). Once we reach even moderate values for the supply index (values in the second quintile of the distribution across cities which includes cities like Minneapolis and Pittsburgh), the city size effect is not statistically significant at any conventional level. In effect, these estimates suggest the migration flows only affect housing costs in a small fraction of cities. This observation is potentially problematic for spatial models which rely exclusively on the adjustment of house price to migration flows as the mechanism generating equilibrium outcomes.

3.3 Wage Equation

We turn, next, to estimates of the wage equation (21). Beaudry et al. [2012] contains a thorough investigation of the determination of wages in the context of a multi-sector search and bargaining model. The main difference in our specification here is the inclusion of potential agglomeration effects, and we will focus our attention on those effects. Column 1 of Table 5 contains OLS estimates of equation (21). Those estimates imply positive effects of the industrial composition variable (and, therefore, positive wage spill-over effects as indicated by the model), and positive effects of the employment rate and city size. Of course, endogeneity considerations mean that these are likely not consistent estimates and in column (2) we present results from estimations that use the main instruments derived from the model: $IV1$, $IV2$, $IV3$, and the interaction of $IV3$ with u, the fraction of land unavailable for development. Unfortunately, collinearity among the instruments results in quite poorly defined estimates. In the third column, we add to the instrument set the climate variables described earlier, and this allows us to obtain better defined estimates. We will focus our discussion on these estimates.

The estimated coefficient on ΔR is positive, significant at the 1% level and similar in magnitude to the OLS estimated coefficient. It is also similar in size to the effect estimated in Beaudry et al. [2012]. In that paper, we show that this coefficient can be interpreted as a multiple of a standard "between" element in a decomposition of the effect of an industrial composition change on the average-city wage. Thus, we

[22] In this specification, we instrument for the change in the average city wage using $IV1$ and $IV2$ but we do not instrument for all of the interactions.

interpret our estimates as saying that, because of spillovers, the effect of a change in industrial composition is 2.5 to 3 times larger than one would predict from a simple decomposition exercise. The employment rate effect, in contrast, is close to zero and not statistically significant at any conventional level. In the context of the model, this implies that the wage bargaining curve is very flat.

Our key point of focus in the wage equation is on the change in city size variable. The estimated coefficient on that variable is quite small and not statistically significant. We can view this estimated effect in the light of two different literatures. The first is the substantial literature estimating the impact of migration-related supply shocks on outcomes in local economies. Perhaps the most famous paper in this literature is the Card [1990] paper on the impact of the Mariel Boatlift on the Miami economy. The Mariel Boatlift stemmed from a one-time event in which the Cuban government allowed a large number of people to leave. Most of these migrants settled in the Miami area, increasing the size of the population by 7% virtually over-night. Strikingly, Card found no impact on either wages or employment rates in Miami after the first few years. That paper has been followed by numerous others, investigating various adjustment mechanisms such as out-migration from a city and technological adjustment [Lewis, 2004, for example]. Even papers that are quite critical of the initial methodology, though, tend to find quite small employment responses to migration shocks [Borjas, Freeman, and Katz, 1996]. The model presented here provides an explanation for these outcomes once we take into account that the agglomeration effects are effectively zero. Specifically, in this model, given the matching technology is constant returns to scale and we assume that entrepreneurs are proportional to the population, the size of the economy does not matter since none of the key parameters in the model change with city size. That means that an economy hit with a migration shock effectively replicates itself, moving to a new equilibrium where the city size is larger but wages and the employment rate are unchanged. Our estimated coefficients fit with this implication of the model.

Given the latter model implication, city size only enters our wage specification because of our hypothesized link between productivity and city size. This raises the second relevant literature: the extensive literature on agglomeration effects for cities (see Rosenthal and Strange [2004] and Melo, Graham, and Noland [2009] for reviews). Part of that literature documents that firms tend to cluster near other firms in the same industry (e.g., Rosenthal and Strange [2003] and Duranton and Overman [2005]). More directly relevant for us are studies examining the relationship of firm productivity or wages to industrial concentration and/or city size. Melo et al. [2009], in a meta-analysis of that literature, show that studies tend to find significant, positive effects of both city size (what they call urbanization) and industrial concentration (what they call localization). The unweighted average of the 729 estimates they examine is 0.058. Our estimated, near-zero effect does not appear to fit with this pattern in the earlier literature. However, when we estimate a simple specification similar to that in the agglomeration literature with only the change in city size on the right-hand side (instrumenting using climate variables and $IV3 \cdot u$, and including year $\times$ industry dummies), we obtain an estimated coefficient of 0.06 (s.e. 0.039). Thus, it appears to be the inclusion of our other controls that sets our estimates apart. As far as we are aware, no other paper controls for our measure of industrial composition, which is based on the relative industrial wage not on any measure of productivity or other links across industries, or for the city-level employment rate. This suggests that part of what is often estimated as an agglomeration effect in fact reflects the effects of these other variables, whose inclusion is theoretically indicated in our model. In addition, though, estimates in the existing literature tend to be smaller when human capital controls are included. Behrens et al. [2012], for example, show that controlling for the level of education in a city reduces estimated effects of city size on average-city earnings by about a third. Given that we control for observable human capital variation and selection on unobserved skills, our small measures are not greatly outside the range of existing estimates.

