Market Potential, Wage Inequality, and Regional Unemployment Rates*

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Abstract

This paper theoretically and empirically analyzes the relationship between regional wages, unemployment rates, and agglomeration by introducing the standard search and matching framework into a new economic geography (NEG) model. First, through the theoretical model, we structurally estimate the NEG wage equation by using Mexican state panel data. Then, we empirically examine the relationship between regional unemployment rates and agglomeration by using Mexican municipal data. We confirm that the geographic accessibility across regional markets increases the nominal wages even when job search frictions are taken into account. Furthermore, we find that unemployment rates in higher density municipalities are lower.

JEL classifications: F12, J61, J64, R12, R23.

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1 Introduction

Since the publication of Krugman (1991), new economic geography (NEG) studies have examined the agglomeration mechanism of economic activities, with particular attention to the increasing returns to scale, monopolistic competition, transport costs, and mobile labor across regions (e.g., Fujita et al., 1999). The NEG literature has also provided theoretical foundations to wage inequality from the perspective of geographical networks. For example, many empirical papers have shown that the goodness of geographical accessibility across the regional markets leads to higher regional nominal wages (e.g., Redding and Venables, 2004; Hanson, 2005; Hering and Poncet, 2010). Moreover, agglomeration economies benefit job matches in regional labor markets. As noted in Marshall (1890), for example, the concentration of economic activities facilitates the job search dealings between employers and job seekers in terms of industry-specific skills. Despite these observational facts, only limited attention has been paid to job search and regional unemployment issues in the NEG literature. Thus, we still fall short of fully understanding the underlying mechanism acting between the regional unemployment rates and agglomeration of economic activities.

In the recent NEG literature, some attempts have been made to tackle certain job search and unemployment issues.[1] For example, Epifani and Gancia (2005) developed a dynamic NEG model by introducing search and matching mechanism. Francis (2009) extended the model of Epifani and Gancia (2005) by endogenously dealing with the job destruction rate.[2] Interestingly, these models commonly predict a lower unemployment rate in agglomerated regions in the long run.[3] On the other hand, motivated by the aggregate observational fact that unemployment rates in high-density regions are higher than those in low-density regions, vom Berge (forthcoming) developed Krugman's (1991) model by introducing a search and

[1]Some theoretical mechanisms to generate unemployment need to be introduced (e.g., efficiency wage, or search and matching). This paper employs the search and matching model proposed by Pissarides (2000). Rogerson et al. (2005) offer a literature review of this issue.

[2]Instead of search and matching, Zierahn (forthcoming) introduces the efficiency wage and congestion costs due to agglomeration into Krugman's (1991) model.

[3]However, Epifani and Gancia (2005) show that the unemployment rate in the agglomerated region takes a higher value in the initial phase of dynamic adjustment process.

matching framework.[4] His model shows that the unemployment rate in agglomerated regions is comparatively higher. However, as mentioned in Zierahn (forthcoming), if the NEG models show full agglomeration under the spatial equilibrium, it means that the unemployed workers do not live in the periphery region, although the agricultural workers still live there in the case of Krugman-type models. That is, under full agglomeration, the unemployment rate in the periphery region is virtually zero, whereas it is always positive in the agglomerated region. As such, the results obtained from the full-agglomeration models do not exactly capture what is going on in the periphery regions. Therefore, we investigate the relationship between regional unemployment rates and agglomeration by using an NEG model with partial agglomeration.

Following the framework proposed by vom Berge (forthcoming), we develop a multi-region Helpman (1998) model by incorporating search and matching mechanism.[5] Unlike Krugman (1991), Helpman (1998) lays more emphasis on the local congestion costs arising from agglomeration. For example, the concentration of economic activities prevents smooth commuting flows and raises the land and housing prices. Consequently, this type of dispersion force leads to a partial agglomeration. Thus, by focusing on Helpman's (1998) model, we offer another insight into the regional distributional pattern of unemployment rates in an agglomeration economy. Furthermore, to capture the essence of how the relationships between regional unemployment rates and agglomeration vary depending on the extent of transport costs, we carry out a numerical analysis of the theoretical model.

