To What Extent Do High Wages Kill Jobs?*

Estimating the Elasticity of The Job Creation Curve

[Job Market Paper]

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Abstract

In search and bargaining models, the effect of higher wages on employment is determined by the elasticity of the job creation curve. In this paper, we use U.S. data over the 1970-2007 period to explore whether labor market outcomes abide by the restrictions implied by such models and to evaluate the elasticity of the job creation curve. The main difference between a job creation curve and a standard demand curve is that the former represents a relationship between wages and employment *rates*, while the latter represents a relationship between wages and employment levels. Although this distinction is quite simple, it has substantive implications for the identification of the effect of higher wages on employment. The main finding of the paper is that U.S. labor market outcomes observed at the city-industry level appear to conform well to the restrictions implied by search and bargaining theory and, using 10-year differences, we estimate the elasticity of the job creation curve with respect to wages to be -0.3.

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Introduction

Debates on policies or institutions that increase labor costs often focus on the extent to which these policies depress employment. This issue arises in discussions of a number of policies, including minimum wages, payroll taxes, job security legislation, and policies related to worker benefits.[1] Despite the common assertion that higher labor costs substantially reduce aggregate employment, much of the evidence on policy parameter shifts finds only modest impacts (Blau and Kahn, 1999). Similar conclusions are reached in the literature directly estimating labor demand elasticities (Hamermesh, 1993). A discordant observation is that much labor market adjustment in the U.S. takes places at fixed wages (Blanchard and Katz, 1992; Krueger and Pischke, 1997). For example, Krueger and Pischke (1997) note that exogenous shifts in population, either at the local or national level, are not systematically associated with changes in wages. These observations imply that labor demand is potentially quite elastic. This suggests a tension in the literature: variation in wages or supply should imply movements along the same demand curve and therefore give the same result.[2]

In this paper, we present and empirically test a variant of a search and bargaining model that has the potential to reconcile this tension. We then use our model to obtain partial and general equilibrium estimates of the impact of labor costs on employment outcomes. In search and bargaining models, labor demand is determined by an equilibrium relationship known as the job creation curve. The job creation curve has many similarities to a standard labor demand curve, but features an important, subtle difference: adjustment to higher wages along a job creation curve determines an employment rate instead of an employment level.[3] We argue that such a difference, while seemingly innocuous, has substantial implications. For example, when labor market outcomes are determined by a job creation curve, the above observations are no longer discordant since the demand for labor is not independent of the supply. Even at fixed wages, increases in the availability of workers increases job creation in a search and bargaining model be-

[1] For example, the California Chamber of Commerce releases an annual list of "job killer" bills which they claim identifies legislation that will "decimate economic and job growth in California". Often the identified bills contain "workplace mandates" which are suggested to increase labor costs.

[2] The two extremes are captured, on the one hand, by a literature on minimum wages which suggests quite inelastic demand (see, for example, Card and Krueger (1994)) and, on the other hand, by a large literature that finds very little wage adjustment to regional supply shocks (see, for example, a review by Friedberg and Hunt (1995)).

[3] This arises because the job creation curve is implicitly defined by a zero profit condition associated with creating a job vacancy. According to this condition, when wages rise the cost of creating and filling a vacancy must fall in order to maintain the value of creating jobs. This cost will depend on the tightness of the labor market (i.e., the employment rate) not the size of the market.

cause it reduces search costs. Therefore, shifts in labor costs or supply can produce very different labor market outcomes.

The framework we present extends the standard search and bargaining model in several directions, reflecting our interest in its empirical evaluation. First, our model consists of a set of local labor markets, called cities, which are linked through goods trade and labor mobility.[4] Identifying the elasticity of the job creation curve requires variation in employment rates that does not simply mimic variation in employment levels. By focusing on city-level outcomes, we are able to distinguish between the two adjustment mechanisms since inter-city migration implies that employment rates and levels do not necessarily move together. We also extend the model to allow for multiple sectors, which is key for our empirical identification strategy. We show that our multi-city, multi-sector model implies testable restrictions that have not previously been recognized in the literature. Finally, we extend the standard model to include heterogeneous talent across the population in terms of abilities to create jobs in different industries.[5] This feature is common in the firm creation literature and, in our model, provides an additional justification for a less than perfectly elastic job creation curve. Our main assumption regarding potential job creators is that they are proportional to the population.[6]

A challenge of the current paper is to present a credible identification strategy for estimating the elasticity of job creation with respect to wages. To do so, we exploit forces that determine wages in a search and bargaining set-up that are independent of the labor demand determination aside from their impact on wages. In particular, changes in workers' bargaining position will impact wages even when the availability of workers is held constant. Using this insight, which is developed in Beaudry, Green, and Sand (2009), we exploit variation in predicted local industrial employment composition or changes in national-level industrial premia to construct instruments for wages at the local level. The intuition behind our instrumental variables strategy is that improvements in workers' outside employment opportunities place upward pressure on wages and are independent of the availability of workers, and thus provide appropriate identifying variation in our

[4] Although labor mobility will allow expected utility to be equalized across localities, the labor market frictions will nevertheless imply that wage determination maintains a local component.

[5] The selection mechanism implied by our entrepreneur heterogeneity approach shares similarities with other work that has modeled industries as collections of heterogeneous producers (Hamermesh (1993, Chapter 4), Jovanovic (1982), Melitz (2003)). The idea that there is heterogeneity among firms has received support from the related empirical literature (see, for example, Bartelsman and Doms (2000)).

[6] This assumption is less common, but appears as a reasonable approximation. In a standard search and bargain model, the elasticity of the job creation curve is driven entirely by the match frictions. In our set-up, this elasticity will reflect both match frictions and the potential supply of job creators.

model. While we demonstrate that our instruments are valid under the assumptions of our model, we also show that the model is over-identified which provides a means of empirically evaluating our approach.[7]

In our framework, we can define two notions of wage elasticity of job creation. The first is a partial equilibrium response that we call industry-level elasticity. This elasticity measures how job creation in one sector responds to changes in wages in that sector, holding the aggregate labor market tightness in a city constant. The second elasticity that we aim to estimate pertains to the total or general equilibrium effect of changes in wages in all sectors of a city. We call this elasticity the local "aggregate" elasticity, and we argue that this elasticity conceptually corresponds most closely to the type of questions of interest to policy makers. The nature of the feedback effects in a search model implies that the aggregate elasticity is smaller than the industry-level elasticity.

Our empirical work is based on U.S. Census data from 1970-2000 and data from the American Community Survey for 2007. Working mainly at the industry-city level, our approach relies on comparing industry-level changes in employment rates across cities with different levels of wage pressures due to changes in bargaining position induced by predicted shifts in industrial composition. We look at effects over periods of 10 years (except for the shorter 7-year period 2000-2007), and therefore the estimates we find are associated with rather long run phenomena.

The main finding of the paper is that the type of labor demand specification implied by our augmented model of search and bargaining – which emphasizes employment rate-wage trade-offs – is given substantial support in the data. In particular, the clear over-identifying restrictions implied by theory are easily accepted. We present estimates of both types of elasticities identified by the model, finding an estimate of -1 for the industry-level elasticity and an estimate of -0.3 for the aggregate elasticity. Thus, our evidence supports claims that the general equilibrium employment rate-labor cost trade-off is relatively inelastic. In addition, the model also provides a rationale for why studies focusing on regional supply adjustments yield results that seem to imply a very elastic labor demand curve. In particular, the assumptions of a constant returns to scale matching technology and potential job creators that are proportional to the population imply that an inflow of workers simply replicates the economy, with no impacts on wages or employment rates. We show that the data conforms to this property, which fits

[7] Our approach to estimation and model evaluation is within the structural tradition, as we derive the conditions under which our model is identified and we use an over-identification test implied by the model to evaluate its relevance. Since one of the main criticisms of structural models is that the identification assumptions are non-transparent and the over-identification test non-intuitive, we present our results within an IV framework that is easy to evaluate.

with other investigations of the nature of the matching function (Blanchard and Diamond, 1989). Expressed in wage/employment-level space, this means that an inflow of workers traces out a flat relationship as employment expands with no effect on wages. Our interpretation implies that this flat relationship is not related to a perfectly elastic labor demand, but is instead a series of equilibrium points reflecting adjustments on both sides of the labor market.

Overall, we view the paper as making three main contributions. First, we show that a standard search and bargaining model extended to include multiple local labor markets and sectors has implications that have not been previously recognized and, importantly, that these implications allow for tight over-identifying restrictions from which to evaluate the model. The fact that we cannot reject these restrictions provides evidence in favor of this class of models in general, and suggests that it is a reasonable framework within which to estimate the effects of labor cost on employment outcomes. Second, we show that estimates using U.S. city-level data can provide a straightforward rationale for the disparate labor demand elasticities that can be inferred from earlier studies. Third, we obtain estimates of general equilibrium impacts of increases in labor costs on the employment rate (which we argue is the most policy-relevant parameter) that imply a relatively inelastic trade-off. One possible implication from this is that as U.S. cities search for ways to spur job creation, focusing on reducing labor costs may yield only modest returns.

A number of papers are related to this work. First, we build on standard equilibrium search models (Pissarides, 2000) to include endogenous industrial composition (Acemoglu, 1999, 2001). In contrast to these latter studies, which are mainly theoretical and focus on factors that influence the composition of jobs, the primary focus of this paper is empirical and investigates the long-run consequences of industrial composition for wage and employment outcomes. This focus also differentiates our work from studies of regional adjustment to aggregate labor demand changes (Blanchard and Katz, 1992; Bartik, 1993, 2006). This paper is also related to work investigating the impact of labor costs on employment, as surveyed by Blau and Kahn (1999), and to a large literature examining local adjustment to supply shocks (see, for example, Lewis (2004), Boustan, Fishback, and Kantor (2007) and Card (2009), among others), and concerned with issues similar to Krueger and Pischke (1997). Our work is different from all of these studies because it is based on an empirical evaluation of a search and bargaining model and, therefore, we highlight very different mechanisms, although our empirical findings are largely consistent with these literatures.

The remaining sections of the paper are as follows. In section 1, we propose an extended search and bargaining model and illustrate the implications of such a model for an empirical specification of the job creation curve. In particular, we use the model to derive both an empirical specification and an instrumental variable strategy for identifying key parameters. In section 2, we present our data and discuss implementation issues. In section 3, we present a large set of results. The model we derive implies a number of estimating strategies and we illustrate how the results from one strategy reinforce the others by satisfying various constraints in the data that are implied by theory. In section 4 we assess the robustness of our results. Section 5 concludes.

1 Theoretical Framework

In this section, we present a multi-sector extension of a standard search and bargaining model with limited entrepreneurial talent. Our goal is to derive an empirical specification of the job creation curve and show how such a job creation curve can be estimated with city-level data. Our framework is general equilibrium in nature, and, therefore, our model highlights the simultaneity of job creation and wage formation. One key objective of this section is to derive an empirical strategy for estimating the elasticity of the job creation curve with respect to wages while taking into account the endogenous formation of wages. We show that the model implies the type of variation that can be used to identify the impact of wages on job creation and provides an intuitive test, in the form of an over-identifying restriction, of the validity of our approach.

The model economy we consider has one final good, denoted Y, which is an aggregation of output from I industries as given by

$$Y = \left(\sum_{i=1}^{I} a_i Z_i^{\chi} \right)^{1/\chi}, \quad \text{where } \chi < 1. \tag{1}$$

The price of the final good is normalized to 1, while the price of the good produced by industry i is given by p_i. In this economy, we assume that there are C local markets called cities and that the industrial goods can be produced in any of these markets. The total quantity of the industrial good Z_i produced in the economy is equal to the sum across cities of X_{ic}, the output in industry i in city c.

1.1 Search

We focus on the steady-state of local economies, called cities, that exhibit search frictions.[8] Each local economy unfolds in continuous time and consists of firms and

[8] To greatly simplify the exposition, we examine the extreme case where workers are not mobile across cities. In a later section, we show that the results derived in this section are robust to an extension of the model allowing for worker mobility and endogenous housing prices.

workers who are risk neutral, infinitely lived, and discount the future at a rate, ρ. Firms and workers come together in pairs to produce via a matching technology and matches separate at an exogenous rate, δ. Let L_c denote the total available number of workers in city c, and $E_c = \sum_i E_{ic}$ and $N_c = \sum_i N_{ic}$ denote 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:

$$M = M\left((L_c - E_c), (N_c - E_c)\right), \tag{2}$$

where the inputs are the available pool of unemployed workers, $L_c - E_c$, 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.

These properties of the matching technology imply that we can write the probability that a worker encounters a vacancy and the probability a firm fills a vacancy as:

$$\psi_c = \frac{M\left((L_c - E_c), (N_c - E_c)\right)}{L_c - E_c} \quad \text{and} \quad \phi_c = \frac{M\left((L_c - E_c), (N_c - E_c)\right)}{N_c - E_c}, \tag{3}$$

respectively. Notice that search is undirected, implying that firms in any industry have the same probability of encountering a worker; that is, what is important for determining vacancy contact rates is the total number of vacancies and the total pool of unemployed workers. In steady state, the flow of workers leaving unemployment must equal the flow of workers exiting employment, implying the equilibrium condition:

$$\delta \frac{E_c}{L_c} = M\left(1 - \frac{E_c}{L_c}, \frac{N_c}{L_c} - \frac{E_c}{L_c}\right). \tag{4}$$

1.2 Bellman Equations

Firms can open jobs in any industry and city. To create a job in industry i in city c, a firm must pay a cost, k_{ic}, the value of which will be determined in equilibrium. 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:

$$\rho V_{ic}^v = -r_i + \phi_c \left(V_{ic}^f - V_{ic}^v\right), \tag{5}$$

where r_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, this value must satisfy

$$\rho V_{ic}^f = p_i - w_{ic} + \epsilon_{ic} + \delta \left(V_{ic}^v - V_{ic}^f\right), \tag{6}$$

where p_i is the price of the industrial good, w_{ic} the wage paid to workers in industry i in city c, and ϵ_{ic} is an industry-city cost advantage where we assume $\sum_c \epsilon_{ic} = 0$. Thus, once a match occurs, a firm enjoys a profit flow of $p_i - w_{ic} + \epsilon_{ic}$, and with probability δ the match is broken.