3.4 Employment Rate Equation

In Table 6, we present results from estimating equation (18). As with estimates of the other equations, the first column contains OLS results in order to show basic patterns. Those estimates reveal a positive and significant effect of the local demand index (as predicted) but also a positive effect of the average wage variable. The latter is the opposite of what the model predicts since it corresponds to the slope of the job creation curve which is predicted to be negative. However, the estimate should fit with this prediction only if endogeneity concerns are addressed. In the second column, we present results from IV estimation using instruments implied by the model: $IV1$, $IV2$, and $IV1-3$ interacted with the measure of the unavailability of developable land. In these estimates, the wage coefficient becomes negative and significant (as the theory predicts). Both the local demand effect and city size have positive coefficients but both are also poorly defined. As before, we believe this is a result of collinearity problems among the instruments. In response, in the third column we present results using $IV1$, $IV2$ and the climate variables as instruments. In this specification, the wage effect is again negative and significant with a coefficient of -0.30. This is very similar to the estimated value for the slope of the job creation curve obtained in Beaudry et al. [2011]. The local demand index now has a positive and significant effect, with a 10% increase in the demand index implying a 2.4% increase in the city employment rate. On the other hand, the change in city size has a coefficient which is negative, small and not significantly different from zero at any conventional significance level. This fits with the result in the wage equation that productivity does not respond to city size – at least once we control for the demand index and the index of wage-related industrial composition.

4 Is Spatial Equilibrium the Proper Way of Interpreting the Cross-city Patterns

Up to now, we have interpreted the data within an equilibrium framework where mobility is assumed to be sufficiently strong to always equate utility across cities. However, as we have noted, for many cities the main mechanism which should bring about such equalization is anemic; that is, we saw that for most U.S. cities housing costs do not respond to migration flows. This opens up the question of whether the data are best interpreted as reflecting points where agents are indifferent between different locations, or alternatively, as points of disequilibrium – perhaps on a path toward the equal utility state. In this section, we want to highlight some patterns which point to the possibility that mobility frictions may hinder the continuous equalization of utility across localities.

The first piece of evidence suggesting that mobility may be quite sluggish comes from comparing estimates of our city-size equation estimated over a window of 20 years versus one of 10 years. As we saw in Table 1 and 3, labor does tend to flow toward cities with higher wages and higher employment. However, it is worth emphasizing that our estimates in these tables indicate that the elasticity of labor flows with respect to wage movements is far from infinite, which in of itself can be interpreted as potential evidence against a fully mobile labour interpretation of the data. More to the point, when we estimate the labour flow equation over a 20 year window, as reported in Table 7 for both OLS and some IV specifications, we find that elasticity of migration to the real wage is twice as big as that found when estimating over a 10 year window. While there can be different interpretations of this finding, it provides some indication that a very slow process of labour reallocation may be at play.

Given this, it is worth re-examining our results for the wage equation from the perspective that short run mobility may be limited. Recall that in our derivation of the wage equation, we made explicit use of the assumption that worker's mobility is sufficient to equalize their utility across cities. In particular, that assumption caused an important simplification of the worker's Bellman equations: it implies that the option to move to another city has no value. This explains why the cost of local housing does not enter the equation for the determination of wages. Here, we want to allow for the possibility that utility may not always be equalized across localities and explore the implications that follow. [23] [24]

To clarify the implications for wage determination of being out of equilibrium in terms of equalized utility, recall that the wage equation is derived from the bargaining condition, (11), which in turn depends on the worker's surplus from being employed relative to being unemployed. With utility equalized across cities, local amenities and house prices enter the employed and unemployed value functions in the same way and, as a result, play no role in the worker's surplus. However, once we allow for disequilibrium, the unemployed option has an extra component: the option to move to a city with higher utility. Given this, the local house prices and amenities

[23]One can show that allowing for disequilibrium in terms of mobility does not affect the specification of the employment rate equation.

[24]This is only possible if we consider a version of the model in which utility is not fully equalized across cities since when they are equalized, wages and house prices are perfectly co-determined and one cannot meaningfully discuss a causal effect of house price changes on wages.

remain relevant in firm-worker bargaining and the wage equation becomes:

$$\Delta \ln \sum_i \eta_{ic} w_{ic} = \tilde{\alpha}_{40} + \tilde{\alpha}_{41} \Delta R_c - \tilde{\alpha}_{42} \Delta \frac{E}{L_c} + \tilde{\alpha}_{45} \Delta \ln P_c^h + \tilde{\alpha}_{44} \Delta \ln \sum \epsilon_{i2c} + \tilde{\alpha}_{46} \Delta \epsilon_{1c}, \tag{26}$$

where we have assumed here that city-size congestion and agglomeration effects are zero in order to focus attention on the house price implications.