Although the NEG models provide insightful policy implications, their theoretical and numerical analyses are usually limited to two-region cases to avoid mathematical difficulties, which are also known as *three-ness* (Combes et al., 2008, Chap. 4). Although we build a multi-region model for the theoretical part, the numerical analysis is restricted to two symmetric regions. In our empirical analysis, however, we use a multi-region model to bridge the gap between theory and empirics. Our empirical attempt is to structurally estimate the

[4] vom Berge (forthcoming) introduces regions into the model developed by Ziesemer (2005), who extended Pissarides (2000, Chap. 3) model by introducing monopolistic competition.

[5] An extension of Helpman (1998) can be found in Pflüger and Tabuchi (2010). They assume that a firm uses land as a production input.

NEG wage equation augmented by a search and matching framework.

Starting with Hanson (2005), the NEG wage equation has been structurally estimated in the existing literature (e.g., Mion, 2004; Brakman et al., 2004).[6] Although Hanson (2005) imposes real wage equalization as a spatial equilibrium condition, such an assumption might be too strong for the real economy. As mentioned in Brakman et al. (2004), the wage equation, real market potential (RMP), and price index obtained by using Helpman (1998) and Krugman's (1991) models take the same forms respectively. As will be shown later, this relationship holds even when job search frictions are introduced into the models. Therefore, we extend the empirical framework proposed by Hanson (2005).

In this paper, we use Mexican state and municipal data. As mentioned in Krugman and Livas-Elizondo (1996), Mexico experienced a dynamic allocation of economic activities after the trade liberalization in the 1980s and 1990s. In the meantime, this movement brought about drastic changes in the country's domestic distributional pattern of employment. According to Hanson (1998), the Mexico–US border states attracted more manufacturing workers. For example, Hanson (1998) shows that the regional share of employment was 21.0% in 1980, but 29.8% in 1993. On the other hand, the manufacturing workers tend to leave the Mexico City metropolitan area (their share came down from 46.4% in 1980 to 28.7% in 1993). However, little attention has been paid to the relationship between regional unemployment rates and agglomeration in the Mexican literature; therefore, in this paper we try to confirm whether agglomerated regions have higher or lower unemployment rates.[7]

It is worthwhile to compare our model with vom Berge's (forthcoming) model: the models have several similarities and differences. For example, our NEG wage equation takes the same form as in vom Berge (forthcoming). From this fact, we test whether a higher RMP explains the higher nominal wages obtained with Mexican state panel data. On the other hand, the key difference between the models is in the distributional pattern of regional unem-

[6]Another approach to estimating the NEG wage equation is based on a two-step method proposed by Redding and Venables (2004). See also Head and Mayer (2006).

[7]The Mexican data might be suitable for our search and matching framework with migration, compared to developed countries. Especially, if the spatial job search (without migration) is striking, our theoretical results are somewhat misleading.

ployment rates. Our model based on Helpman (1998) shows lower unemployment rates in the agglomerated region, whereas vom Berge's (forthcoming) model based on Krugman (1991) shows the opposite result. As shown in vom Berge (forthcoming), the aggregate relationship between unemployment rates and population (labor force) densities tends to be positive in the developed countries. However, the relationship between two after controlling for endogeneity problems is still unclear, for which further empirical analysis is required. In this paper, by coping with the omitted variables and simultaneity biases, we can more accurately examine the relationship between regional unemployment rates and agglomeration.

The remainder of this paper is organized as follows. In Section 2, we build a multi-region Helpman (1998) model consisting of a standard search and matching framework. In Section 3, we numerically analyze a two-region case. In Section 4, we detail the estimation strategy for the multi-region model. Section 5 explains the data used. Section 6 discusses the estimation results of this paper. Finally, Section 7 concludes the paper.