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

$$\rho U^e_{ic} = w_{ic} + \delta(U^u_{ic} - U^e_{ic}), \tag{7}$$

where w_{ic} is the wage paid to the worker in industry i in city c. When an individual is unemployed, he receives a flow utility from an unemployment benefit, b, plus a city-specific amenity, τ_c.[9] The probability that a potential worker finds a job is ψ_c. Let μ denote the probability that an individual is matched with his previous industry, and $1-\mu$ the probability that he draws a job from all industries (including i). Thus, the value of unemployment must satisfy:

$$\rho U^u_{ic} = b + \tau_c + \psi_c \left(\mu \cdot U^e_{ic} + (1-\mu) \cdot \sum_j \eta_{jc} U^e_{jc} - U^u_{ic} \right). \tag{8}$$

The important aspect of equation (8) is that, as long as $\mu < 1$, the utility level associated with having lost one's job in industry i depends on the utility associated with jobs in other industries. The instantaneous probability of finding a job in industry j is given by $\psi_c \cdot (1-\mu) \cdot \eta_{jc}$, where η_{jc} represents the fraction of vacant jobs that are in industry j. This implies that a worker finding a job in another industry is assumed to find it in proportion to the relative size of that industry.[10]

In writing the above equations, 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:

$$\left(V^f_{ic} - V^v_{ic} \right) = (U^e_{ic} - U^u_{ic}) \cdot \kappa, \tag{9}$$

[9] We have not included an amenity term in the flow utility when employed to simplify notation. No results would change if we included such a term since what is important for wage determination is the difference in utility between being unemployed or employed. The amenity term τ should therefore be interpreted as the difference in flow utility associated with amenities when unemployed versus when someone is employed.

[10] In this formulation, we are assuming that workers can only search while being unemployed. While this is a strong assumption, it has the attractive feature of allowing the problem to be solved explicitly and thereby amenable to simple empirical exploration. For these reasons we maintain this assumption throughout and leave for future work the implications for industrial composition with on-the-job search.

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, N_{ic}, is determined by the free entry condition:

$$k_{ic} = V_{ic}^{v}. \tag{10}$$

The cost k_{ic} should be viewed as the cost of creating a marginal job. If this cost were fixed, then cities would generally specialize in only one industry. Since we want to generate cities with employment across a wide range of industries, we model k_{ic} as increasing in the number of new jobs being created locally in that industry. To do this, we model the supply of jobs as being determined by the decisions of a set of potential job creators who differ in terms of set-up costs. In particular, we assume that in each period, an individual (in addition to being a worker), has the option of creating a job. With probability $\tilde{\Omega}_{ic}$, an individual in city c draws the possibility of creating a job in industry i. With this draw he learns his cost of creating his job, which is drawn from the distribution $f(\cdot)$. Denote the expected value of creating a job in industry i in city c as Π_{ic}. This implies that all jobs with costs lower than Π_{ic} will be undertaken. Therefore, the number of jobs created, N_{ic} in industry i in city c will be

$$N_{ic} = L_c \cdot \tilde{\Omega}_{ic} \cdot F(\Pi_{ic}), \tag{11}$$

where $F(\cdot)$ is the CDF associated with $f(\cdot)$. Thus, in equilibrium,

$$F^{-1}\left(\frac{N_{ic}}{L_c \cdot \tilde{\Omega}_{ic}}\right) = k_{ic}, \tag{12}$$

where $\tilde{\Omega}_{ic}$ can be interpreted as a city-industry comparative advantage in creating certain types of jobs. It will be convenient to decompose this advantage into two terms: $\tilde{\Omega}_{ic} = \Omega_i + \Omega_{ic}$, where Ω_i represents an industry effect that reflects systematic job creation probabilities for industries that is common to all cities, and Ω_{ic} reflects a city-industry component with the property that $\sum_c \Omega_{ic} = 0$.

This formulation implies that higher quality entrepreneurs enter the market and create jobs first. As employment expands, the value of creating jobs must rise in order to maintain zero profits for the marginal entrepreneur who is of increasingly lower quality. This has the effect in our model to provide an additional reason for a less than perfectly elastic job creation curve, because the supply of potential job creators is negatively related to wages (positively related to the value of a vacancy, V_{ic}^{v}.). This relationship is what we mean when we refer to limited entrepreneurial talent: at any given wage, only a subset of potential job creators will be able to profitably create jobs.

1.3 Solving

At the city level, prices of industrial goods are taken as given and an equilibrium is defined by values of N_{ic}, w_{ic}, and $\frac{E_c}{L_c}$ such that equations (4) through (10) are satisfied. At the economy-wide level, prices adjust to ensure that markets for industrial goods clear. Price changes occur when there are shifts in demand for industrial goods, captured in the model by the a_i parameters. Local outcomes respond to industry prices and local advantages, captured by the Ω_{ic}s and ϵ_{ic}s. We will take the above description of a steady-state equilibrium as representing an equilibrium at a point in time and examine how this equilibrium changes in response to changes in the exogenous driving forces, a_i, Ω_{ic}, and ϵ_{ic}.

Below, we develop our empirical strategy by solving for steady-state relationships. First, we are interested in job creation, or labor demand, given by equations (5), (6) and (10). Our main estimating equation is a linearized version of the job creation condition implied by the model which relates industry-city employment rates to industry-city wages and overall city-wide labor market conditions which are summarized by the employment rate. In order to estimate this relationship, we must solve inherent endogeneity problems that are implied by the model. To do this, we solve for the wage, or labor supply, equation which is given by (8),(7), (5), (6), and (9). This equation highlights forces that shift wages but do not directly affect labor demand; namely, workers' bargaining position. We show that a worker's bargaining position is affected by outside employment opportunities and we develop an instrumental variables strategy to isolate these forces.

1.3.1 Job Creation

Using equations (5) and (6), we can write the value of a vacancy as:

$$\rho V_{ic}^{v} = \alpha_{c1} \cdot r_i + \alpha_{c2} \cdot (p_i - w_{ic} + \epsilon_{ic}), \tag{13}$$

where $\alpha_{c1} = -\frac{(\rho+\delta)}{\rho+\delta+\phi_c}$ and $\alpha_{c2} = \frac{\phi_c}{\rho+\delta+\phi_c}$. The impact of an increase in the flow of profits, $p_i - w_{ic} + \epsilon_{ic}$, on the value of a vacancy is given by α_{c2}. This value depends on a city's vacancy contact rates, ϕ_c, which, in turn, depend on a city's employment rate, $\frac{E_c}{L_c}$. It is useful to make this relationship explicit by taking a linear approximation around the point where cities have an identical employment rate. This condition occurs when cities have identical industrial compositions (we assume for simplicity that $\eta_{ic} = \frac{1}{I}$ where I is the number of industries), $\epsilon_{ic} = 0$ and $\Omega_{ic} = 0\ \forall ic$. In addition, for reasons we will make clear shortly, it will be useful to work in log changes between two periods. Equation (14) is a rewrite of (13) using a log-linear approximation:

$$\Delta \ln V_{ict}^{v} = \tilde{\alpha}_{it} + \alpha_2 \Delta \ln w_{ict} + \alpha_3 \Delta \ln \frac{E_{ct}}{L_{ct}} + \alpha_4 \Delta\epsilon_{ict}, \tag{14}$$

where $\Delta x_{it} = x_{it} - x_{it-1}$ and we have added time subscripts because we will use data from several periods. The $\tilde{\alpha}_i$s correspond to industry-year specific effects, and, hence, can be captured in an empirical specification by industry-year dummy variables, the coefficients α_2 and α_3 are predicted to be negative and are evaluated at common vacancy filling rates, and the last term represents an error term that depends on the city-industry cost advantages. The predicted signs of α_2 and α_3 are intuitive, since, all else equal, the return to opening new jobs will be lower when wages are higher and the labor market is tighter, implying a longer time to fill a vacancy.

We also wish to link $\frac{N_{ic}}{L_c}$ to $\frac{E_{ic}}{L_c}$ for our empirical relationship. Notice that from the equilibrium condition (4), we can always write:

$$\delta \cdot E_c = \phi_c \cdot [N_c - E_c], \tag{15}$$

which also implies: $\delta \cdot E_{ic} = \phi_c \cdot [N_{ic} - E_{ic}] \quad \forall i$. Rearranging and dividing both sides by L_c, we obtain:

$$\frac{N_{ic}}{L_c} = \left[\frac{\delta + \phi_c}{\phi_c}\right] \cdot \frac{E_{ic}}{L_c}. \tag{16}$$

Substituting this expression into the cost function, log-linearizing and taking differences between two periods, we derive

$$\Delta \ln k_{ict} = \theta_1 \Delta \ln \frac{E_{ict}}{L_{ct}} + \theta_2 \Delta \ln \frac{E_{ct}}{L_{ct}} + \theta_3 \Delta \tilde{\Omega}_{ict}, \tag{17}$$

where θ_1 and θ_2 are positive coefficients, reflecting that set-up costs increase (or average entrepreneur quality declines) as employment expands in a city, and θ_3 is a negative coefficient that reflects the impact of increasing the size of the pool of potential job creators on $\Delta \ln k_{ict}$.

Finally, we can use the free entry condition, (10), to equate equations (14) and (17) to give us an empirical specification for job creation:

$$\Delta \ln \frac{E_{ict}}{L_{ct}} = \varphi_{it} + \varphi_2 \Delta \ln w_{ict} + \varphi_3 \Delta \ln \frac{E_{ct}}{L_{ct}} + \zeta_{ict}, \tag{18}$$

where the φ_{it} represent a set of industry-year dummies, $\varphi_2 = \frac{\alpha_2}{\theta_1} < 0$ is the elasticity of labor demand with respect to wages holding the employment rate constant, and $\varphi_3 = \frac{\alpha_3 - \theta_2}{\theta_1} < 0$ which reflects both the effects of tighter labor markets on duration of vacancies as well as the fact that entry costs are increasing in the number of jobs created, thus implying a lower return on opening new jobs. The last term, $\zeta_{ic} = \frac{1}{\theta_1}(\alpha_4 \Delta \epsilon_{ic} - \theta_3 \Delta \Omega_{ic})$, is an error term that depends on city cost and job creation advantages.

Equation (18) relates city-industry employment to wages and the city-wide employment rate and forms the basis of our empirical investigation. This equation can be interpreted as a labor demand equation at the city-industry level. Notice that this equation involves a reflection problem (Manski, 1993; Moffitt, 2001). To see this, note that $\Delta \ln \frac{E_{ct}}{L_{ct}}$ can be approximated by $\sum_i \eta_{ict} \Delta \ln \frac{E_{ict}}{L_{ct}}$ so that the change log employment rate in a given city-industry cell, $\Delta \ln \frac{E_{ic}}{L_c}$, depends on the average across such cells. We could address this issue directly via an instrument or solve out for $\Delta \ln \frac{E_{ct}}{L_{ct}}$. However, this will not solve all of the simultaneity problems inherent in equation (18), since, as we will make clear in the following section, within-industry wage changes, $\Delta \ln w_{ict}$, are also a function of the city-wide employment rate as well as endogenously determined. Thus, to make progress towards estimating the relationship given by the empirical job creation equation (18), we must use variation in wages that is uncorrelated with employment rates or the error term given in (18). The following section discusses the wage determination process in the search and bargaining model and illustrates our procedure for dealing with the apparent simultaneity issues.

1.3.2 Determination of Wages

Using equations (5) and (6), we can derive an expression for $V^f_{ic} - V^v_{ic}$. Similarly, equations (7) and (8) can be used to derive and expression for $U^e_{ic} - U^u_{ic}$. Using these expressions along with the bargaining equation (9), we can write the following wage equation:

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

Equation (19) links wages in industry i in city c to the national price of the industrial good, p_i, and the average level of wages in city c.[11] Equation (19) captures the notion that in a multi-sector search and bargaining model sectoral wages act as strategic complements; that is, high wages in one sector are associated with high wages in other sectors. In fact, the structure of this relationship is again in the form of a classic reflection problem (Manski, 1993; Moffitt, 2001) in that the sectoral wage depends on the average of such wages in a city. We address this by taking expectations of both sides of (19), rearranging, and substituting back into equation (19), to derive an expression for wages that is a function of nationally determined prices and of the exogenous productivity terms ϵ:

$$w_{ic} = d_{ic} + \gamma_{c1} \epsilon_{ic} + \left(\frac{\gamma_{c2}}{1 - \gamma_{c2}} \right) \gamma_{c1} \sum_j \eta_{jc} (p_j - p_1) + \gamma_{c1} \left(\frac{\gamma_{c2}}{1 - \gamma_{c2}} \right) \sum_j \eta_{jc} \epsilon_{jc}, \tag{20}$$

[11] The coefficients in (19) are $\gamma_{c0} = \frac{(\rho+\delta+\psi_c\mu)(\rho+\delta+\phi_c)\kappa}{[(\rho+\delta+\psi_c\mu)+\kappa(\rho+\delta+\phi_c)](\rho+\delta+\psi_c)}(b + \tau_c)$, $\gamma_{c1} = \frac{\rho+\delta+\psi_c\mu}{(\rho+\delta+\phi_c)\kappa+(\rho+\delta+\psi_c\mu)}$ and $\gamma_{c2} = \frac{(\rho+\delta+\phi_c)\kappa}{[(\rho+\delta+\psi_c\mu)+\kappa(\rho+\delta+\phi_c)]} \frac{\psi_c(1-\mu)}{(\rho+\delta+\psi_c)}$. See Beaudry, Green, and Sand (2009) for additional details on deriving this expression.

where $d_{ic} = \gamma_{c0}\left(1 + \frac{\gamma_{c2}}{1-\gamma_{c2}}\right) + \gamma_{c1}\left(\frac{\gamma_{c2}}{1-\gamma_{c2}}\right)p_1 + \gamma_{c1}p_i$. In equation (20), we have expressed prices in relation to the price of an arbitrarily chosen good denoted p_1 in order to help emphasize how a pure shift change in industrial composition affects wages (where by a pure shift we mean a change in the ηs that does not change the total number of jobs).