Column 1 of Table 8 contains OLS coefficients from estimating equation (26). As expected, the coefficient on ΔR is again positive but smaller than in the estimation not including the house price. The employment rate again enters with a small and insignificant coefficient. The change in the house price has a positive sign, which fits with theoretical implications: when house prices rise, worker surplus from employment decreases and wage bargaining implies that they need to be compensated with higher wages. Thus, factors that push up housing prices can push up wages when mobility is sufficiently low that the national economy is out of equilibrium.

As in all of our estimates, we next turn to IV implementations of the equation. In column 2 of Table 8, we present estimates using $IV1-3$ and $u \cdot IV3$ as instruments. Relative to the OLS estimates, the ΔR coefficient is somewhat larger, while the other two coefficients are somewhat smaller. We get very similar results when we use the climate variables as instruments instead of the land supply elasticity (column 3). The smaller coefficient on ΔR when we include the house price variable fits with a notion that a shift in industrial composition toward higher paying industries has the effect in terms of increasing bargaining power in all sectors that we have so far emphasized, but also has an impact on housing prices. Specifically, as we saw earlier, increased wages likely lead to increased costs of house construction and, thus, increased housing costs. We can see from estimation of (26) that those increased housing costs, in turn, push up wages. Thus, the effect we obtain from the specification without house prices is a total effect reflecting both the direct bargaining effect and the indirect effect through house prices. Under the disequilibrium assumption, we can control for the latter, indirect route, and the direct bargaining effect therefore becomes smaller. It is interesting to note the interaction between wages and housing costs implied by our estimates of (26) and those of the housing cost equation. We see from these two equations that wages have a much stronger effect on housing costs than housing cost have on wages. For example, an exogenous increase in housing costs of 1% has an effect on wages of .25% while the effect of wages on housing costs is estimated to be approximately one-for-one. If the data reflected spatial equilibrium then wages and house prices would be perfectly co-determined and, in principle, we could not obtain well-defined estimates of the impact of house prices on wages. The fact that we are able to do so may be further evidence that the economy is not in spatial equilibrium. We are, however, cautious about emphasizing this conclusion since econometric shortcomings might result in such estimates even with spatial equilibrium.

Since we are suggesting that the observed cross-city patterns over a 10 year window may reflect slow movements toward a spatial equilibrium – as opposed to being in continual spatial equilibrium – it appears relevant to contrast this interpretation with that in Blanchard and Katz [1992]. A main finding in Blanchard and Katz [1992] is that an increase in labor demand appears to be associated with offsetting in-migration and very little change in wages. This observation has been taken as evidence that labour is close to perfectly mobile across U.S. localities. Our empirical results are very much in line with those of Blanchard and Katz [1992], however the proper interpretation is not so clear. First, to see how our results line up with those in Blanchard and Katz [1992], note that their measure of labour demand corresponds to the index $\sum_i \eta_{ic} g_i$ which is included in our estimation on the employment rate equation. In column 3 of Table 8, we see that the coefficient on this index is approximately 0.2, that is, an increase in labour demand of 1% increases the employment rate by 0.2%. We can now use this estimated effect in conjuction with our estimate of the migration flows given by the city size equation to get an estimate of a change in labour demand on the supply of workers. Since the impact of employment rate changes on migration flows is estimated to be around 6 (from estimates of Equation 1), we infer the effect of a 1% increase in labour demand on the local supply supply of workers to be 1.2 (6×0.2), which is line with the previous finding. Moreover, given that we saw that wages respond little to changes in the employment rate, this is consistent with the pattern observed by Blanchard and Katz [1992]. The issue is how these data should be interpreted. We believe that these results are consistent with the view that, although agents respond very aggressively to changes in labour demand, migration flows across U.S. cities may be insufficient to equate utility over the short run.

The results and discussion of this section have been aimed at highlighting patterns of the data that may pose some challenges to the commonly used notion of spatial equilibrium. In particular, we have emphasized that observed labor flows and wage determination patterns are at least suggestive of the possibility that cross-city mobility may be insufficiently responsive for the economy to be interpreted as continuously being in a spatial equilibrium state. This opens up the question of whether there are other forces not included in the model which may help the attainment of a spatial equilibrium. For example, if local technological knowledge advantages are very temporary, as such information may flow rapidly between cities, then limited labour mobility may not be a great hindrance to the attainment of spatial equilibrium. To examine this possibility along one dimension, in Table 9 we provide estimates of the within industry convergence rates of wages across-cities. In the first column, we report the OLS estimates of the effect of initial wages (by industry-city cells) on subsequent change in wages over a 10 year window. In the second column we instrument the initial wages with the levels one decade earlier. From the IV results, we can see that over the period considered, there is virtually no indication that wages are converging across locality. This result, combined with both the evidence that labour flows may be sluggish and that labour flows may have very limited effects on local housing costs, imply that city-level outcomes over the short and medium term may reflect an adjustment process toward spatial equilibrium as opposed to being in spatial equilibrium.