2 The Model

Following vom Berge (forthcoming), we extend the multi-region Helpman (1998) model by introducing a search and matching framework. We consider an economy with R regions with manufacturing and land sectors. The manufacturing sector is monopolistically competitive, with each firm producing one variety of a differentiated good under increasing returns to scale. Labor is a unique production input. On the other hand, the land sector is perfectly competitive, and land endowment in each region is fixed. There are two types of workers, the employed and the unemployed. In the long run, we assume that both the worker types are mobile across regions without migration costs. Job search frictions are introduced into the regional labor markets. The unemployed workers search for jobs in their own living regions, with spatial and on-the-job searches not allowed. For the present purpose, we focus on the steady state analysis.

2.1 Matching Function

Let us first assume that there are search frictions in the regional labor markets. The number of matches between job seekers and vacancies is determined by the following matching function:

$$m_i L_i = m(u_i L_i, v_i L_i), \quad i = 1, 2, \ldots, R \tag{1}$$

where m_i is the matching rate, u_i is the unemployment rate, v_i is the vacancy rate in terms of labor, and L_i is the labor force, with the subscript i indicating region i. Note that job matches are made only within region i. The matching function is assumed to be increasing in both variables, homogeneous of degree one, concave, twice continuously differentiable, and $m(u_i L_i, 0) = m(0, v_i L_i) = 0$.[8]

Given the matching function (1), the rates at which the vacancies are filled and an unemployed worker leaves unemployment can be expressed respectively as

$$q(\theta_i) \equiv \frac{m(u_i L_i, v_i L_i)}{v_i L_i} \quad \text{and} \quad \theta_i q(\theta_i) \equiv \frac{m(u_i L_i, v_i L_i)}{u_i L_i},$$

where $\theta_i \equiv v_i / u_i$ denotes the labor market tightness. From the above assumptions, we can easily verify that both $q(\theta_i) > 0$ and $q'(\theta_i) < 0$ hold.

2.2 Consumer and Worker

For simplicity, we consider a static consumer problem; that is, we assume that consumers do not save any part of their incomes but spend all of them in each period.[9]

Each consumer has an identical Cobb–Douglas preferences for two goods; that is,

$$\mathbb{U}_i = \frac{1}{\mu^\mu (1-\mu)^{1-\mu}} M_i^\mu H_i^{1-\mu} \tag{2}$$

where $0 < \mu < 1$ is an expenditure share for manufactured goods, M_i a composite of the consumption of manufactured goods in region i, and H_i the consumption of land in region

[8] See Petrongolo and Pissarides (2001) for details of the matching function, including empirical findings.
[9] This simplification, however, does not change the essential results of our model.

i. The composite of manufactured goods is given by the constant elasticity of substitution (CES) function

$$M_i = \left(\sum_{j=1}^{R} \int_0^{n_j} m_{ji}(\nu)^{(\sigma-1)/\sigma} \mathrm{d}\nu \right)^{\sigma/(\sigma-1)},$$

where $m_{ji}(\nu)$ is region i's consumption of variety ν produced in region j, n_j the number of varieties produced in region j, and $\sigma > 1$ the elasticity of substitution between any two varieties.

From utility maximization, we obtain the following demand functions:

$$H_i = \frac{(1-\mu)Y_i}{p_i^H}, \quad M_i = \frac{\mu Y_i}{G_i}, \quad m_{ji}(\nu) = \mu p_{ji}(\nu)^{-\sigma} G_i^{\sigma-1} Y_i, \tag{3}$$

where the price index in region i is

$$G_i = \left(\sum_{j=1}^{R} \int_0^{n_j} p_{ji}(\nu)^{1-\sigma} \mathrm{d}\nu \right)^{1/(1-\sigma)}, \tag{4}$$