We can use (19) to relate the price differential $p_i - p_1$ to the average national level wage premium in i relative to the baseline industry 1, which we denote ν_i[12]

$$\nu_i = w_i - w_1 = \gamma_1 \cdot (p_i - p_1) + \hat{d}_i. \tag{21}$$

Substituting (21) into (20), we get

$$w_{ic} = \tilde{d}_{ic} + \left(\frac{\gamma_{c2}}{1-\gamma_{c2}}\right)\left(\frac{\gamma_{c1}}{\gamma_1}\right)\sum_j \eta_{jc}\nu_j + \gamma_{c1}\epsilon_{ic} + \gamma_{c1}\left(\frac{\gamma_{c2}}{1-\gamma_{c2}}\right)\sum_j \eta_{jc}\epsilon_{jc}, \tag{22}$$

where $\tilde{d}_{ic} = d_{ic} + \left(\frac{\gamma_{c2}}{1-\gamma_{c2}}\right)\left(\frac{\gamma_{c1}}{\gamma_1}\right)\sum_j \eta_{jc}\hat{d}_{ic}$. Equation (22) provides a direct expression of how 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 will 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 (22) is one related to the proportion of good jobs in a city. The fact that within industry-city wages are related to this index is an important observation, since we will use this fact to construct instruments in the following subsection.

In interpreting the effect of R_c on wages from equation (22), we are performing a partial equilibrium exercise as we treat the employment rate in a city (as reflected in the γ parameters), and the sectoral composition, as given. Again, it is useful to make the dependence of wages on the city's employment rate more explicit by taking a linear approximation of (22) under the same conditions that were used to derive equation (13). Furthermore, to eliminate the city-level fixed effects driven by the amenity, τ, we focus on the difference in wages within a city-industry cell across two steady state equilibria, denoted Δw_{ic}. This is given by equation (23):

$$\Delta w_{ic} = \Delta d_i + \left(\frac{\gamma_2}{1-\gamma_2}\right)\Delta\sum_j \eta_{jc}\nu_i + \gamma_5\Delta\frac{E_c}{L_c} + \Delta\xi_{ic}, \tag{23}$$

where Δd_i is an industry specific effect ($\Delta d_i = \gamma_1\frac{\gamma_2}{1-\gamma_2}\Delta p_1 + \gamma_1\Delta p_i$) that does not vary across cities, and hence can be captured in an empirical specification by including industry dummies, and $\Delta\xi_{ic} = \gamma_1\Delta\epsilon_{ic} + \gamma_1\frac{\gamma_2}{1-\gamma_2}\sum_j\frac{1}{I}\Delta\epsilon_{jc}$ is the error term,

[12] This expression is derived by noting that $w_{ic} - w_{1c} = \gamma_{c1}(p_i - p_1) + \gamma_{c1}(\epsilon_{ic} - \epsilon_{1c})$ and taking the average across cities. γ_1 is the average of γ_{c1} across cities, and $\hat{d}_i$ is an industry specific constant. The industry specific constant $\hat{d}_i$ is equal to $\sum_c(\gamma_{c1} - \gamma_1)(\epsilon_{ic} - \epsilon_{1c})$. When we later take a first order approximation around an equilibrium where the ϵs equal zero, this term will be equal to zero.

with I being the total number of industries. In (23), the γ coefficients are the same as presented after equation (19), except now they are evaluated at common match probabilities, ψ and ϕ. The added coefficient, γ_5, reflects the effect of a change in the employment rate on wage determination; an effect which depends on all the parameters of the model.

To obtain our final equation for wages, we divide both sides of (23) by w_1 in order to focus on a log specification and add time subscripts since we will pull data from different periods:

$$\Delta \ln w_{ict} = d_{it} + \beta_2 \Delta R_{ct} + \beta_3 \Delta \ln \frac{E_{ct}}{L_{ct}} + \Delta \xi_{ict}, \tag{24}$$

where the d_{it}s are time varying industry dummies, $\beta_2 = \frac{\gamma_2}{1-\gamma_2}$ gives the impact of a change in industrial composition on wages, $R_{ct} = \sum_i \eta_{ic} \left(\frac{w_i}{w_1} - 1 \right)$ is our index of industrial composition, and $\beta_3 = \frac{\gamma_5}{w_1} \frac{E}{L}$ is the coefficient capturing the effect of city-level employment rates on wages, and and $\Delta \xi_{ict}$ is the error term defined by $\Delta \xi_{ict} = \frac{\gamma_1}{w_1} \Delta \epsilon_{ict} + \frac{\gamma_1}{w_1} \frac{\gamma_2}{1-\gamma_2} \sum_j \frac{1}{I} \Delta \epsilon_{jct}$.

1.4 Dealing with Endogeneity

The wage equation (24) developed in the previous section highlights the difficulties in identifying the parameters in the job creation equation (18). In particular, the same forces (the ϵ_{ic}s) that push up wages also increase the value of a vacancy. Similar to supply and demand equations in neoclassical models, equations (18) and (24) represent search and bargaining counterparts. Thus, we suffer from a classic identification problem. However, changes in worker bargaining position, represented by ΔR_{ct}, offer a possible solution in the form of an exclusion restriction. We can obtain a reduced form by substituting (24) into (18):[13]

$$\Delta \ln \frac{E_{ict}}{L_{ct}} = (\varphi_{it} + \varphi_2 \cdot d_{it}) + \varphi_2 \cdot \beta_2 \Delta R_{ct} + (\varphi_2 \cdot \beta_3 + \varphi_3) \cdot \Delta \ln \frac{E_{ct}}{L_{ct}} + (\varphi_2 \Delta \xi_{ict} + \zeta_{ict}) \,. \tag{25}$$

Ignoring for now the reflection problem associated with the right-hand side variable $\Delta \ln \frac{E_{ct}}{L_{ct}}$, equation (25) can be consistently estimated under the condition that ΔR_{ct} is uncorrelated with $(\varphi_2 \Delta \xi_{ict} + \zeta_{ict})$. However, since $\Delta R_{ct} = \sum_i \eta_{ict} \cdot \left(\frac{w_i}{w_1} - 1 \right)$ is a function of the ηs there is still the potential for endogeneity. In particular, the ηs can be written as functions of the ϵs and Ωs which are contained in the error terms of equations (18) and (25).[14] Below we discuss instruments developed in Beaudry, Green, and Sand (2009) to deal with these issues and the conditions

[13] Equation (18) is basically an empirical, multi-sector counter part to equation 1.24 in Pissarides (2000).

[14] This can be seen from (10) and (4) and noting that $\eta_{ict} = \frac{N_{ict}}{\sum_i N_{ict}}$. See Appendix D for details.

required for their validity. The instruments we construct are designed to isolate forces affecting changes in average city rents, which, in turn, affect wages. We can use these instruments either to identify the coefficient on ΔR_{ct} in the reduced form equation, (25), or we can instrument for $\Delta \ln w_{ict}$ our original job creation condition, (18).

While the instruments that we construct address endogeneity problems associated with wages or rents, we still must address the reflection problem which relates to the right-hand side variable $\Delta \ln \frac{E_{ct}}{L_{ct}}$, discussed previously. We have two options; we can either construct and instrument for changes in employment rates or we can solve out for them. We explore both approaches below.

1.4.1 Endogeneity of Industrial Composition

The requirement for OLS to give consistent estimates of the coefficients in (25) can be expressed as follows:

$$\lim_{C,I\to\infty} \frac{1}{I}\frac{1}{C}\sum_{i=1}^{I}\sum_{c=1}^{C}\Delta R_c \Delta \Upsilon_{ic} = \lim_{C,I\to\infty} \frac{1}{I}\frac{1}{C}\sum_{c=1}^{C}\Delta R_c \sum_{i=1}^{I}\Delta \Upsilon_{ic} = 0, \tag{26}$$

where $\Delta R_c = \Delta \sum_j \eta_{jc} \cdot \left(\frac{w_j}{w_1} - 1\right)$ and $\Delta \Upsilon_{ic} = \varphi_2 \left(\frac{\gamma_1}{w_1}\Delta\epsilon_{ict} + \frac{\gamma_1}{w_1}\frac{\gamma_2}{1-\gamma_2}\sum_j \frac{1}{I}\Delta\epsilon_{jct}\right) + \frac{1}{\theta_1} \cdot (\alpha_4 \Delta\epsilon_{ic} - \theta_3 \Delta\Omega_{ic})$, the error term in (25). To understand the circumstances under which this condition is met, it is helpful to express ϵ_{ic} (and Ω_{ic}, as well) as the sum of a common component, which reflects absolute advantage, and a second component which captures relative advantage. For example, let $\hat{\epsilon}_{ct}$ represent the common component of the ϵs and let v^{ϵ}_{ict} represent the relative advantage component, with $\epsilon_{ict} \equiv \hat{\epsilon}_{ct} + v^{\epsilon}_{ict}$, where, by definition, the v^{ϵ}_{ict}s across industries within a city sum to zero. In Appendix D, we show that the consistency condition in (26) is met under the assumption that the absolute advantage component, $\hat{\epsilon}_{ct}$, follows a random walk and is independent of the relative advantage components of the ϵs and of the Ωs (past and present). This can be seen from Equation (26) since the change in industrial composition captured in ΔR_c necessarily reflects relative advantage components while $\sum_{i=1}^{I}\Delta\Upsilon_{ic}$ depends only on the absolute advantage component of the ϵs (since the v^{ϵ}_{ict}s sum to zero). If this condition is met, one need not worry about endogeneity involving the wage premia $(\frac{w_i}{w_1} - 1)$ since the latter do not vary with c. In intuitive terms, there must be no link between whether a city has experienced a shift in industrial composition toward high paying industries (a shift in ΔR_c) and other, general improvements affecting wages in all industries in the city. If this were not true, then the estimated effect of ΔR_c would partly reflect changes in the general conditions in a city rather than just capturing the impact of compositional shifts.

While we believe that the assumption ensuring consistency of the OLS estimates is possible, we are more comfortable with the much weaker assumption that the city-level common component of ϵ has increments independent of past values of itself and of the relative advantage components of ϵ and Ω. Based on this assumption, we can construct two instruments: one corresponding to each of the components of ΔR_c reflected in the decomposition of $\Delta R_{ct} = \sum_i (\eta_{ict} - \eta_{ict-1}) \cdot \nu_{it-1} + \sum_i \eta_{ict} \cdot (\nu_{it} - \nu_{ict-1})$. To construct the first instrument, we first predict a level of employment for industry i in city c in period t using the formula:

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

That is, we predict current employment in industry i in city c using the employment in that industry in period $t-1$ multiplied by the growth rate for the industry at the national level. Using these predicted values, we construct a set of predicted industry specific employment shares, $\hat{\eta}_{ict} = \frac{\hat{E}_{ict}}{\sum_i \hat{E}_{ict}}$, for the city in period t and form a measure given by

$$IV1_{ct} = \sum_i \nu_{it-1}(\hat{\eta}_{ict} - \eta_{ict-1}). \tag{27}$$

This instrument isolates the variation in ΔR_{ct} that stems from changes in the employment composition, but instead of using actual employment share changes we use predicted changes based on national-level employment growth, breaking the direct link between city-level employment and wage changes. Essentially, $IV1$ focuses attention on the question, "what is the impact on local wages of a national-level demand shift (stemming from, for example, trade or preference shocks) if that shift is distributed across cities according to start-of-period employment shares?" Recall that the use of this type of variation is implied by the model, where shifts in national-level demand, the a_is, result in shifts in local employment shares because of local differences in comparative advantage that will be reflected in initial period employment shares.

Our second instrument isolates the variation in ΔR_{ct} stemming from changes in national wage premia over time, weighted by the importance of the relevant industry in the local economy. Thus, our second instrument is given by

$$IV2_{ct} = \sum_i \hat{\eta}_{ict}(\Delta \nu_{it}). \tag{28}$$

These instruments are functions of relative error component, v^{ϵ}_{ict-1}, but not of the common error components. Thus, in Appendix D, we show that these instruments provide consistent estimates under the condition that $\Delta\hat{\epsilon}_c$ is independent of v^{ϵ}_{ict-1} and v^{Ω}_{ict-1}; i.e., that changes in the absolute advantage of a city are independent of the past level of comparative advantage for the various industries in a city. This is a weaker assumption than that required for consistency under OLS because it allows for the possibility that a city that shifts in the direction of a higher wage industrial composition is also a city experiencing improvements in general. We just require that those general improvements must be independent of past comparative advantage. This type of random walk assumption makes some researchers uncomfortable, but we provide a means of testing it in section 3.

1.4.2 Endogeneity of Employment Rates

The last endogeneity issue relates to the potential correlation between the change in the employment rate, $\Delta \ln \frac{E_c}{L_c}$, and the error term in (18) or (25). This will be made explicit in a later section of the paper when we derive an empirical expression for the aggregate employment rate, and show that it will depend on the ϵs and the Ωs that constitute the error term. As mentioned earlier, there are two ways that we can deal with this problem. First, we will address this issue with an instrumental variable strategy in which we again use national-level information on growth patterns to predict city-level changes in employment rates. The approach is similar to that used by Blanchard and Katz (1992) and Bartik (1993) in closely related problems. Details of the construction of this instrument are left to the empirical section. Second, we can solve out for $\Delta \ln \frac{E_c}{L_c}$ by aggregating the industry-level equations. We also pursue this method below.

1.5 Worker Heterogeneity

The model presented above assumes that all workers are identical. In our empirical work, we wish to address worker heterogeneity. As we have indicated, the aim of the paper is to provide an estimate of how employment, on average, is affected by an across-the-board increase in the cost of labor. By its very nature, this question is about an aggregate labor market outcome: the effect of an increase in the average cost of work on the average employment rate. To answer such a question in a tractable way, it is necessary to adopt assumptions on how to aggregate outcomes across the vast heterogeneity of skills in the labor force. Depending on the assumptions that one makes, there are several ways to approach this issue.