5 Conclusion

In this paper, we present and empirically evaluate a search and bargaining model in a spatial equilibrium setting. Building on previous work, Beaudry et al. [2012, 2011], we extend a search and bargaining model with multiple industries and cities to allow for agglomeration or congestion externalities. In contrast to Walrasian spatial equilibrium setups, our model is characterized by search frictions and wage bargaining, giving rise to equilibrium unemployment. We empirically evaluate the implications gained from a spatial equilibrium model with these additional characteristics using U.S. Census and ACS data on cities over 1970-2007.

The structure of our model gives rise to a system of four equations that jointly determine city size, housing costs, wages and employment rates. The model makes clear potential endogeneity concerns and provides instruments with which to identify key parameters. Our instruments use national-level patterns to predict industrial composition shifts that affect the outside options, and, hence, wages, of workers at the local level. Using this idea, we are able to identify the effect of wages on variables of interest and evaluate the relative importance of wages and employment opportunities for migration decisions. We find that, consistent with Blanchard and Katz [1992], households are much more responsive to changes in local employment rates than to wages. Our results suggest that migration responses are nearly three times larger for changes in employment rates compared to changes in wages.

The relative responsiveness of migration to changes in wages and employment rates is important since the high sensitivity of migration decisions to local unemployment previous documented in the literature – and confirmed here– is often taken as evidence that mobility is likely sufficient strong to assure that utility is always equalized across localities. However, the much smaller effect on mobility we find for wages cast some doubt regarding the validity of such inference. We also found other pieces of evidence supporting the idea that utility may not be constantly equalized across localities. In particular, we find that for the majority of the cities in our sample, housing prices do not respond significantly to migration, with the exception of a few land constrained cities which respond strongly to worker inflows. Thus, for the unconstrained, elastic housing supply cities, the unresponsiveness of housing prices to migration puts into question their role for equating utility across cities. Further, our observation that local wages respond weakly but significantly to changes in local housing costs provides some support to a more disequilibrium interpretation of the data. These estimates also provide insight regarding of the relative importance of the effect of housing cost on wages versus the effect of local wages on housing cost. We find that housing costs respond very strongly to wages – in a proportion near to one-to-one, while the direct effect of housing cost on wage is found to be 5 times smaller.

Finally, although our model incorporates possible agglomeration externalities, we find little evidence of their existence, either positive or negative, over the medium term, ten-year windows that we examine. Taken together with our other results, this provides insight into the nature of the spatial equilibrium process across U.S. cities over 10-year periods. For the majority of the cities in our sample, housing prices do not respond to migration, implying that the spatial equilibrium has a recursive structure – local technology dictates a city's wage structure, employment rate and housing costs. Agents relocate across cities in response to differences between cities, but their movements have very little feedback effects. This, in turn, implies significant migration frictions, otherwise individuals would tend to end up in only a few cities.

References

M. Amior. Housing Costs and Local Earnings Inequality. Technical report, Department of Economics, University College London., 2012.

J. D. Angrist and J.-S. Pichke. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press, 2009.

T. J. Bartik. *Who Benefits from State and Local Economic Development Policies?* Kalamazoo, MI: W.E. Upjohn Institute for Employment Research., 1991.

P. Beaudry, D. A. Green, and B. Sand. How Elastic is the Job Creation Curve ? . Technical report, University of British Columbia, 2011.

P. Beaudry, D. A. Green, and B. M. Sand. Does Industrial Composition Matter for Wages? A test of search and bargaining theory. *Econometrica*, 2012.

K. Behrens, G. Durnanton, and F. Robert-Nicoud. Productive cities: Sorting, selection and agglomeration. Technical report, CEPR Discussion Papers 7922, C.E.P.R. Discussion Papers., 2012. URL http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1640998.

O. Blanchard and L. Katz. Regional Evolutions. *Brookings Papers on Economic Activity. Microeconomics*, 1992. URL http://www.jstor.org/stable/10.2307/2534556.

G. J. Borjas, R. B. Freeman, and L. F. Katz. Searching for the Effect of Immigration on the Labor Market. *The American Economic Review*, 86(2), 1996. URL http://www.jstor.org/stable/pdfplus/2118131.pdf?acceptTC=true.

D. Card. The impact of the Mariel boatlift on the Miami labor market. *Industrial and Labor Relations Review*, 43(2):245–257, 1990. URL http://www.nber.org/papers/w16396http://www.nber.org/papers/w3069.pdf.

P. Combes and G. Duranton. The productivity advantages of large cities : Distinguishing agglomeration from firm selection. *...Discussion Paper No ...*, 2012. URL http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1356400.

G. Dahl. Mobility and the return to education: Testing a Roy model with multiple markets. *Econometrica*, 70(6):2367–2420, 2002. URL http://onlinelibrary.wiley.com/doi/10.1111/j.1468-0262.2002.00443.x/abstract.