Y_i the regional income, p_i^H the land price in region i, and $p_{ji}(\nu)$ the region i's consumer price of variety ν imported from region j. By substituting demand functions (3) into utility function (2), we obtain the indirect utility $\mathbb{V}_i$ of an individual living in region i as follows:

$$\mathbb{V}_i = \frac{I_i}{G_i^{\mu} (p_i^H)^{1-\mu}}, \tag{5}$$

where I_i is the income of the individual living in region i. Indirect utility can be interpreted as the real income, which is the individual's income I_i deflated by the cost-of-living index $G_i^{\mu}(p_i^H)^{1-\mu}$. In the long-run, individuals decide to migrate depending on the expected real income differentials.

As mentioned earlier, there are two types of workers in the economy, the employed and the unemployed. Let $\mathbb{V}_i^e$ and $\mathbb{V}_i^u$ denote the indirect utilities for the employed and the unemployed, respectively. We assume that while the employed earns w_i, the unemployed receives unemployment benefit z from the government. The unemployment benefit is exogenously given. The government imposes a tax τ for all the workers in order to finance the unemployment benefits. Further, we assume that the rate of interest r is common across all regions. Thus, the steady state Bellman equations for the employed and the unemployed are given, respectively, as follows:

$$\begin{aligned} rE_i &= \mathbb{V}_i^e + \delta_i(U_i - E_i), \\ rU_i &= \mathbb{V}_i^u + \theta_i q(\theta_i)(E_i - U_i), \end{aligned} \tag{6}$$

where E_i and U_i are the present discounted values (PDV) of the expected real income stream for the employed and unemployed, respectively, and δ_i is the job destruction rate in region i. Although we assume that the job destruction rate is identical across all the regions in our numerical analysis, this assumption is relaxed in the empirical part, as shown in Section 4.

2.3 Producer Behavior

We assume that the prices of all the varieties produced within a region are identical in view of the same production technology used and, therefore, denote the price of all the varieties produced in region i as p_i. We assume that a manufactured good is traded between regions i and j with iceberg transport cost T_{ij}. Thus, if a unit of any variety of a manufactured good is shipped from region i and region j, only $1/T_{ij}$ of the unit arrives. The price of a variety of the manufactured good produced in region i is sold at price p_i in that region. If this variety is shipped from region i to region j, the delivered price is given by

$$p_{ij} = p_i T_{ij}, \quad T_{ij} = T_{ji} \geq 1, \quad T_{ii} = 1, \quad i, j = 1, 2, \ldots, R.$$

The total amount of goods that a firm produces to satisfy the consumption demand of all the regions, therefore, becomes

$$x_i = \sum_{j=1}^{R} m_{ij} T_{ij}. \tag{7}$$

All the firms require not only fixed and marginal labor input for producing the varieties but also recruiters for hiring their workers.[10] Thus, the total labor input in region i is given

[10] This formulation is developed by Ziesemer (2005) and vom Berge (forthcoming), following Pissarides (2000, Chap. 3).

by

$$\ell_i = F + cx_i + \gamma N_i \tag{8}$$

where F and c are respectively the fixed and marginal labor requirements for production, γ is the marginal labor requirement for recruiting per vacancy, and N_i is the number of vacancies that a firm needs to post. The first two terms correspond to the standard Dixit–Stiglitz assumption of increasing returns to scale. The third term indicates that a firm needs to hire recruiters to keep their workers from decreasing because the workers quit their jobs at a job destruction rate of δ_i.

A vacant job is filled with a probability $q(\theta_i)$ and an occupied job is destructed with a probability of δ_i. Thus, the dynamics of total labor input is give by

$$\dot{\ell}_i = q(\theta_i)N_i - \delta_i \ell_i. \tag{9}$$

Since $\dot{\ell}_i = 0$ in the steady state, by substituting (8), the number of vacancies in the steady state becomes

$$N_i = \frac{\delta_i(F + cx_i)}{q(\theta_i) - \gamma\delta_i}, \tag{10}$$

where we assume that $q(\theta_i) > \gamma\delta_i$ to satisfy that the number of vacancies takes a positive value.