Our first approach, which we use for our main set of results, is to treat individuals as potentially representing different bundles of efficiency units of work, where these bundles are treated as perfect substitutes in production. Therefore, we control for skill differences in wages via a regression adjustment. However, we do not account for differences in worker attributes when aggregating the number of workers across industries and cities in the calculation of employment rates. In Appendix B, we present a formal justification for such an approach. Heuristically, the structure of the basic search model allows one to write the wage of any skill type in reference to the wage of some arbitrary type, which rationalizes the use of the regression adjusted wages. In addition, random matching implies that the probability of meeting a worker of a given skill type will equal the product of the vacancy filling rate and the proportion of that worker's type in the local economy. Thus, the effects of labor market tightness and skill can be separated and, we argue in the appendix, that the latter effects can be expected to be relatively small. Hence, the value of a vacancy will depend on the skill distribution of the workforce in general, but it is probably only of second-order importance. Due to the difficulty of controlling for such effects, we neglect them in our baseline empirical work. However, in the robustness section we will assess the sensitivity of our results to controlling for alternative measures of the distribution of skill in a locality.

An alternative assumption is that labor markets are segregated along observable skill dimensions and that our model applies to homogeneous workers within these markets. Thus, we also preform analysis separately by education group as a specification check. Finally, if one assumes that the matching function is not over workers, but over efficiency units, then it is appropriate when aggregating workers over industries and cities to use efficiency weighted worker counts. When we construct our employment variables in this manner it does not substantially affect our main results but clouds interpretation. Thus, we leave results using efficiency units to an appendix.

1.6 Mobility

The model presented above assumes that workers are not mobile across localities. It may seem, at first, that allowing for worker mobility could overturn the result that wages differ across localities because of local bargaining conditions. However, this will not generally be the case, even when we allow for directed search across cities. In Appendix C, we offer two extensions of the model that take into account worker mobility. In the first extension, unemployed workers are not perfectly mobile, but are only occasionally offered the opportunity to switch cities. Because of this friction, wages (and outside options) will maintain a local component. When the option to switch cities arises, workers choose the city that maximizes the value of their search. Since this choice will not depend on the initial location of the worker, it acts as a common element across workers and is captured by an intercept.[15] In this extension of the model, none of our empirical specifications are affected and the model's implications will continue to hold.

In the second extension, we introduce local housing prices and allow workers to choose a city that maximizes expected utility, taking into account housing costs and local amenities. In this extension, we modify workers' Bellman equations,

[15]Random search across cities has the same implication.

(8) and (7), to include a negative function of the local housing price. Importantly, housing prices will not directly affect wage negotiation because it is a cost that is incurred whether or not an individual is employed (i.e. wages depend on the difference $U^e_{ic} - U^u_{ic}$). However, housing prices will have to adjust to equilibrate expected utility across cities. In Appendix C, we offer a simple model of housing costs that depend positively on local amenities and city size. We show that this implies that a city with a higher employment rate and expected wages (i.e., high values of R_{ct}) will attract more workers. This in-migration will drive up local housing costs to the point where expected utility is equalized across cities, but before wage equalization occurs. Thus, the forces we emphasize in our model also have implications for worker mobility and housing costs. Towards the end of the paper, we explore this issue further.

2 Data Description and Implementation Issues

The data we use in this paper come from the U.S. decennial Censuses from the year 1970 to 2000 and from the American Community Survey (ACS) for 2007.[16] For the 1970 Census data, we use both metro sample Forms 1 and 2 and adjust the weights for the fact that we combine two samples. We focus individuals residing in one of our 152 metropolitan areas at the time of the Census. Census definitions of metropolitan areas are not comparable over time. The definition of cities that we use in this paper attempts to maximize geographic consistency across Census years. Since most of our analysis takes place at the city-industry level, we also require a consistent definition of industry affiliation. Details on how we construct the industry and city definitions are left to Appendix A.

As discussed earlier, our approach to dealing with worker heterogeneity is to control for observed characteristics in a regression context. Since most of our analysis takes place at the city-industry level, we use a common two-step procedure. Specifically, using a national sample of individuals, we run regressions separately by year of log weekly wage on a vector of individual characteristics and a full set of city-by-industry dummy variables.[17] We then take the estimated coefficients on the city-by-industry dummies as our measure of city-industry average wages, eliminating all cells with less than 20 observations.

[16]Our data was extracted from IPUMS, see Ruggles, Sobek, Alexander, Fitch, Goeken, Hall, King, and Ronnander (2004)

[17]We take a flexible approach to specifying the 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.

Our interpretation of the regression adjusted wage measure is that it represents the wage paid to workers for a fixed set of skills. However, since we only observe the wage of a worker in city j if that worker chooses to live and work in j, self-selection of workers across cities may imply that average city wages are correlated with unobserved worker characteristics, such as ability. In this case, our wage measure will not represent the wage paid per efficiency unit, but will also reflect (unobservable) skill differences of workers across cities. To address this potential concern, when we estimate our wage equations we control for worker self-selection across cities with a procedure developed and implemented by Dahl (2002) in a closely related context.

Dahl proposes a two-step procedure that first estimates various location choice probabilities for individuals, given their characteristics such as birth state. In the second step, flexible functions of the estimated probabilities are included in the wage equation to control for the non-random location choice of workers.[18] The actual procedure that we use is an extension of Dahl's approach to account for the fact we are concerned with cities rather than states, as in his paper, and that we also include individuals who are foreign born. When we estimate the wage equations, the selection correction terms enter significantly, which is a necessary condition for the removal of any selection effects (Dahl, 2002). Our results with or without the Dahl procedure are very similar, which is to be expected since our instruments should induce movements in wages that are uncorrelated with the characteristics of the workforce. Nevertheless, all estimates presented below include the selection corrected wages.[19]

One of our main covariates of interest is 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. We estimate the wage premia in a regression at the national level in which we control for the same set of individual characteristics described for our first-stage wage regression and also include a full set of industry dummy variables. This regression is estimated separately for each Census year. The coefficients on the industry dummy variables are what we use as the industry premia in constructing our R measures.

The dependent variable in our analysis is the log change in industry-city-level employment rates. We construct the industry-level employment rate by summing the number of individuals working in that particular industry divided by the city

[18]Since the number of cities is large, adding the selection probability for each choice is not practical. Therefore, Dahl (2002) suggests an index sufficiency assumption that allows for the inclusion of a smaller number of selection terms, such as the first-best or observed choice and the retention probability. This is the approach that we follow.

[19]Details on the implementation of Dahl's procedure are contained in Appendix E. Results without the selection correction are very similar to those reported here, and are available upon request.

working-age population. Using employment to population ratios means that we include individuals who are classified as being out of the labor force as being relevant for labor market tightness. This is consistent with previous work on matching functions (Blanchard and Diamond, 1989) and on local labor market conditions (Bartik, 2006). Nevertheless, we have assessed the sensitivity of our results to this assumption and found it to be robust to an alternative definition of employment rates that restricts the population to include only those individuals that report themselves as being in the labor force.[20] For most of our estimates, we use decadal differences within industry-city cells for each pair of decades in our data (1980-1970, 1990-1980, 2000-1990) plus the 2007-2000 difference, pooling these together into one large dataset and including period specific industry dummies. In all the estimation results we calculate standard errors allowing for clustering by city and year.[21]

3 Results

We begin the discussion of our results by first focusing on city-industry level equations. Recall from the previous discussion that the model implies two ways of estimating the relationship given by (18). The first approach is to estimate this equation directly, using the instruments developed in section (1.4) to instrument for Δw_{ict}. This approach is similar to estimating a supply-demand type system where we use supply-shifters (changes in predicted bargaining position) to identify the demand side response to increases in labor costs. The second approach is to substitute the wage equation given by (24) directly into the job creation equation to arrive at equation (25). In addition, as mentioned previously, either equation (18) or (25) can be solved out for $\Delta \ln \frac{E_{ct}}{L_{ct}}$ by aggregating over industries. This presents an alternative method for addressing the reflection problem and we pursue this approach in a later subsection. Toward the end of this section, we present several robustness checks.

3.1 Basic Results

Since the demand response to changes in wages is of more direct interest, we begin with estimates of specification (18) in Table 1. All regressions reported in this ta-

[20]We have also assessed the sensitivity of our results to using efficiency weighted counts of workers. In this case, we calculate employment rates as before, but weighing observations by the relative average wage of their demographic group throughout our time period. This has little impact on our results, and estimates using this specification can be made available upon request.

[21]We cluster at the city-year level because this is the level of variation in our data. Clustering only by city has little effect on the estimates of standard errors that we report.

ble also contain a full set of year-by-industry dummies (4×144), but we suppress the presentation of these coefficients for brevity. Column (1) reports OLS results. Perhaps not surprisingly, the estimated effect of wages on employment has a perverse sign, which probably reflects the fact that forces that increase wages can also increase the value of vacancies (the ϵs), highlighting the identification problem inherent in the system.

Columns (2-4) contain results from estimates of (18) using the instruments developed in section (1.4). Recall that $IV1$ isolates changes in average city rent, ΔR_{ct}, that stem from predicted changes in industrial composition. That is, $IV1$ induces within-industry wage changes by impacting workers outside options through local employment composition. $IV2$, on the other hand, isolates the effect on within-industry wage changes stemming from variation in ΔR_{ct} that work through changes in national-level industrial premia. Crucially, though, the model implies that both types of variation in average city rent should impact within-industry wage movements in the same way. This implies that each instrument should give similar employment responses to wage changes induced by either type of variation, and provides a test of the search and bargain model: under this model, the estimated coefficient on $\Delta \ln w_{ic}$ obtained from either $IV1$ or $IV2$ should be equal. Given the very different types of variation used by each instrument, we view this as quite a stringent test.

Both instruments perform well in the first-stage; F-statistics for wages, reported in the bottom rows of Table (1), indicate that our instruments are good predictors of within-industry wage changes and that weak instruments are not a particular concern. This result is not surprising given that Beaudry, Green, and Sand (2009) find that shifts in local industrial composition have significant wage impacts.[22]

As we stated earlier, $\Delta \ln \frac{E_{ct}}{L_{ct}}$ is also likely to be endogenous and we respond to that problem using an instrument that is similar to $IV1$.[23] In particular, we use as an instrument $\sum_i \eta_{ict-1} g_{it}$, where g_{it} is the growth rate of employment in industry i at the national level. Thus, the instrument is the weighted average of national-level industrial employment growth rates, where the weights are the start of period industrial employment shares in the local economy. 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. Because the ϵ_{ic}s that drive the error term are local demand shocks that sum to zero across cities, their movements are not correlated with the g_{it}s by construction. Finally, under the assumption that $\Delta\epsilon_{ict}$ is independent of v^{ϵ}_{ict}, the changes in ϵ_{ict} that constitute ζ_{ict} will be independent

[22]For example, in Table 2 of Beaudry, Green, and Sand (2009), the coefficient on ΔR_{ct} in a wage regression estimated from $IV1$ or $IV2$ is 2.80 (s.e. 0.36) and 2.91 (s.e. 0.33), respectively.

[23] This instrument is similar to that used in Blanchard and Katz 1992.

of the η_{ict-1}s used as weights in the instrument, resulting in a zero correlation between the instrument and the error term.

The IV results reported in columns (2-4) of Table 1 show that labor costs are negatively associated with sector employment rates, as predicted by theory. In addition, the magnitude of the estimated coefficients on $\Delta \ln w_{ict}$ obtained from either $IV1$ or $IV2$ are nearly identical. As argued earlier, we view this result as being particularly important. From a theoretical point of view, bargaining implies that improvements in workers' outside employment opportunities should have the same impact on wages regardless of whether the improvements arise from growth in a high paying industry in a locality or increases in industrial premia in existing industries. Since we expect similar wage impacts brought about from either source of variation, we also expect labor demand responses to be similar since employers are only concerned about the bargained wage. From an empirical point of view, this result provides an important test of our assumptions underlying identification. Heuristically, since both instruments are valid under the same assumptions but rely on very different sources of variation, departures from these assumptions will be weighted differently and cause estimates to diverge.[24] That fact that we do not observe this provides a stringent test of the validity of our instrumental variables approach.

We are now in a position to interpret these results. Consider a wage increase in a particular industry, holding overall employment rates constant. If the industry in question is not so large as to impact significantly overall employment rates, this results in a labor demand elasticity at the industry level of about -1. What about improvements of wages in a city more generally? Since all industries will adjust employment downward in response, there will be feed back effects on overall employment rates. Allowing these dynamics to play out results in a city-level labor demand elasticity of $\frac{\varphi_2}{1-\varphi_3}$ or of about -0.30. In other words, since φ_3 is predicted to be less than zero in a search and bargaining model, overall wage increases in a locality have a built in dampening effect on employment responses because they simultaneously increase the availability of workers. In our model, this leads to reduced search costs (because vacancy contact rates are higher) or improved average entrepreneur quality (which can be thought of as a reduction in entry costs). Thus, we find that city-level job creation curves are relatively wage inelastic; with an increase in wage of 10% impling a reduction in the city-level employment rate of about 3%.

We also fit several models for our reduced form specification given by equation (25). These results are contained in Table 2, which has a format that is similar to the previous table. Recall that this specification is obtained by substituting the

[24]After removing year effects, the correlation between $IV1$ and $IV2$ is 0.18.

wage equation (24) into the job creation equation (18), and gives an expression for the profit maximizing industry-city employment rate responses taking into account the bargained, equilibrium wage movements and changes in local aggregate employment. Our main coefficient in this specification is that on the change in average city rent variable, ΔR_{ct}. We estimate this equation via OLS as well as using our instruments developed previously. Again, all specifications include a full set of time-varying industry dummies, which are suppressed from the table.