A. Deaton and D. Lubotsky. Mortality, inequality and race in american cities and states. Technical report, NBER, 2001.

G. Duranton and H. G. Overman. Testing for localization using micro- geographic data Testing for Localisation Using Micro-Geographic Data. *Review of Economic Studies*, 72(4):1077–1106, 2005. URL http://eprints.lse.ac.uk/581/.

R. Fonseca, P. Lopez-garcia, and C. A. Pissarides. Entrepreneurship, start-up costs and employment. *European Economic Review*, (45):692–705, 2001.

E. L. Glaeser and J. D. Gottlieb. The Wealth of Cities: Agglomeration Economies and Spatial Equilibrium in the United States. *Journal of Economic Literature*, 47 (4):983–1028, Dec. 2009. ISSN 0022-0515. doi: 10.1257/jel.47.4.983. URL http://pubs.aeaweb.org/doi/abs/10.1257/jel.47.4.983.

E. Lewis. How Did the Miami Labor Market Absorb the Mariel Immigrants? *Working Papers*, (04), 2004. URL http://ideas.repec.org/p/fip/fedpwp/04-3.html.

P. C. Melo, D. J. Graham, and R. B. Noland. A meta-analysis of estimates of urban agglomeration economies. *Regional Science and Urban Economics*, 39(3):332–342, May 2009. ISSN 01660462. doi: 10.1016/j.regsciurbeco.2008.12.002. URL http://linkinghub.elsevier.com/retrieve/pii/S0166046208001269.

E. Moretti. Real Wage Inequality. Technical report, UC Berkeley, 2011a. URL http://emlab.berkeley.edu/~moretti/inequality.pdf.

E. Moretti. Local labor markets. In *Handbook of Labor Economics*, volume 4, chapter 14. 2011b. doi: 10.1016/S0169-7218(11)02412-9. URL http://www.jstor.org/stable/10.2307/1837178.

J. H. Park. Estimation of Sheepskin Effects and Returns to Schooling Using he Old and the New CPS Measures of Educational Attainment. Technical report, Princeton University, Industrial Relations Section, 1994.

Pissarides. *Equilibrium Unemployment Theory*. 2nd ed., Cambridge (MA): MIT Press., 2000.

C. A. Pissarides and J. Wadsworth. Unemployment and the Inter-Regional Mobility of Labour. *The Economic Journal*, 99(397):739–755, 1989. URL http://www.jstor.org/stable/10.2307/2233768.

S. S. Rosenthal and W. C. Strange. Geography, Industrial Organization, and Agglomeration. *Review of Economics and Statistics*, 85(2):377–393, May 2003. ISSN 0034-6535. doi: 10.1162/003465303765299882. URL http://www.mitpressjournals.org/doi/abs/10.1162/003465303765299882.

S. S. Rosenthal and W. C. Strange. Evidence on the Nature and Sources of Agglomeration Economies. In *Handbook of Urban and Regional Economics*. 2004. URL http://www.rotman.utoronto.ca/~wstrange/RS_

EvidenceontheNatureandSourcesofAgglomerationEconomies8-24-03.pdf.

S. Ruggles, T. J. Alexander, K. Genadek, R. Goeken, and M. Schroeder, Matthew B. Sobek. Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]. Technical report, University of Minnesota, 2010.

A. Saiz. The geographic determinants of housing supply. *The Quarterly Journal of Economics*, (August), 2010. URL http://qje.oxfordjournals.org/content/125/3/1253.short.

A Data

The Census data was obtained with extractions done using the IPUMS system (see Ruggles, Alexander, Genadek, Goeken, and Schroeder, Matthew B. Sobek [2010]. The files were the 1980 5% State (A Sample), 1990 State, 2000 5% Census PUMS, and the 2007 American Community Survey. For 1970, Forms 1 and 2 were used for the Metro sample. The initial extraction includes all individuals aged 20 - 65 not living in group quarters. All calculations are made using the sample weights provided. For the 1970 data, we adjust the weights for the fact that we combine two samples. We focus on the log of weekly wages, calculated by dividing wage and salary income by annual weeks worked. We impute incomes for top coded values by multiplying the top code value in each year by 1.5. Since top codes vary by State in 1990 and 2000, we impose common top-code values of $140,000$ in 1990 and $175,000$ in 2000.

A consistent measure of education is not available for these Census years. We use indicators based on the IPUMS recoded variable EDUCREC that computes comparable categories from the 1980 Census data on years of school completed and later Census years that report categorical schooling only. To calculate potential experience (age minus years of education minus six), we assign group mean years of education from Table 5 in Park [1994] to the categorical education values reported in the 1990 and 2000 Censuses.