A firm maximizes the PDV of its expected profit with respect to the production quantity x_i and the number of vacancies N_i as follows:[11]

$$\begin{aligned} &\max_{x_i, N_i} \int_0^\infty e^{-rt} \left[p_i(x_i)x_i - w_i(F + cx_i + \gamma N_i)\right] \mathrm{d}t \\ &\text{s.t.} \quad \dot{x}_i = \frac{1}{c}\left[\left(q(\theta_i) - \gamma\delta_i\right) N_i - \delta_i(F + cx_i)\right] \\ &\lim_{t\to\infty} \left[\lambda(t)e^{-rt}x_i(t)\right] = 0 \end{aligned} \tag{11}$$

where $p_i(x_i)$ is the mill price in region i, and $\lambda(t)$ the Lagrange multiplier. Solving the current value Hamiltonian, we obtain the optimal mill price with a constant markup on

[11] Using (8), (9), and the envelop theorem, we obtain the dynamic equation on production $\dot{x}$ in (11).

marginal costs as follows:

$$p_i = \frac{\sigma}{\sigma - 1} c w_i \left(1 + \frac{r\gamma}{q(\theta_i)}\right) \left(1 - \frac{\gamma\delta_i}{q(\theta_i)}\right)^{-1}. \tag{12}$$

Note that the price is higher than that of the standard Dixit–Stiglitz monopolistic competition model because the multiplication of the second and third terms is greater than one. Intuitively, the marginal cost consists of three parts. The first two terms give the worker's wage for producing an additional quantity x_i and the expected cost of hiring a worker, respectively, and the third term captures the cost of hiring the workers engaged in the production and recruitment.[12] If the job search cost is zero ($\gamma = 0$), this price takes the same form obtained from the standard Dixit–Stiglitz model.

Let V_i and J_i be the PDVs of the expected profit of the vacant and occupied jobs respectively. Then, the steady state Bellman equation for a vacancy is given by

$$rV_i = -\gamma \tilde{w}_i + q_i(\theta_i)(J_i - V_i), \tag{13}$$

where $\tilde{w}_i \equiv w_i/p_i$ is the real wage with respect to a firm.

All the profit opportunities arising from creating new jobs are exploited in equilibrium, in which the value of the vacant jobs becomes zero ($V_i = 0$). Hence, this equilibrium condition yields

$$J_i = \frac{\gamma \tilde{w}_i}{q(\theta_i)}. \tag{14}$$

This equation means that since $1/q(\theta)$ is the expected duration of a vacant job, the expected profit from a new job is equal to the expected cost of hiring a worker in equilibrium.

[12] To understand the third term, we manipulate (10) to obtain

$$\frac{\delta_i(F + cx_i)}{q(\theta)N_i} = 1 - \frac{\gamma\delta_i}{q(\theta_i)} < 1.$$

The left-hand side shows how the quitting workers engaged in production are filled up from among the newly hired workers, implying that a part of the newly hired workers are engaged in recruitment.

2.4 Wage Bargaining

In a standard search and matching model, each firm is assumed to have only one job. Although a firm in our model employs many workers, we consider a bargaining process in a similar manner. Following Pissarides (2000, Chap. 3), we assume that the wages of workers are fixed in the Nash bargains, where the firm gets involved with each worker separately, considering the wages of all other workers as given. This assumption allows us to consider a one-to-one relationship between a worker and a job. The total surplus arising from a job match (i.e., the net benefit of the worker and the firm arising from the firm producing additional goods and the unemployed worker starting to work) is shared through a Nash bargaining process between the worker and the firm:

$$\tilde{w}_i = \arg\max (E_i - U_i)^{\beta} (J_i - V_i)^{1-\beta},$$

where $0 \leq \beta \leq 1$ is the bargaining power of the workers. From the first-order condition, the result of the bargaining is given by