The first column of Table 2 displays the OLS results. In contrast to the wage variable in the previous specification, in which there are no conditions that we would expect it to be exogenous, there are plausible conditions in which ΔR_{ct} may not suffer from endogeneity problems.[25] Here, we find the OLS estimate of the coefficient on ΔR_{ct} has at least the predicted sign. That is, increases in workers' outside employment opportunities are associated negatively with industry-city employment rates. This occurs in the model because the bargained wage is a positive function of local average rents. When we turn to IV results, given in columns (2)-(4) of Table 2, in which we instrument for both ΔR_{ct} and $\Delta \ln \frac{E_{ct}}{L_{ct}}$, this negative relationship is strengthened. Again, regardless of the whether we use $IV1$ or $IV2$, our estimates are very similar. We interpret these results as reinforcing our previous finding; holding predicted demand conditions constant, cities that experience an improvement in industrial mix have less employment growth at the industry level.

3.2 Additional Specifications

In the previous subsection, we addressed the reflection problem relating to city-wide employment rates via instrumental variables. In this subsection, we use the alternative approach of solving out for city employment rates. We view this approach as an additional check on our identification strategy, since both approaches should yield similar results. We begin by deriving a city-level equation for the reduced form specification. Aggregating over industries, we can write (25) as:

$$\Delta \ln \frac{E_{ct}}{L_{ct}} = \sum_i \eta_{ict} \cdot \frac{\varsigma_{it}}{1-\varsigma_3} + \frac{\varsigma_2}{1-\varsigma_3}\Delta R_{ct} + \sum_i \eta_{ict}\frac{\varsigma_{ict}}{1-\varsigma_3} \tag{29}$$

where $\varsigma_{it} = \varphi_{it}+\varphi_2 \cdot d_{it}$, $\varsigma_2 = \varphi_2 \cdot \beta_2$, $\varsigma_3 = \varphi_2\beta_3+\varphi_3$, and $\varsigma_{ict} = \varphi_2\Delta\xi_{ict}+\zeta_{ict}$.[26] Noticing that ς_{it} can be related to national-level industry growth rates, we can approximate $\sum_i \eta_{ict} \cdot \varsigma_{it}$ by a set of year dummies and the term $\sum_i \eta_{ict-1} \cdot g_{it}$, where g_{it} is the

[25] In fact, Beaudry, Green, and Sand (2009) find that OLS and IV estimates of the wage equation (24) give very similar estimates of β_2.

[26] In performing this aggregation, we have made use of the approximation $\sum_i \eta_{ict-1}\Delta \ln \frac{E_{ict}}{L_{ct}} \approx \Delta \ln \frac{E_{ct}}{L_{ct}}$.

growth rate of employment in industry i at the national level, as before.[27] Hence, we can write a specification that aggregates over industries as:

$$\Delta \ln \frac{E_{ct}}{L_{ct}} = d_t + \frac{1}{1-\varsigma_3} \cdot \sum_i \eta_{ict} \cdot g_{it} + \frac{\varsigma_2}{1-\varsigma_3} \Delta R_{ct} + \sum_i \eta_{ict} \frac{\varsigma_{ict}}{1-\varsigma_3}, \qquad (30)$$

where d_t represents a set of year dummy variables and $\sum_i \eta_{ict} \frac{\varsigma_{ict}}{1-\varsigma_3}$ is an error term. The variable $\sum_i \eta_{ict} \cdot g_{it}$ is city-level predicted employment growth.[28] By assumption, it is uncorrelated with the error term. Also notice that its coefficient, $\frac{1}{1-\varsigma_3}$, is implied to be positive; that is, $\sum_i \eta_{ict-1} \cdot g_{it}$ is designed so that high values represent favorable demand shifts (the a_is) in industries which are initially well represented in the city, increasing overall employment rate growth at the city level. ΔR_{ct} is our index for changes in industrial composition and its coefficient, $\frac{\varsigma_2}{1-\varsigma_3}$ is predicted to be negative. Essentially, the specification given in (30) says that if demand conditions are the same in cities A and B, in the sense of having the same predicted employment growth rates, the city with the greater increase in R_{ct} will have less actual growth in employment rates. In terms of the model, this occurs because increases in R_{ct} cause an increase in the bargained wage, thus lowering job creation.

We present estimates of the city-level equation given in (30) in columns (1)-(4) of Table 3. This table has a format similar to Table 1.[29] The instrumental variables results, given in columns (2)-(4) are in close accord with theory: increases in workers' bargaining position, as captured by ΔR_{ct}, decreases city-level employment growth while predicted growth has positive impacts.

Having solved out for $\Delta \ln \frac{E_{ct}}{L_{ct}}$ in equation (30), it is natural to derive a specification at the industry-city level that eliminates $\Delta \ln \frac{E_{ct}}{L_{ct}}$ by substituting (30) into (25). As mentioned before, this provides an alternative means to instrumental variables

[27] To see this, rewrite (25) as

$$\Delta \ln E_{ict} = \varsigma_{it} + \varsigma_2 \Delta R_{ct} + \varsigma_3 \cdot \Delta \ln E_{ct} + (1-\varsigma_3) \cdot \Delta \ln L_{ct} + \varsigma_{ict}.$$

Taking the sum of this equation over cities using the weights $\omega_c = \frac{E_{c0}}{\sum_c E_{c0}}$, where 0 denotes the initial year, gives:

$$\sum_c \omega_c \Delta \ln E_{ict} = \varsigma_{it} + \varsigma_2 \sum_c \omega_c \Delta R_{ct} + \varsigma_3 \cdot \sum_c \omega_c \Delta \ln E_{ct} + (1+\varsigma_3) \cdot \sum_c \omega_c \Delta \ln L_{ct} + \sum_c \omega_c \varsigma_{ict}.$$

This implies that ς_{it} can be written as $\varsigma_{it} = \sum_c \omega_c \Delta \ln E_{ict} + d_t - \sum_c \omega_c \varsigma_{ict}$, where d_t is a year fixed effect. Now taking the sum over i: $\sum_i \eta_{ict} \varsigma_{it} = \sum_i \eta_{ict} \cdot g_{it} + d_t - \sum_i \eta_{ict} \sum_c \omega_c \varsigma_{ict}$. Since $\varsigma_{ict} = \varphi_2 \Delta \xi_{ict} + \zeta_{ict}$ and by assumption, $\sum_c \Delta \xi_{ict} = \sum_c \zeta_{ict} = 0$, this last term behaves approximately like white noise. The term d_t varies only by year and can be captured in an empirical specification by year dummies.

[28] This is the same variable we used to instrument $\Delta \ln \frac{E_{ct}}{L_{ct}}$ in the industry-city level equations in section 3.1.

[29] Although we do not present the coefficients here, all estimates of specification (30) include year fixed effects.

of addressing the reflection problem intrinsic to the model. With the substitution, we obtain the specification:

$$\Delta \ln \frac{E_{ict}}{L_{ct}} = \lambda_{it} + \lambda_2 \cdot \Delta R_{ct} + \lambda_3 \cdot \sum_i \eta_{ict-1} \cdot g_{it} + \varepsilon_{ict}, \tag{31}$$

where λ_{it} are time-varying industry dummies, ε_{ict} is an error term, and λ_2 and λ_3 can both be verified to be negative.

Estimates of (31) are given in columns (5)-(8) of Table 4. As can be seen from the instrumental variables results in columns (6)-(8), the estimated λ_2 is indeed negative, as predicted, and similar whether we use $IV1$ or $IV2$. It is also interesting to observe the estimated coefficient on the predicted growth variable, λ_3. In the industry-city level specifications it is negative, significantly different from zero, and very stable in all specifications. This is in contrast to the coefficient on the same variable in the city-level specification given by (30), $\frac{1}{1-\varsigma_3}$, which is predicted and estimated to be positive. The sign reversal is intuitive; at the city level, increases in demand necessarily cause an increase in the aggregate employment rate, while at the industry level, the increase in labor market tightness will cause relatively less job creation and, thus, result in a negative impact on industry-level employment growth rates. Put in other words, comparing two cities with similar changes in outside options for workers, the city with the greater increase in aggregate demand will experience less employment rate growth at the industry level because that city will have a lower return to creating jobs for three reasons; increases in $\ln \frac{E_{ct}}{L_{ct}}$ will: (1) increase the cost of opening a vacancy (through θ_2 in equation (17)), (2) lower the vacancy contact rate (through α_3 in equation (13)), and (3) increase the bargained wage (through β_3 in equation (24)).[30] Since the sign reversal of the coefficient on predicted employment growth between the city level and industry-city level specifications is a restriction implied by theory, we view the fact that the data are supportive of this restriction as strong evidence in favor of the framework.

Just as we obtained equation (30) by aggregating over the reduced from specification (25), we can perform similar calculations to get a specification at the city level by aggregating over (18) that takes the form:

$$\Delta \ln \frac{E_{ct}}{L_{ct}} = d_t + \frac{1}{1-\varphi_3} \cdot \sum_i \eta_{ict-1} \cdot g_{ct} + \frac{\varphi_2}{1-\varphi_3} \cdot \sum_i \eta_{ict-1} \left(\Delta w_{ict} - \Delta w_{it}\right) + \tilde{\zeta}_{ct}, \tag{32}$$

[30]The coefficient λ_3 is equal to $\frac{\varphi_2 \cdot \beta_3 + \varphi_3}{1-\varphi_2 \cdot \beta_3 - \varphi_3} = \frac{\alpha_2 \cdot \beta_3 + \alpha_3 - \theta_2}{\theta_1 - \alpha_2 \cdot \beta_3 - \alpha_3 + \theta_2} < 0$. Increases in the bargained wage occur because lower contact rates for vacancies essentially shifts bargaining power in the workers' favor.

where d_t represent year fixed effects and $\tilde{\zeta}_{ct}$ is an error term.[31] The variable $\sum_i \eta_{it-1} \cdot (\Delta \ln w_{ict} - \Delta w_{it})$ represents the change in the average city wage relative to the national average.

Estimates of (32) are presented in Table 5. This table has a similar format to those that proceed it, and also contains a full set of year dummies. IV estimates of the coefficient $\frac{\varphi_2}{1-\varphi_3}$ in columns (2)-(4) range from about -0.27 to -0.31, which can be interpreted as city-level elasticities of labor demand with respect to wages. Recall from Table 1, which examines the baseline industry-city level equation (18), we obtained estimates of φ_2 and φ_3 of about -1 and -2, respectively. We argued that this implied city-level wage elasticities of $\frac{\varphi_2}{1-\varphi_3} \approx -0.3$, which is precisely what is obtained in alternative city-level approach.[32]

4 Robustness

In this section, we are interested in assessing the robustness of our results to a variety of specification checks. We begin by including a city's labor force growth as an additional regressor in our basic specifications. This serves as a check that vacancies are constant returns to scale with respect to labor force growth; in other words, under the assumptions of our model, changes in the size of the labor force should have no impact on employment rates once we control for local demand conditions and labor costs. Next, we examine robustness to alternative means of addressing worker heterogeneity, either by controlling for local skill composition or estimating the model separately by skill group.

4.1 Exploring the Effects of Labor Force Size on Employment Determination

Table 6 contains results from our baseline specification (18) and our aggregated specification (32) where we include labor force growth as an additional control variable. The first column shows the estimates when all regressors are treated exogenously, while in columns (2)-(4) we instrument for changes in within-industry wage and city employment rates. In columns (1)-(4), we treat the growth in a

[31] In deriving equation (32), we have again made use of the approximation $\sum_i \eta_{ict-1} \cdot \Delta \ln \frac{E_{ict}}{L_{ct}} \approx \Delta \ln \frac{E_{ct}}{L_{ct}}$. The variable $\sum_i \eta_{ict-1} \cdot g_{ct}$ in this specification can be justified along the same lines as footnote 27, except that we must now take into account changes in national-level industrial premia, resulting in the variable $\sum_i \eta_{ict-1} (\Delta w_{ict} - \Delta w_{it})$.

[32] A similar connection can be made from estimates of $\lambda_2 \approx -1$ in column (8) of Table 4, $\frac{\varsigma_2}{1-\varsigma_3} \approx -0.66$ in column (4) of Table 3, and $\varphi_2\beta_3 \approx -2.7$ and $(\varphi_2\beta_3 + \varphi_3) \approx -2.1$ (which gives the ratio $\left(\frac{-2.7}{1+2.1}\right) \approx -0.87$) in Table 2. The model implies that these coefficients should all be the same. Given the approximations we have made and the imprecision of some the estimates, we view this as being reasonably satisfied.

city's labor force as exogenous. Importantly, when we instrument for wages and employment rate, the labor force growth variable never enters significantly in any of the specifications and the estimated coefficients on $\Delta \ln w_{ict}$ and $\Delta \ln \frac{E_{ct}}{L_{ct}}$ change very little from the results presented in Table 1. We view this as strong support for our constant returns to scale assumption. It should be kept in mind that since we are examining decadal differences, these results should be interpreted as long-term consequences of increasing the size of a city's labor force.

One possibility is that growth in the labor force is not exogenous and treating it as such may lead to incorrect inferences. The direction of the bias is difficult to determine *a priori* since measurement error may cause a downward bias while endogeneity would likely produce an upward bias. We attempt to address this possibility by constructing an instrument set for labor force growth that is based on long-term city climate variables. The motivation for this instrument set comes from Dahl (2002) who empirically tests a Roy (1951) model of self-selection of workers across states. He finds that while migrant patterns of workers are partially motivated by comparative advantage, amenity differences across states also play a role in worker movements. Building on this insight, we create our instrument set based on long-term average climate patterns of U.S. cities by collecting data from a number of sources on average temperatures and precipitation for each city in our sample. Consistent with the idea that workers are drawn to cities by amenity factors, we find that indicators of mild climates are significant predictors of city labor force growth.