Census definitions of metropolitan areas are not comparable over time since, in general, the geographic areas covered by them increase over time and their definitions are updated to reflect this expansion. The definition of cities we use attempts to maximize geographic comparability over time and roughly correspond to 1990 definitions of MSAs provided by the U.S. Office of Management and Budget.[25] To create geographically consistent MSAs, we follow a procedure based largely on Deaton and Lubotsky [2001] which uses the geographical equivalency files for each year to assign individuals to MSAs or PMSAs based on FIPs state and PUMA codes (in the case of 1990 and 2000) and county group codes (for 1970 and 1980). Each MSA label we use is essentially defined by the PUMAs it spans in 1990. Once we have this information, the equivalency files dictate what counties to include in each city for the other years. Since the 1970 county group definitions are much courser than those in later years,

[25] See http://www.census.gov/population/estimates/pastmetro.html for details.

the number of consistent cities we can create is dictated by the 1970 data. This process results in our having 152 MSAs that are consistent across all our sample years. Code for this exercise was generously provided by Ethan G. Lewis.

We use an industry coding that is consistent across Censuses and is based on the IPUMS recoded variable `IND1950`, which recodes census industry codes to the 1950 definitions. This generates 144 consistent industries.[26]

Our measure of housing prices follows Moretti [2011a]. In particular, we use the IPUMs variable "gross monthly rent" called `RENTGRS`. This measure includes the contract rent plus utility costs, and IPUMs suggests that it is more comparable across individuals than "contract monthly rent". However, we find very similar results using either measure. As in Moretti [2011a], we limit the sample to rental units with 2 or 3 bedrooms, and we correct for top coding by multiplying top-coded values by 1.3.

A.1 Geographic Data

City geographic data on land availability and estimated housing supply elasticity were downloaded from Albert Saiz's web page found here:

http://real.wharton.upenn.edu/ saiz/SUPPLYDATA.zip Saiz [2010] provides a detailed description on the construction of this data.

A.2 Climate Instruments

The data we use for the city climate variables comes from the 1988 edition of the County and City Data Book.[27] We extract the following metro area variables:

1. Average daily temperature in July
2. Average daily high temperature in July
3. Average daily temperature in January
4. Average daily low temperature in January
5. Annual precipitation
6. Annual degree cooling days
7. Annual degree heating days

The data are consistent with the idea that mild climates have become more desirable over time, consistent with our hypothesis of the changing valuation of climate as a city amenity.

[26] See http://usa.ipums.org/usa-action/variableDescription.do?mnemonic=IND1950 for details.
[27] Details can be found here: http://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/9251.

Table 1: Estimate of City Size Equation (16)

	OLS	IV		
	(1)	(2)	(3)	(4)
Δw_{ct}	0.47	3.17*	2.74	2.34
	(0.28)	(1.43)	(1.51)	(1.31)
$\Delta \log \frac{E}{L}_{ct}$	0.0082	5.43*	7.79*	6.60*
	(0.30)	(2.00)	(2.38)	(1.93)
$\Delta \log p^h_{ct}$	-0.022	-1.27	-1.44	-0.94
	(0.16)	(0.93)	(1.15)	(0.93)
Year	Yes	Yes	Yes	Yes
Observations	568	568	568	568
R^2	0.15			
IV Set:		IV1,IV3,u· IV3	IV2,IV3,u · IV3	IV1,IV2,IV3,u· IV3
F-Stats:				
Δw_{ct}		49.09	46.11	60.93
$\Delta \log \frac{E}{L}_{ct}$		7.15	12.65	9.98
$\Delta \log p^h_{ct}$		39.37	39.12	35.51
AP p.val:				
Δw_{ct}		0.00	0.00	0.00
$\Delta \log \frac{E}{L}_{ct}$		0.00	0.00	0.00
$\Delta \log p^h_{ct}$		0.00	0.00	0.00
Over-id. p-val		.	.	0.19

NOTES: Robust standard errors are given in parentheses. (*) denotes significance at the 5% level. All models estimated on a sample of 142 U.S cities using Census and ACS data for 1970-2007. The dependent variable is the decadal log change in adult population.

Table 2: First Stage: Equation (16)

	Col (2)			Col (3)			Col (4)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Δw_{ct}	$\Delta \log \frac{E}{L}_{ct}$	$\Delta \log p^h_{ct}$	Δw_{ct}	$\Delta \log \frac{E}{L}_{ct}$	$\Delta \log p^h_{ct}$	Δw_{ct}	$\Delta \log \frac{E}{L}_{ct}$	$\Delta \log p^h_{ct}$
IV1	5.107*	-0.960*	7.041*				4.112*	-0.737*	5.996*
	(0.520)	(0.353)	(0.929)				(0.512)	(0.354)	(0.967)
IV2				3.586*	-0.781*	3.968*	3.091*	-0.692*	3.246*
				(0.411)	(0.228)	(0.577)	(0.343)	(0.241)	(0.495)
IV3	-0.0748	0.206*	-0.236	0.402*	0.118*	0.429*	-0.000748	0.190*	-0.158
	(0.0765)	(0.0537)	(0.125)	(0.0615)	(0.0367)	(0.109)	(0.0726)	(0.0510)	(0.127)
$u \cdot IV3$	0.0919	0.0251	0.457*	0.0134	0.0407	0.356*	0.0584	0.0326	0.421*
	(0.0486)	(0.0322)	(0.0874)	(0.0433)	(0.0315)	(0.0819)	(0.0414)	(0.0314)	(0.0814)
Observations	568	568	568	568	568	568	568	568	568
R^2									