$$(1-\beta)(E_i - U_i)J_i' = \beta(J_i - V_i)E_i'.$$

By substituting (6) and (14) and imposing the equilibrium condition $V_i = 0$, we obtain the following equation

$$\tilde{w}_i = rU_i + \beta \left(\frac{\sigma - 1}{c\sigma} - rU_i \right).$$

Following some manipulations, we obtain the following relationship between the nominal wage and the labor market tightness:

$$g_i(w_i, \theta_i) = (1-\beta)\left(1 - \frac{z_i}{w_i}\right) - \beta \frac{\gamma\left[r + \delta_i + \theta_i q(\theta_i)\right]}{q(\theta_i) - \gamma\delta_i} = 0. \tag{15}$$

This corresponds to the wage-setting curve in Pissarides (2000), however, it shows a nonlinear function with respect to wage and labor market tightness in our case. From implicit function theorem, we obtain

$$\frac{\mathrm{d}w_i}{\mathrm{d}\theta_i} = -\frac{\partial g_i/\partial \theta_i}{\partial g_i/\partial w_i} > 0,$$

where we assume a homogeneous degree one in the matching function.[13] Since the unemployment rates u_i and labor market tightness θ_i are negatively correlated, this result means that there is a negative relationship between the wage and unemployment rates.[14]

2.5 Short-Run Equilibrium

We now consider a short-run equilibrium, which is characterized by a general equilibrium in each region without migration. By substituting the price in (12) into the current profit in (11) and imposing a zero-profit condition, the equilibrium output is given by

$$x_i = \frac{F(\sigma-1)}{c}\left(1+\frac{\sigma r\gamma}{q(\theta_i)}\right)^{-1}. \tag{16}$$

Note that the equilibrium output is lower than the output of a standard Dixit–Stiglitz monopolistic competition model.

Substituting the equilibrium output (16) and the number of vacancies (10) into the total labor input (8), we obtain the equilibrium total labor input in region i:

$$\ell_i = F\sigma\left(1+\frac{r\gamma}{q(\theta_i)}\right)\left(1+\frac{\sigma r\gamma}{q(\theta_i)}\right)^{-1}\left(1-\frac{\delta_i\gamma}{q(\theta_i)}\right)^{-1}. \tag{17}$$

In addition, from the labor market clearing condition $n_i\ell_i = (1-u_i)L_i$, the number of firms is given by

$$n_i = \frac{(1-u_i)L_i}{F\sigma}\left(1+\frac{r\gamma}{q(\theta_i)}\right)^{-1}\left(1+\frac{\sigma r\gamma}{q(\theta_i)}\right)\left(1-\frac{\delta_i\gamma}{q(\theta_i)}\right). \tag{18}$$

From (7), the total sales of the variety produced in region i amount to

$$x_i = \mu\sum_{j=1}^{R} p_i^{-\sigma}G_j^{\sigma-1}Y_jT_{ij}^{1-\sigma}. \tag{19}$$

[13]Under the assumption of a homogeneous degree one in the matching function, we confirm that $q(\theta_i) + \theta_i q'(\theta_i) > 0$ holds.

[14]This result shows the existence of wage curve (Blanchflower and Oswald, 1994). In the case where the regional labor markets are homogeneous with respect to job destruction rates and job matches, a negative correlation can exist between the regional unemployment rates and nominal wages. This result is quite similar to Sato (2000), who shows that even if the workers are mobile, the wage curve can be observed by using a search theoretical framework under the assumption of different productivities across the regions and a monocentric city structure.