The validity of the climate instruments rests on the assumption that the relationship between city climate and city-industry job creation and cost advantages (the Ωs and ϵs) is constant over time. In this case, these variables represent time-invariant city-specific factors that are differenced out of the estimating equation. This assumption may not be valid if the evolution of these advantages are related to long-term climate conditions.[33]

The estimates in column (5) of Table 6 show the results using all of the instruments including the climate variables. The first stage F-statistic on labor force growth, reported in the second last row of the table, is about 24.0, indicating that we predict labor force growth very well. The estimated coefficient on the labor force growth variable is -0.12 (0.072), which is larger than the non-instrument re-

[33]Another possibility that may complicate the interpretation of the results based on the climate instruments is that the skill composition of the change in labor force size induced by such amenity factors may not be representative of shifts in labor force size in general. For example, Sand (2007) finds that college graduates are relatively more responsive to climate conditions than those with less education. In this case, estimates based on this instrument set may have the LATE interpretation of the effect of a change in the size of the labor force due to an influx of college graduates. We turn to the effects of city skill composition on our basic results in the following section.

sults but still not statistically significant. The estimated coefficients on $\Delta \ln w_{ict}$ and $\Delta \ln \frac{E_{ict}}{L_{ct}}$, are slightly lower, but still imply a city labor demand elasticity of $\frac{-.77}{1+1.28} = -0.34$, which is well in line with our previous estimates. We also explored using the climate instrument in the city-level specification (32), reported in column (7). Again, despite the fact that the labor force variable is well identified, this exercise only reinforces our previous finding that labor force growth is not related to employment rates.

We also explore the effects of labor force growth in the reduced form specification given by (25). These results are reported in Table 7 and are very similar to those above. We conclude that labor force growth has no impact on employment rates.

4.2 Exploring Worker Heterogeneity

The model we developed in section 1 conceptually applies to workers of a single skill group. In section 1.5 we discussed how we address worker heterogeneity while at the same time focusing on the workforce as a whole. In this section, we assess the sensitivity of this approach in two ways. First, as mentioned earlier, job creation will, in general, depend on the skill distribution of the workforce. Hence, we evaluate the sensitivity of our results to including variables designed to capture changes in the skill distribution of a city's labor force. Second, in keeping with the conceptual idea that the model applies to workers of a single type, we estimate our basic specification separately for workers with high school education or less and those with some post secondary or more.

Table 8 presents results obtained by adding additional regressors to capture changes in the skill distribution of a city's workforce. The first variable we construct is the average efficiency units per person.[34] Increases in this variable indicate that the workers in a city have become, on average, more productive and is designed to capture the effect that a firm opening a new vacancy has a higher probability of meeting a higher quality worker. We also construct an instrument designed to capture plausibly exogenous movements in this variable. To do this, we draw on literature that uses "enclaves" to predict immigration flows. In particular, we exploit the fact that immigrants from different sending countries have on average different educational attainment as well as other observable characteristics that influence a worker's efficiency weight. We construct this instrument the following way: we assume immigrants from sending country h entering the country over a particular decade, denoted by M_{ht}, locate to cities based on where previous waves of immigrants from the same sending country had settled. Denote the fraction of immigrants from sending country h living in city c at time t, as λ_{hct}.

[34]For additional details on how we calculate efficiency units, see Appendix A.

The predicted number of immigrants that will move to city c in year t, $\hat{M}_{ct}$, can be written as:

$$\hat{M}_{ct} = \sum_h \lambda_{hct-1} \cdot M_{ht}.$$

Similarly, we can construct the predicted number of workers in efficiency units that move to city c in year t as $\hat{M}^{EU}_{ct} = \sum_h \lambda_{hct-1} \cdot M_{ht} \cdot \omega_{ht-1}$, where ω_{ht-1} is the efficiency weight per worker from sending country h in the base year. To predict changes in the average efficiency units per worker, assuming no other changes in population, we construct the following instrument:

$$IV^{EU}_{ct} = \left(\frac{\hat{M}^{EU}_{ct}}{\hat{M}_{ct}} - EU_{ct-1} \right) \cdot \frac{\hat{M}_{ct}}{\hat{M}_{ct} + L_{ct-1}}, \tag{33}$$

where $\frac{\hat{M}^{EU}_{ct}}{\hat{M}_{ct}}$ is the predicted average efficiency units per worker arriving in city c in year t.[35]

The results that include changes in efficiency units per worker as an additional control are presented in columns (1)-(4) of Table 8. In the first column, all variables are treated as if exogenous and changes in efficiency units per worker does not enter significantly. IV results are given in columns (2)-(4), where we include the IV^{EU}_{ct} instrument in an attempt to capture exogenous variation in the skill composition of a city's workforce that is induced by non-economically driven migration. In line with previous literature, the immigration enclave instrument predicts changes in a city's skill composition quite well.[36] Nevertheless, in no specification is the skill variable significant, and, more importantly, it alters the magnitude of the estimated demand elasticities very little. To further probe sensitivity of our results to changes in city skill distribution, columns (5)-(8) add alternative measures of a city's skill. In columns (5) and (6), we include the change in the fraction of college graduates as an additional control. When treated exogenously, as in column (5), it enters in significantly but does not change the main conclusions regarding demand elasticities. In column (6), we instrument the change in the proportion of college graduates with an enclave instrument similar to (33). This results in imprecise estimates that are not significantly different from zero despite a strong first-stage. In the remaining columns, (7) and (8), we include the change in the proportion of workers with education greater than high school. Again, inclusion of this variable does not alter the main conclusions of the paper thus far. We conclude that changes in a city's skill distribution have, at best, only a second order effect

[35]The formulation of this instrument is similar to Doms and Lewis (2006), and in the same spirit as Card and DiNardo (2000) and Card (2001, 2009), among others.

[36]The first-stage t-ratio on IV^{EU}_{ct} in the change in efficiency units per worker equation is over 8.0 in all specifications.

on job creation and do not appreciably affect the estimated magnitude of our key parameters.

In Table 9 we estimate our basic specification separately by education group. The education groups we consider are those with high school education or less and those with some post secondary or more.[37] When we perform this exercise, we are assuming that there are two completely segregated markets defined by education.[38] The dependent variable in Table 9 is the change in log city-industry employment rates for a particular education group. Similarly, wages and their instruments are constructed separately by education group.[39] However, we maintain the use aggregate, city-wide employment rates (over all education groups) to capture the effects of limited entrepreneurial talent (which should operate at the city level) and vacancy contact rates.[40] Columns (1)-(4) pertain to the low-education group and columns (5)-(8) to the high-education group. As can be seen from the table, the results by education do not differ dramatically from our earlier estimates. The low-education group may have elasticities that are smaller than the high-education group, but these are not very significant.

4.3 Further Model Implications

The multi-city, multi-sector search and bargaining model that we present implies that shifts in industrial composition toward or away from higher paying industries affect the bargained wage in all sectors of the local economy. This occurs because these shifts influence the outside options of workers, and we use this implication to obtain estimates of the elasticity of the job creation curve with respect to wages. As noted in section 1.6 that deals with an extension of the model that incorporates worker mobility, these same shifts should be associated with worker mobility and local housing prices. That is, conditional on the tightness of the labor market, a pure compositional shift toward higher paying industries will increase the average

[37]We have assessed the sensitivity of our results to finer breakdowns in education which typically resulted in very imprecise estimates. Finer skill definitions dramatically reduces the number of city-industry cells to work with, and, thus, produces sample size problems.

[38]Empirical evidence suggests that workers within our education classes are perfect substitutes, but that there is imperfect substitution of workers between the high- and low-education groups (Card, 2009). This type of substitution is ruled out in this framework.

[39]For example, $IV1$ and $IV2$ are constructed using city-industry shares and national wage premia that are estimated off of education specific samples.

[40]While it may be argued that vacancy contact rates for a particular education group would vary with education specific employment rates, using education specific employment rates made very little difference in practice. In addition, to the extent that one believes vacancy contact rates play little role in job creation compared to limited entrepreneurial ability, the aggregate employment rate specification would be preferred.

city wage and, thus, be associated with in-migration and higher housing costs. This is laid out more formally in Appendix C, where we show that higher expected wages and employment rates make for a more attractive city.

In this subsection, we briefly explore whether these predictions are born out in the data. Table 10 investigates whether changes in the within-industry average city wage and city-level employment rates are correlated with in-migration and housing prices, proxied by the rental rate of a two or three bedroom apartment.[41] The table has a similar lay-out to previous ones; it contains regression coefficients estimated on our city-level data and all specifications contain year fixed-effects which are suppressed from the table. In the first four columns, the dependent variable is the log change of the size of a city's labor force. The first column is estimated via OLS, while the remaining three columns instrument for city wage using either $IV1$ or $IV2$ and for employment rate using the Blanchard-Katz instrument used earlier. When we use our instruments, we find that both wages and employment rates are significant, and indicate a positive association with in-migration as the mobility-extended model predicts. In the final four columns of the table, the dependent variable is the log change in the rent of a two or three bedroom apartment. Again, the estimated coefficients on city wages and employment rates are supportive of our interpretation of the data.[42] That is, the forces in our model that drive wages also drive worker mobility flows, with housing prices being an equilibrating mechanism.

5 Conclusion

In this paper, we extend and estimate an empirically tractable version of a search and bargaining model. Our goal is to highlight the implications of such a model for labor demand and to provide estimates of the responsiveness of employment outcomes to changes in average wages. In a search and bargaining model, labor demand is determined by points along the job creation curve, which is implicitly defined by a zero profit condition for the creation of a vacancy. According to this

[41] Appendix A contains details on the construction of this variable.

[42] Our analysis suggest that changes in industrial composition affect wages, which affects mobility and finally affects housing prices. Alternatively, one may think that the main causality runs in the opposite direction, with housing prices (for some unspecified reason) being the initial driving force. Although we have trouble formalizing this line of reasoning, we nevertheless explored its empirical relevance by including changes in housing costs as an additional regressor in our baseline regressions. When we use weather patterns to instrument changes in housing prices, as would be appropriate if housing prices reflect a change in the desire to locate to certain climates, we find no significant affect of housing prices on wages or employment rate outcomes. We interpret this result as supporting the direction of causality suggested by our model.

condition, when wages rise the tightness of the labor market must fall in order to maintain the value of creating jobs. Therefore, the job creation curve defines a relationship between wages and employment rates rather than employment levels, as in more standard set-ups. We argue that this seemingly small difference has substantial implications. Chief among these is that shifts in labor supply and labor costs can produce very different labor market outcomes; that is, supply and wage shocks do not imply movements along the same demand curve in a search and bargaining model. This insight has the potential to explain the wide range of labor demand elasticities that can be inferred from the literature.

In order to empirically evaluate the relevance of the search and bargaining framework, we extend an otherwise standard Pissarides (2000) model in several directions. First, our model includes multiple local labor markets linked through trade and labor mobility. There is substantial variation in employment levels and rates across cities, allowing for the identification of city-level job creation curves. Second, we extend the model to include multiple sectors, which is crucial for our identification strategy. Using insight developed in Beaudry, Green, and Sand (2009), we use predicted industrial composition shifts to identify movements in average city wages induced by shifts in the outside options of workers. In a search and bargaining model, improvements in the outside employment opportunities of workers increases the bargained wage across all sectors within a locality. Finally, we extend the standard model to include heterogeneous talent across the population in terms of abilities to create jobs in different industries. With this extension, the job creation curve may be less than perfectly elastic because of both search costs and the limited availability job creators.

We use U.S. Census data from 1970-2007 to investigate whether city-level labor market outcomes conform to the restrictions implied by the job creation curve. Working mainly at the industry-city level, our approach relies on comparing industry level changes in employment rates between cities with different changes in within-industry wages. We look at effects over periods of 10 years and, therefore, our estimates should be interpreted as representing long-run labor market outcomes. We present estimates of both types of elasticities identified by the model. Considering the effect of an increase in the cost of labor on a particular sector's employment rate while holding the overall tightness of the labor market in the city constant, we find an elasticity close to -1. We also examine how the local labor market as a whole reacts to a general increase in wages, allowing for interaction across sectors through the availability of workers and job creators. For this aggregate elasticity we obtain an estimate of approximately -0.3.

This paper has several contributions. First, we show that a standard search and bargaining model extended to include multiple local labor markets and sectors has implications that have not been previously recognized. In particular, shifts in industrial composition toward or away from higher paying industries impact wages within all sectors of a local economy because these shifts affect the outside options of workers bargaining with their employer. A critical feature of this insight is that it can be used to construct empirically testable restrictions of the data. Furthermore, we demonstrate how this variation can be used to evaluate the elasticity of job creation curves using city-level data. Second, we show that U.S. city-level outcomes over the past several decades abide by the restrictions implied by the search and bargaining model; that is, the model's over-identifying restrictions are easily passed in the data. While these facts do not necessarily prove that the theory is correct, we nevertheless believe that this provides compelling evidence in favor of the framework. Given these findings, we also provide estimates of the elasticity of the city-level job creation curves. This is a key parameter that can be used to evaluate any number of policies that affect labor costs. Finally, by making explicit the relationship between wages, employment levels and employment rates, we believe that the model provides a potential reconciliation of the otherwise puzzling range of labor demand elasticities that can be inferred from the literature.

In this paper, we have emphasized the role of labor costs in determining employment outcomes and found that a reduction of labor costs at the city level of 10% will increase employment rate by about 3%. To the extent that this is not a large effect, it is of interest to note that our model also implies a potential importance of rigidities outside of the labor market for job creation. In particular, factors that affect the 'ease' of job creation will also influence employment outcomes.[43] While the approach taken in this paper is unable to evaluate the empirical importance of these factors, given the recent emphasis on policies that encourage job creation, it appears an important area for future work.

A Data

The Census data was obtained with extractions done using the IPUMS system (see Ruggles, Sobek, Alexander, Fitch, Goeken, Hall, King, and Ronnander (2004). 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

[43] In our model, factors that affect the ease of job creation are subsumed in the parameters $\tilde{\Omega}_{ic}$, which may include, for example, restrictive zoning rules, taxes faced by business owners, and the costs of obtaining licensing. These factors are emphasized by Krueger and Pischke (1997) in another context. Carroll, Holtz-Eakin, Rider, and Rosen (2000), for example, find that a reduction in entrepreneurs' personal income taxes encourage them to create more jobs.

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.[44] 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, 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. Our definitions differ slightly from those in Deaton and Lubotsky (2001) in order to improve the 1970-1980-1990-2000 match.