Standard errors in parentheses

Table for First Stage

* $p < 0.05$

Table 3: City Size and Real Wages

	Equation 16		
	(1)	(2)	(3)
$\Delta w_{ct} - 0.35 \times \Delta p^h_{ct}$	2.02*		
	(0.60)		
$\Delta w_{ct} - 0.40 \times \Delta p^h_{ct}$		2.28*	
		(0.70)	
$\Delta w_{ct} - 0.45 \times \Delta p^h_{ct}$			2.61*
			(0.83)
$\Delta \log \frac{E}{L}_{ct}$	6.54*	6.64*	6.77*
	(1.74)	(1.77)	(1.80)
Year	Yes	Yes	Yes
Observations	568	568	568
R^2			
IV Set:	IV1,IV2,IV3	IV1,IV2,IV3	IV1,IV2,IV3
F-Stats:			
$\Delta w_{ct} - \alpha \cdot \Delta p^h_{ct}$	57.46	45.63	33.47
$\Delta \log \frac{E}{L}_{ct}$	12.51	12.51	12.51
AP p.val:			
$\Delta w_{ct} - \alpha \cdot \Delta p^h_{ct}$	0.00	0.00	0.00
$\Delta \log \frac{E}{L}_{ct}$	0.00	0.00	0.00
Over-id. p-val	0.20	0.19	0.17

NOTES: Robust standard errors are given in parentheses. (*) denotes significance at the 5% level. All models estimated on a sample of 142 U.S cities using Census and ACS data for 1970-2007. The dependent variable is the decadal log change in adult population.

Table 4: Estimates of Housing Price Equation (17)

	OLS	IV	
	(1)	(2)	(3)
Δw_{ct}	1.27*	1.25*	1.28*
	(0.045)	(0.093)	(0.079)
$\Delta \log L_c$	0.059*	0.28*	
	(0.030)	(0.086)	
$e \cdot \Delta \log L_c$	-0.028*	-0.12*	
	(0.013)	(0.028)	
$e \cdot [e < .2] \cdot L_c$			0.057*
			(0.027)
$e \cdot [e < .4] \cdot L_c$			-0.16
			(0.085)
$e \cdot [e < .6] \cdot L_c$			0.060
			(0.084)
$e \cdot [e < .8] \cdot L_c$			-0.13
			(0.077)
$e \cdot [e < 1] \cdot L_c$			0.017
			(0.031)
Constant	0.76*	0.75*	0.76*
	(0.0091)	(0.019)	(0.0086)
Year	Yes	Yes	Yes
Observations	568	568	568
R^2	0.93		
IV Set:		IV1,IV2,IV3,u · IV3	IV1,IV2
F-Stats:			
Δw_{ct}		60.58	105.59
$\Delta \log L_c$		9.21	
$e \cdot \Delta \log L_c$		10.88	
AP p.val:			
Δw_{ct}		0.00	0.00
$\Delta \log L_c$		0.00	
$e \cdot \Delta \log L_c$		0.00	
Over-id. p-val		0.06	0.04

NOTES: Robust standard errors in parentheses. (*) denotes significance at the 5% level. All models estimated on a sample of 142 U.S cities using Census and ACS data for 1970-2007. The dependent variable is the decadal log change in the price of 2 or 3 bedroom units .

Table 5: Estimates of Wage Equation (21)

	OLS	IV	
	(1)	(2)	(3)
ΔR_{ct}	2.53*	4.34*	2.80*
	(0.057)	(1.62)	(0.43)
$\Delta \log \frac{E}{L}$	0.25*	1.61	0.047
	(0.017)	(1.54)	(0.25)
$\Delta \log L_c$	0.023*	-0.25	-0.028
	(0.0042)	(0.23)	(0.038)
Year × Ind.	Yes	Yes	Yes
Observations	31978	31978	31978
R^2	0.27		
IV Set:		IV1-3, $u \cdot$ IV3	IV1-3,u· IV3,C
F-Stats:			
ΔR_{ct}		167.54	91.52
$\Delta \log \frac{E}{L}_{ct}$		7.69	4.87
$\Delta \log L_c$		16.47	21.01
AP p.val:			
ΔR_{ct}		0.00	0.00
$\Delta \log \frac{E}{L}_{ct}$		0.33	0.00
$\Delta \log L_c$		0.08	0.00
Over-id. p-val		0.31	0.28

NOTES: Standard errors, in parentheses, are clustered at the city-year level. (*) denotes significance at the 5% level. All models estimated on a sample of 152 U.S cities using Census and ACS data for 1970-2007. The dependent variable is the decadal change in regression adjusted city-industry wages.