Choosing the convenient units of measurement for marginal labor requirement $c = (\sigma - 1)/\sigma$ and fixed labor requirement $F = \mu/\sigma$, we simplify the model outcomes. Thus, from (12), (16), and (19), the NEG wage equation is obtained:

$$w_i = \Gamma(\theta_i) \left[\mu \sum_{j=1}^{R} Y_j G_j^{\sigma-1} T_{ij}^{1-\sigma} \right]^{1/\sigma}, \tag{20}$$

where

$$\Gamma(\theta_i) = \left(1 + \frac{\sigma r \gamma}{q(\theta_i)}\right)^{1/\sigma} \left(1 + \frac{r\gamma}{q(\theta_i)}\right)^{-1} \left(1 - \frac{\delta_i \gamma}{q(\theta_i)}\right). \tag{21}$$

The sum in the bracket gives the RMP $\equiv \mu \sum_{j=1}^{R} Y_j G_j^{\sigma-1} T_{ij}^{1-\sigma}$, expressing the sum of the regional income discounted by the price index, and weighted by the transport cost. Even if we take into account the frictions in the regional labor markets, we see that the standard implication from NEG holds; that is, the goodness of accessibility to other markets increases the nominal wages.

From the assumption of identical prices among all the varieties produced within the regions, the price index takes the following form:

$$G_i = \left[\sum_{j=1}^{R} n_j (p_j T_{ji})^{1-\sigma} \right]^{1/(1-\sigma)}. \tag{22}$$

By substituting (12) and (18) into (22) and using normalization, we obtain

$$G_i = \left[\sum_{j=1}^{R} (1 - u_j) L_j \Gamma(\theta_j)^{\sigma} (w_j^{1-\sigma} T_{ji})^{1-\sigma} \right]^{1/(1-\sigma)}. \tag{23}$$

As mentioned earlier, the results on wage equation, RMP, and price index are essentially identical with vom Berge (forthcoming).

The regional income Y_i gives the sum of the income of every employed and unemployed worker living in region i. The respective disposable incomes of the employed and unemployed workers are $I_i^e = w_i + h - \tau$ and $I_i^u = z + h - \tau$, where h is the rent of land and τ the tax rate. Since all the individuals consume land equally, the rent of land is also equally redistributed.[15]

[15] See Appendix A for the details of derivation.

Thus, the rent of land is given by

$$h = \frac{1-\mu}{\mu} \frac{\sum_{j=1}^{R}[w_j(1-u_j)+zu_j-\tau]L_j}{\sum_{j=1}^{R} L_j}. \tag{24}$$

Therefore, the regional income Y_i becomes

$$Y_i = [w_i(1-u_i)+zu_i-\tau]L_i + \frac{1-\mu}{\mu}\frac{L_i}{\sum_{j=1}^{R} L_j}\left[\sum_{j=1}^{R}\big(w_j(1-u_j)+zu_j-\tau\big)L_j\right]. \tag{25}$$

Next, we consider labor market tightness and the unemployment rates. Given w_i, labor market tightness is determined as in (15). Since the inflows and outflows of unemployment are equalized in the steady state equilibrium, we obtain $\delta_i(1-u_i)L_i = \theta_i q(\theta_i)u_i L_i$. Solving this with respect to u_i, we obtain the so-called Beverage curve:

$$u_i = \frac{\delta_i}{\delta_i + \theta_i q(\theta_i)}. \tag{26}$$

The equilibrium condition of the land market determines the price of land. Since the land endowment is fixed, the consumption of land in region i is given by $H_i = \bar{S}_i/L_i$, where $\bar{S}_i$ is the land endowment in region i. Thus, we obtain the price of land p_i^H in region i as follows:

$$p_i^H = \frac{(1-\mu)Y_i}{\bar{S}_i/L_i} \tag{27}$$

In equilibrium, the tax rate τ is determined to balance the budget for tax revenue and expenditure for unemployment benefits as follows:

$$\tau \sum_{j=1}^{R} L_j = z\sum_{j=1}^{R} u_j L_j. \tag{28}$$

3 Long-Run Equilibrium: A Two-Region Case

In this section, we numerically analyze the properties of our model.[16] We limit our numerical analysis to a two-region case ($R = 2$). This assumption is relaxed in our empirical analysis in Section 4.