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.[45] We have also replicated our results using data only for the period 1980 to 2000, where we can use 1980 industry definitions to generate a larger number of consistent industry categories.[46] We are also able to define more (231) consistent cities for that period.

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

[45]See http://usa.ipums.org/usa-action/variableDescription.do?mnemonic=IND1950 for details.

[46] The program used to convert 1990 codes to 1980 comparable codes is available at http://www.trinity.edu/bhirsch/unionstats . That site is maintained by Barry Hirsch, Trinity University and David Macpherson, Florida State University. Code to convert 2000

We create a variable to proxy for the cost of housing in a city by using a measure of the rental rate of a two or three bedroom apartment in that city. To construct this variable, we use the Census variable for 'contract rent' and restrict it to the reported rent for two or three bedroom apartments in each of our MSAs. This is a similar procedure to that used recently by Moretti (2008). See that paper for a discussion on the appropriateness of this measure for local housing costs.

A.1 Enclave Instrument

The construction of the enclave instrument is similar to that of Doms and Lewis (2006) and uses their origin country groupings. The country of origin groups are (1) Mexico, (2) Central America, (3) South America, (4) Central Europe and Russia, (4) Caribbean, (5) China, (6) South East Asia, (7) India, (8) Canada, U.K., and Australia, (10) Africa, (11) Korea and Japan, (12) Pacific Islands, (13) Israel and NW Europe, (14) Middle East, (15) Central Asia, (16) Cuba, and (17) Souther Europe and can be identified from the IPUMS variable `bpl ``Birthplace [general version]''` . To identify the inflows of immigrants, we use the IPUMS variable `yrimmig ``Year of immigration''`.

A.2 Climate Instrument

The city level climate variables were extracted from "Sperling's Best Places to Live" (http://www.bestplaces.net/docs/DataSource.aspx). Their data is compiled from the National Oceanic and Atmospheric Administration. The variables we use in this paper are the average daily high temperatures for July and January in degrees Fahrenheit. Alternative variables available from the same source are annual rainfall in inches and a comfort index. The comfort index is a variable created by "Sperling's Best Places to Live" that uses afternoon temperature in the summer and local humidity to create an index in which higher values reflect greater "comfort". We have also compiled climate data from an alternative source to use as a robustness check. These data come from "CityRating.com's" historical weather data, and include variables on average annual temperature, number of extreme temperature days per year, humidity, and annual precipitation. Data from this source could only be collected for 106 cities, and, therefore, not included in this analysis.

industry codes into 1990 codes was provided by Chris Wheeler and can be found at http://research.stlouisfed.org/publications/review/past/2006. See also a complete table of 2000-1990 industry crosswalks at http://www.census.gov/hhes/www/ioindex/indcswk2k.pdf

B Worker Heterogeneity

Consider a simple search and bargaining model in which there are two types of workers: high- and low-skill. Let θ denote the fraction of high-skill workers and $\eta > 1$ denote relative productivity of high versus low skill workers.

The Bellman equations for firms can be written as:[47]

$$rV = -\gamma + \phi \cdot (\theta \cdot J_H + (1-\theta) \cdot J_L - V) \tag{B-1}$$

$$rJ_i = \eta_i \cdot p - w_i + s \cdot (V - J_i) \tag{B-2}$$

Combining (B-1) and (B-2), gives the value of a vacancy:

$$rV = \frac{-(r+s) \cdot \gamma + \phi\,(\theta \cdot (\eta \cdot p - w_H) + (1-\theta) \cdot (p - w_L))}{r+s+\phi}. \tag{B-3}$$

Workers of each skill type of the following Bellman equations:

$$rU_i = b + \varphi \cdot (E_i - U_i) \tag{B-4}$$

$$rE_i = w_i + s\,(U_i - E_i)\,, \tag{B-5}$$

for type $i \in \{\text{High}, \text{Low}\}$. Wages are set according to the rule $(1-\beta)(E_i - U_i) = \beta(J_i - V)$. This gives

$$w_i = (1-\beta) \cdot rU_i + \beta \cdot (\eta_i p - rV) \tag{B-6}$$

The Bellman equations for workers gives rU_i as

$$rU_i = \frac{b \cdot (r+s) + \varphi\,(w_i)}{r+s+\varphi}. \tag{B-7}$$

Hence, wages can be written as:

$$w_i = \beta\Psi(\eta_i \cdot p - rV) + \frac{(1-\beta) \cdot \Psi \cdot b(r+s)}{r+s+\varphi} \tag{B-8}$$

for each type where $\Psi = \frac{r+s+\varphi}{r+s+\beta\varphi}$. Then the wage differential between high- and low-skill workers is:

$$w_H - w_L = \beta\Psi p \cdot (\eta - 1) > 0. \tag{B-9}$$

We can also calculate the difference in the flow profits for a firm meeting a high- versus low-skill worker:

$$(\eta \cdot p - w_H) - (p - w_L) = p \cdot (\eta - 1) \cdot (1 - \beta\Psi) > 0 \tag{B-10}$$

[47] Here, we assume that firms meeting either high- or low-skill workers will form matches. This can be seen as a restriction that η cannot be too large.

Notice that we can write the high-skill wage in terms of the low-skill wage, which rationalizes the use of regression adjusted wages. Also, we can rearrange the job creation equation so that it depends on low-skill wage, plus θ times the difference in flow of profits. This reduces the value of a vacancy to a function of three variables $rV = G(\theta, \frac{E}{L}, w_L; \beta, \eta, r, s)$ where $\phi = \phi\left(\frac{E}{L}\right)$ and $\varphi = \varphi\left(\frac{E}{L}\right)$ are a function of the employment rate.

Setting $\gamma = 0$, we can write

$$rV = \frac{\phi}{r+s+\phi} \cdot (\theta \cdot p \cdot (\eta - 1) \cdot (1 - \beta\Psi) + p - w_L). \tag{B-11}$$

The term interacting with the skill variable, θ, in equation (B-11) will be proportional to $(1 - \beta\Psi)$, which is equal to:

$$1 - \beta\Psi = \frac{(1-\beta)(r+s)}{r+s+\beta\psi} \tag{B-12}$$

If $r + s$ is small relative to ψ (Blanchard, 1998), this term will also be small. Hence, we assume these skill effects only secondary and we can focus on $rV = \tilde{G}(\frac{E}{L}, w_L; \beta, \eta, r, s)$. This justifies using efficiency wages while not making any adjustments for $\frac{E}{L}$ in the baseline empirical work. We assess the sensitivity of this assumption in a robustness section by including measures of city skill, skill breakdowns, and efficiency units. None of our results seem to be sensitive to any of these alternative specifications.

C Worker Mobility

The purpose of this section is to extend our search and bargaining model to include worker mobility and to demonstrate that this extension does not change the main implications of our model. We consider two extensions of the model. In the first case, suppose unemployed workers have the option of occasionally switching cities. When this situation arises, with probability μ_1, workers choose to move to the city that maximizes their expected utility, $\max_{c'} U^u_{c'}$. To incorporate this extension, we can write workers' unemployment Bellman equation as:

$$\rho U^u_c = b + \tau_c + (1-\mu_1)\psi_c \cdot \left(\sum_j \eta_{jc} U^e_{jc} - U^u_c\right) + \mu_1 \cdot (\max_{c'} U^u_{c'} - U^u_c), \tag{C-13}$$

where we have assumed that $\mu = 1$ to simplify exposition.[48] The outside options of workers are now changed and wage negotiation will take this into account. Importantly, the form of this change does not alter any of our results because $\max_{c'} U^u_{c'}$

[48]This is without loss and has the implication that unemployed flows depend only on city rather than industry-city.

does not depend on workers' initial location and, therefore, is captured in our empirical specifications by year-by-industry dummy variables. It should be noted that in this case, however, the parameters we estimate will have a slightly different interpretation because they will depend on μ_1 (the ease of switching cities).

In the second extension, we include housing prices and local amenities, as in the case of the Roback (1982) model. We continue to allow workers to search across cities and choose the city that maximizes expected utility, as above. When doing so, workers take into account local housing costs and amenities. To incorporate this extension, assume that workers care about wages, the price of housing in a city, p^h_{ct}, and about a local amenity, Ψ_c. In this case, a worker's (indirect) flow utility when employed in industry i in city c could be expressed as, $w_{ic} - \vartheta p^h_{ct} + \Psi_c$. Accordingly, his or her flow utility when unemployed will be given by $b + \tau_c - \vartheta p^h_{ct} + \Psi_c$. The first thing to notice about this extension is that housing prices do not directly impact wage negotiation because housing costs are incurred in both the employed and unemployed state. In order for expected utilities to equalize across cities, housing prices must adjust. To capture this, we summarize the functioning of the housing market by assuming that housing prices can be expressed as a positive function of the population of a city and of amenities, given by:

$$p^h_{ct} = d_0 + d_1 \cdot L_{ct} + d_2 \cdot \tau_c.$$

It is straight forward to derive an expression for housing prices, p^h_{ct}, that depends on local expected wages (and hence, on R_{ct}), amenities, and employment rates or labor market tightness. Housing prices will adjust such that a city with a favorable composition of jobs (due to the Ωs and ϵs) and higher amenities have benefits that are captured by local landowners. Wage differences across cities will not be equalized because in-migration will drive of local housing costs causing the movement of workers between cities to stop before wage equalization occurs. We conclude this section by noting that the forces emphasized in our model have testable implications for labor mobility and housing prices, but do not alter the main conclusions of our baseline model.

Finally, since in equilibrium workers will equalize expected utility across locations the term $\max_{c'} U^u_{c'} - U^u_c$ in equation C-13 will equal zero. Therefore, the equilibrium equations derived in the model section of this paper are not affected by this extension of worker mobility.

D Consistency

We are interested in the conditions under which our instruments can provide consistent estimates. Apart from the instruments being correlated with ΔR_{ic} and

Δw_{ic}, the condition we require for a given instrument, Z_c, is

$$\lim_{C,I\to\infty} \frac{1}{I}\frac{1}{C}\sum_i\sum_c Z_c \Delta\Upsilon_{ic} = 0. \tag{D-14}$$

We will handle the limiting arguments sequentially, allowing $C \to \infty$ first.[49] Recall that $IV1$ is given by:

$$Z_c = \sum_j \eta_{jc}(g*_j - 1)(w_j - w_1), \tag{D-15}$$

where $g*_j = \frac{1+g_j}{\sum_k \eta_{kc}(1+g_k)}$ and g_j is the growth rate in employment in industry j at the national level. Given this, (D-14) becomes:

$$\lim_{C\to\infty} \frac{1}{C}\sum_j (w_j - w_1)\sum_c \eta_{jc}(g*_j - 1)\sum_i \Delta\Upsilon_{ic}. \tag{D-16}$$

We can derive an equation for shares as:

$$\eta_{ic} = \frac{\tilde{\Omega}_{ic}\cdot F(V^v_{ic})}{\sum_i \tilde{\Omega}_{ic}\cdot F(V^v_{ic})} \tag{D-17}$$

Taking linear approximation, again, around the point where $\Omega_{ic} = \epsilon_{ic} = 0$ yields the following expression:[50]

$$\eta_{ic} \approx \frac{1}{I} + \pi_1\left(\epsilon_{ic} - \frac{1}{I}\sum_i \epsilon_{ic}\right) + \pi_2\left(\Omega_{ic} - \frac{1}{I}\sum_i \Omega_{ic}\right) \tag{D-18}$$

The πs are positive coefficients obtained from linear approximation. We can decompose the ϵs and Ωs into absolute and comparative advantages, $\epsilon_{ic} = \hat{\epsilon}_c + v^{\epsilon}_{ic}$ and $\Omega_{ic} = \hat{\Omega}_c + v^{\Omega}_{ic}$, which gives:

$$\eta_{ic} = \frac{1}{I} + \pi_1\cdot v^{\epsilon}_{ic} + \pi_2\cdot v^{\Omega}_{ic} \tag{D-19}$$

Similarly, substituting $\epsilon_{ic} = \hat{\epsilon}_c + v^{\epsilon}_{ic}$ and $\Omega_{ic} = \hat{\Omega}_c + v^{\Omega}_{ic}$ into the last term of (D-16), gives:

$$\sum_i \Delta\Upsilon_{ic} = [\lambda_1 + \lambda_2]\cdot I\cdot \Delta\hat{\epsilon}_c + \lambda_3\cdot I\cdot \Delta\hat{\Omega}_c, \tag{D-20}$$

which depends only on the increments of the absolute advantage components. From equation (D-19), the city-industry shares depend only on the relative advantage components. Thus, (D-16) equals zero provided that $E(\Delta\hat{\epsilon}_c) = E\Delta\hat{\Omega}_c = 0$, and that $\Delta\hat{\epsilon}_c$ and $\Delta\hat{\Omega}_c$ are independent of past values of the relative advantage

[49] Throughout this appendix we omit the t subscript for simplicity.

[50] Recall that if $\Omega_{ic} = \epsilon_{ic} = 0$ then the industry shares are equal across cities. We further assume, for simplicity, that the shares are equal to $\frac{1}{I}$ at this point.

components, v^{ϵ}_{ic} and v^{Ω}_{c}. In other words, general improvements in a city must be unrelated to past industry relative advantages.

Similarly, the relevant condition when using $IV2$ is given by

$$\lim_{C\to\infty} \frac{1}{C} \sum_j \Delta(w_j - w_1) \sum_c \eta_{jc} \sum_i \Delta\Upsilon_{ic}, \tag{D-21}$$

and the same conditions ($\Delta\hat{\epsilon}_c$ to be independent of past values of v^{ϵ}_{ic} and of v^{Ω}_{ic}) ensure that this condition equals zero.

An important point follows from this discussion. If the key identifying assumption underlying the IVs is not true (i.e., changes in absolute advantage are not independent of past comparative advantage) then the two IV's weight the problematic correlation (between $\Delta\hat{\epsilon}_c$ and v^{ϵ}_{ic}) differently (in particular, $IV1$ weights using the weights $(w_j - w_1)$, while $IV2$ uses the weights $\Delta(w_j - w_1)$) and estimates based on the different IVs should differ.