Table 6: Employment Rate Equation (18)

	OLS	IV	
	(1)	(2)	(3)
$\sum_i \eta_i(w_{ic} - w_i)$	0.14*	-0.27*	-0.30*
	(0.032)	(0.090)	(0.095)
$\Delta \log L_c$	-0.0063	0.010	-0.021
	(0.010)	(0.094)	(0.040)
$\sum_i \eta_{ic} \cdot g_i$	0.10*	0.19	0.24*
	(0.043)	(0.14)	(0.068)
Year	Yes	Yes	Yes
Observations	568	568	568
R^2	0.46		
IV Set:		IV1-2,u · IV1-3	IV1-2,C
F-Stats:			
Δw_{ct}		19.96	12.81
$\Delta \log L_c$		0.83	7.22
AP p.val:			
Δw_{ct}		0.00	0.00
$\Delta \log L_c$		0.44	0.00
Over-id. p-val		0.03	0.62

NOTES: Robust standard errors given in parentheses. (*) denotes significance at the 5% level. All models estimated on a sample of 142 U.S cities using Census and ACS data for 1970-2007. The dependent variable is the decadal log change in city employment rate.

Table 7: City Size and Wages: 20 Year Differences

	Equation 16		
	(1)	(2)	(3)
$\Delta^2 w_{ct} - 0.35 \times \Delta^2 p^h_{ct}$	5.55*		
	(1.16)		
$\Delta^2 w_{ct} - 0.40 \times \Delta^2 p^h_{ct}$		6.28*	
		(1.34)	
$\Delta^2 w_{ct} - 0.45 \times \Delta^2 p^h_{ct}$			7.21*
			(1.61)
$\Delta^2 \log \frac{E}{L}_{ct}$	6.25*	6.32*	6.40*
	(2.20)	(2.25)	(2.34)
Year	Yes	Yes	Yes
Observations	426	426	426
R^2			
IV Set:	IV1,IV2,IV3	IV1,IV2,IV3	IV1,IV2,IV3
F-Stats:			
$\Delta^2 w_{ct} - \alpha \cdot \Delta^2 p^h_{ct}$	65.97	52.23	37.87
$\Delta^2 \log \frac{E}{L}_{ct}$	13.97	13.97	13.97
AP p.val:			
$\Delta^2 w_{ct} - \alpha \cdot \Delta^2 p^h_{ct}$	0.00	0.00	0.00
$\Delta^2 \log \frac{E}{L}_{ct}$	0.00	0.00	0.00
Over-id. p-val	0.16	0.15	0.14

NOTES: Robust standard errors given in parentheses. (*) denotes significance at the 5% level. All models estimated on a sample of 142 U.S cities using Census and ACS data for 1970-2007. The dependent variable is the decadal log change in adult population.

Table 8: Allowing for Disequilibrium: Equation 26

	OLS	IV	
	(1)	(2)	(3)
ΔR_{ct}	1.09*	1.70*	1.45*
	(0.056)	(0.44)	(0.31)
$\Delta \log \frac{E}{L}_{ct}$	0.092*	-0.11	-0.11
	(0.017)	(0.29)	(0.14)
$\Delta \log p^h_{ct}$	0.33*	0.21*	0.25*
	(0.0065)	(0.074)	(0.064)
Year $\times$ Ind.	Yes	Yes	Yes
Observations	31978	31978	31978
R^2	0.32		
IV Set:		IV1-3,u · IV3	IV1-3,u · IV3,C
F-Stats:			
ΔR_{ct}		153.27	67.27
$\Delta \log \frac{E}{L}_{ct}$		7.42	4.16
$\Delta \log p^h_{ct}$		24.06	10.44
AP p.val:			
ΔR_{ct}		0.00	0.00
$\Delta \log \frac{E}{L}_{ct}$		0.00	0.00
$\Delta \log p^h_{ct}$		0.00	0.00
Over-id. p-val		0.17	0.64

Notes: Standard errors, in parentheses, are clustered at the city-year level. (*) denotes significance at the 5% level. All models estimated on a sample of 152 U.S cities using Census and ACS data for 1970-2007. The dependent variable is the decadal change in regression adjusted city-industry wages.

Table 9: City × Industry Wage Convergence

	OLS	IV
	(1)	(2)
w_{ict-1}	-0.31*	0.033
	(0.0053)	(0.035)
Year × Ind.	Yes	Yes
Observations	31978	25891
R^2	0.30	
IV Set:		w_{ict-2}
F-Stats:		
Δw_{ct-1}		286.23
AP p.val:		
Δw_{ct-1}		0.00

NOTES: Standard errors, in parentheses, are clustered at the city-year level. (*) denotes significance at the 5% level. All models estimated on a sample of 152 U.S cities using Census and ACS data for 1970-2007. The dependent variable is the decadal change in regression adjusted city-industry wages.