E Selection Correction

The approach we use to address the issue of selection on unobservables of workers across cities follows Dahl (2002). Dahl argues that, under a sufficiency assumption, the error mean term in the wage equation for individual i can be expressed as a flexible function of the probability that a person born in i's state of birth actually chooses to live in city c in each Census year.[51] Dahl's approach is a two-step procedure that first requires estimates of the probability that i made the observed choice and then adds functions of these estimates into the wage equation to proxy for the error mean term. Dahl also presents a flexible method of estimating the migration probabilities that groups individuals based on observable characteristics and uses mean migration flows as the probability estimates. We closely follow Dahl's procedure aside from several small changes to account for the fact that we use cities rather than states and to account for the location of foreign born workers.

Dahl's approach first groups observations based on whether they are "stayers" or "movers". Dahl defines stayers as individuals that reside in their state of birth in the Census year. Since we use cities instead of states, we define stayers as those individuals that reside in a city that is at least partially located in individual's state of birth in a given Census year. Movers are defined as individuals that reside in a city that is not located in that individual's state of birth in a given Census year. We also retain foreign born workers, whereas Dahl drops them. For these workers,

[51] This sufficiency assumption essentially says that knowing the probability of an individual's observed or "first-best" choice is all that is relevant for determining the selection effect, and that the probabilities of choices that were not made do not matter in the determination of ones wage in the city where they actually locate.

we essentially treat them as “movers” and use their country of origin as their “state of birth”.[52] Within the groups defined as stayers, movers, and immigrants, we additionally divide observations based on gender, education (4 groups), age (5 groups), black, and hispanic indicators. Movers are further divided by state of birth. For stayers, we further divide the cells based on family characteristics.[53] Immigrants are further divided into cells based on country of origin as described above.

As in Dahl (2002), we estimate the relevant migration probabilities using the proportion of people within cells, defined above, who made the same move or stayed in their birth state. For each group, we calculate the probability that an individual made the observed choice and for movers, we follow Dahl in also calculating the retention probability (i.e. the probability that individual i was born in a given state, and remained in a city situated at least partly in that state in general). For movers, the estimated probabilities that individuals are observed in city c in year t differ based on individuals' state of birth (and other observable characteristics). Thus, identification of the error mean term comes from the assumption that the state of birth does not affect the determination of individual wages, apart from through the selection term. For stayers, identification comes from differences in the probability of remaining in a city in ones birth state for individuals with different family circumstances. For immigrants, we assign the probability that an individual was observed in city c in a given Census year using the probabilities from immigrants with the same observable characteristics in the preceding Census year.[54] This follows the type of ethnic enclave assumption used in several recent papers on immigration, essentially using variation based on the observation that immigrants from a particular region tend to migrate to cities where there are already communities of people with their background.

Having estimated the observed choice or “first-best” choice of stayers, movers, and immigrants and the retention probability for movers, we can then proceed to the second step in adjusting for selection bias. To do this, we add functions of these estimated probabilities into the first stage individual-level regressions used to calculate regression adjusted average city-industry wages. For movers, we add a quadratic of the probability that an observationally similar individual was born in a given state and was observed in a given city and a quadratic of the probability that an observationally similar individual stayed in their birth state. For stayers, we add a quadratic of the probability that an individual remained in their state of birth. For immigrants, we add a quadratic of the probability that an similar

[52] We use the same country of origin groups as for the enclave instrument.

[53] Specifically, we use single, married without children, and married with at least one child under the age of 5.

[54] For cities in the 1980 Census not observed in the 1970 Census, we use the 1980 probabilities.

individual was observed in a given city in the preceding Census year. Dahl allows the coefficients on these functions to differ by state, whereas we assume that they are the same across all cities.

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Table 1: Estimates of the Job Creation Equation (18)

	OLS	IV1	IV2	IV1&IV2
	(1)	(2)	(3)	(4)
$\Delta \log w_{ict}$	0.125*	-1.022*	-0.932*	-0.954*
	(0.0158)	(0.279)	(0.231)	(0.221)
$\Delta \log \frac{E_{ct}}{L_{ct}}$	0.812*	-1.832*	-2.111*	-1.982*
	(0.0505)	(0.858)	(0.792)	(0.746)
N	33993	33993	33993	33993
R^2	0.506			
F-stat($\Delta \log w_{ict}$)		21.23	38.01	29.41
F-stat($\Delta \log \frac{E_{ct}}{L_{ct}}$)		8.160	13.18	9.642
Over-id (p-val.)		.	.	0.680

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 log city-industry employment rates.

Table 2: Estimates of the Reduced Form Equation (25)

	OLS	IV1	IV2	IV1&IV2
	(1)	(2)	(3)	(4)
ΔR_{ct}	-0.930*	-2.845*	-2.749*	-2.780*
	(0.162)	(0.742)	(0.670)	(0.641)
$\Delta \log \frac{E_{ct}}{L_{ct}}$	0.874*	-2.152*	-2.247*	-2.204*
	(0.0487)	(0.762)	(0.665)	(0.656)
N	33993	33993	33993	33993
R^2	0.506			
F-stat(ΔR_{ct})		71.89	162.3	204.3
F-stat($\Delta \log \frac{E_{ct}}{L_{ct}}$)		8.160	13.18	9.642
Over - id (p-val.)		.	.	0.863

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 log city-industry employment rate.

Table 3: Estimates of Aggregate Reduced Form Specification (30)

	OLS	IV1	IV2	IV1&IV2
	(1)	(2)	(3)	(4)
ΔR_{ct}	0.0152	-0.709*	-0.636*	-0.661*
	(0.124)	(0.245)	(0.194)	(0.171)
$\sum_i \eta_{i,c,t-1} \cdot g_{it}$	0.127*	0.202*	0.194*	0.197*
	(0.0371)	(0.0416)	(0.0349)	(0.0350)
N	608	608	608	608
r^2	0.479			
F-stat(ΔR_{ct})		142.6	257.7	243.0
Over-id(p-val.)		.	.	0.782

NOTES: Standard errors are in parentheses. (*) 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. Dependent variable is the decadal change in log city employment rate.

Table 4: Estimates of Reduced Form Equation (31)

	OLS	IV1	IV2	IV1&IV2
	(1)	(2)	(3)	(4)
ΔR_{ct}	-0.0977	-1.071*	-1.111*	-1.097*
	(0.178)	(0.415)	(0.260)	(0.258)
$\sum_i \eta_{i,c,t-1} \cdot g_{it}$	-0.535*	-0.429*	-0.425*	-0.426*
	(0.0514)	(0.0610)	(0.0484)	(0.0487)
N	33993	33993	33993	33993
R^2	0.502			
F-stat(ΔR_{ct})		124.6	256.3	209.8
Over-id(p-val.)		.	.	0.922

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. Dependent variable is the decadal change in log city-industry employment rate.

Table 5: Estimates of Aggregate Job Creation Equation (32)

	OLS	IV1	IV2	IV1&IV2
	(1)	(2)	(3)	(4)
$\Delta \log w_{ct}$	0.126*	-0.311*	-0.265*	-0.279*
	(0.0311)	(0.129)	(0.0896)	(0.0817)
$\sum_i \eta_{i,c,t-1} \cdot g_{it}$	0.0917*	0.219*	0.205*	0.210*
	(0.0350)	(0.0565)	(0.0440)	(0.0445)
N	608	608	608	608
R^2	0.497			
F-stat($\Delta \log w_{ct}$)		33.79	59.48	39.95
Over-id(p-val.)		.	.	0.728

NOTES: Standard errors are in parentheses. (*) 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. Dependent variable is the decadal change in log city employment rate.

Table 6: Assessing the Impact of City Size

	OLS	IV1	IV2	IV1&IV2	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \log w_{ict}$	0.138*	-1.008*	-0.912*	-0.933*	-0.773*	
	(0.0161)	(0.327)	(0.246)	(0.241)	(0.223)	
$\Delta \log \frac{E_{ct}}{L_{ct}}$	0.817*	-1.794*	-2.027*	-1.911*	-1.286*	
	(0.0480)	(0.824)	(0.833)	(0.765)	(0.620)	
$\Delta \log w_{ct}$						-0.270*
						(0.0883)
$\sum_i \eta_{i,c,t-1} \cdot g_{it}$						0.252*
						(0.0657)
$\Delta \log L_{ct}$	-0.101*	-0.00742	-0.0132	-0.0122	-0.115	-0.0373
	(0.0107)	(0.0425)	(0.0369)	(0.0369)	(0.0721)	(0.0374)
N	33993	33993	33993	33993	33993	608
R^2	0.508					
F-stat($\Delta \log w_{ict}$ or $\Delta \log w_{ct}$)		15.44	32.93	25.97	15.21	14.69
F-stat($\Delta \log \frac{E_{ict}}{L_{ct}}$)		8.577	12.00	9.443	5.096	.
F-stat($\Delta \log L_{ct}$)					24.00	12.34
Over-id(p-val.)		.	.	0.697	0.996	0.998

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. Dependent variable is the decadal change in the log city-industry employment rate.

Table 7: Assessing the Impact of City Size

	OLS	IV1	IV2	IV1&IV2	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
ΔR_{ct}	-0.657*	-2.723*	-2.641*	-2.666*	-2.147*	-0.668*
	(0.174)	(0.818)	(0.693)	(0.680)	(0.620)	(0.176)
$\Delta \log \frac{E_{ct}}{L_{ct}}$	0.876*	-2.023*	-2.090*	-2.058*	-1.323*	
	(0.0469)	(0.728)	(0.695)	(0.669)	(0.595)	
$\sum_i \eta_{i,c,t-1} \cdot g_{it}$						0.233*
						(0.0542)
$\Delta \log L_{ct}$	-0.0780*	-0.0226	-0.0240	-0.0236	-0.109	-0.0297
	(0.0107)	(0.0347)	(0.0320)	(0.0323)	(0.0661)	(0.0340)
N	33993	33993	33993	33993	33993	608
R^2	0.507					
F-stat(ΔR_{ct})		68.60	169.3	218.1	108.2	88.26
F-stat($\Delta \log \frac{E_{ict}}{L_{ct}}$)		8.577	12.00	9.443	5.096	.
F-stat($\Delta \log L_{ct}$)					24.00	12.34
Over-id(p-val.)		.	.	0.889	0.775	0.994

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. Dependent variable is decadal change in log city-industry employment rate.

Table 8: Assessing the Impact of City Skill

	OLS	IV1	IV2	IV1&IV2	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log w_{ict}$	0.125*	-1.037*	-0.774*	-0.849*	-1.161*	-1.308*	-0.698*	-0.735*
	(0.0157)	(0.270)	(0.272)	(0.221)	(0.285)	(0.447)	(0.189)	(0.217)
$\Delta \log \frac{E_{ct}}{L_{ct}}$	0.801*	-2.092*	-2.999*	-2.329*	-2.355*	-2.435*	-1.842*	-1.876*
	(0.0529)	(0.926)	(1.229)	(0.891)	(0.937)	(1.193)	(0.700)	(0.708)
$\Delta \frac{\text{Efficiency Units}}{L_{ct}}$	0.0519	2.096	2.747	2.138				
	(0.0952)	(1.285)	(1.838)	(1.338)				
Δ BA or $>$					1.901*	3.366		
					(0.626)	(2.859)		
Δ SP or $>$							1.645*	1.406
							(0.419)	(0.816)
N	33993	33993	33993	33993	33993	33993	33993	33993
R^2	0.506							
F-stat($\Delta \log w_{ict}$)		14.22	25.41	22.08	28.93	22.15	27.70	22.03
F-stat($\Delta \log \frac{E_{ict}}{L_{ct}}$)		6.577	10.24	8.098	9.185	7.918	7.150	8.168
Fstat(Educ.Var.)		21.85	27.65	21.99	.	14.57	.	25.24
Over-id(p-val.)		.	.	0.292	0.377	0.268	0.108	0.197

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. Dependent variable is decadal changes in log city-industry employment rate.

Table 9: Results by Education Group

	OLS	IV1	IV2	IV1&IV2	OLS	IV1	IV2	IV1&IV2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δw_{ict}	0.0614*	-0.881*	-0.928*	-0.911*	0.126*	1.659	-1.218*	-1.150*
	(0.0152)	(0.323)	(0.269)	(0.253)	(0.0191)	(8.120)	(0.217)	(0.210)
$\Delta \log \frac{E_{ct}}{L_{ct}}$	1.174*	-1.972	-1.830	-1.904*	0.220*	-10.36	-0.750	-0.928
	(0.0692)	(1.140)	(0.943)	(0.952)	(0.0670)	(28.44)	(0.629)	(0.655)
N	24375	24375	24375	24375	11651	11651	11651	11651
R^2	0.484				0.498			
F-stat($\Delta \log w_{ict}$)		20.89	25.84	24.75		11.52	28.39	21.35
F-stat($\Delta \log \frac{E_{ict}}{L_{ct}}$)		6.055	9.214	7.164		2.339	7.871	5.828
Over-id(p-val.)		.	.	0.874		.	.	0.147

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. Dependent variable is the decadal change in log city-industry employment rate.

Table 10: Further Model Implications

	OLS	IV1	IV2	IV1&IV2	OLS	IV1	IV2	IV1&IV2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log w_{ct}$	0.460*	1.993*	1.309*	1.523*	1.352*	1.865*	1.677*	1.735*
	(0.179)	(0.559)	(0.538)	(0.464)	(0.116)	(0.394)	(0.322)	(0.311)
$\Delta \log ER_{ct}$	-0.0260	4.927*	6.479*	5.829*	0.161	1.999*	2.425*	2.247*
	(0.200)	(1.788)	(1.601)	(1.532)	(0.170)	(0.924)	(0.987)	(0.883)
N	608	608	608	608	608	608	608	608
R^2	0.179				0.523			
F-stat ($\log w_{ct}$)		27.46	41.80	33.27		27.46	41.80	33.27
Over - id				0.244				0.567

NOTES: Standard errors are in parentheses. (*) 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. Dependent variable is either the decadal change in log labor force size or rental rate of a two or three bedroom apartment.