[16]Numerical analysis is conducted using the Ox Console 6.21 (Doornik and Ooms, 2006).

3.1 Spatial Equilibrium

We assume that in the long-run, the workers are mobile across all regions in response to the expected real income differentials. For convenience of notation, we denote shares of labor force in regions 1 and 2 as $s_1 = L_1/(L_1 + L_2)$ and $s_2 = 1 - s_1$, respectively. The regional differentials in the expected real incomes are then expressed as follows:

$$\Delta\omega(s_1) \equiv \omega_1(s_1) - \omega_2(s_1), \tag{29}$$

where the expected real income and the real incomes of the employed and the unemployed living in region i are given as follows, respectively:

$$\omega_i(s_1) = (1 - u_i)\mathbb{V}_i^e(s_1) + u_i\mathbb{V}_i^u(s_1), \quad \mathbb{V}_i^e(s_1) = \frac{w_i + h - \tau}{G_i^\mu (p_i^H)^{1-\mu}}, \quad \mathbb{V}_i^u(s_1) = \frac{z + h - \tau}{G_i^\mu (p_i^H)^{1-\mu}}. \tag{30}$$

Note that the wage w_i, price index G_i, land price p_i^H, land rent h, and tax τ are functions of s_i. A spatial equilibrium arises at $s_1^* \in (0, 1)$ when $\Delta\omega(s_1) = 0$, at $s_1 = 0$ when $\Delta\omega(0) \leq 0$, or at $s_1 = 1$ when $\Delta\omega(1) \geq 0$. We assume that the migrants are myopic, that is, they have static expectations. Thus, any adjustment process over time t is governed by the following differential equation:

$$\frac{\mathrm{d}s_1}{\mathrm{d}t} \equiv \dot{s}_1 = \Delta\omega(s_1)s_1(1 - s_1), \tag{31}$$

where the equilibrium is stable if the slope of $\dot{s}_1$ is negative.

The parameter setting for the numerical analysis is shown in Table 1. The matching function is assumed to take the Cobb–Douglass form with constant returns to scale, $m(u_iL_i, v_iL_i) = A(u_iL_i)^\alpha(v_iL_i)^{1-\alpha}$, where A denotes the matching efficiency and α matching elasticity. Here, we assume that the matching functions are identical across all the regional labor markets.

Panel (a) of Figure 1 illustrates the differential equations for three cases of transport costs ($T = 1.5, 1.6, 1.7$). When $T = 1.7$, there are three equilibria, of which two are stable at $s_1 = 0.06, 0.94$ and one is unstable at $s_1 = 0.50$. When $T = 1.6$, there are two stable equilibria at $s_1 = 0.30, 0.70$ and one unstable equilibrium at $s_1 = 0.50$. However, the stable equilibria shift toward the inside. When $T = 1.5$, the equilibrium is unique and stable at $s_1 = 0.5$.

Panel (b) of Figure 1 describes the unemployment differentials between regions 1 and 2 under the short-run equilibrium. We can see that when $s_1 > 0.5$ (i.e., higher labor force density in region 1), the unemployment rate in region 1 is always lower than that in region 2, which is a robust relationship under different values of transport costs. This result derives from the fact that the nominal wage in a denser region is always higher, resulting in a lower unemployment rate. By contrast, vom Berge (forthcoming) shows the opposite results against ours. This is because the nominal wage in a denser region is lower in the Krugman (1991) model. In the next subsection, we extend this unemployment analysis by focusing on the spatial equilibrium.

Panel (c) of Figure 1 summarizes the spatial equilibria with respect to transport costs. The solid and dashed lines indicate stable and unstable equilibria respectively. A partial agglomeration arises when the transport costs are high.[17] In our model, the break point and sustain point coincide with each other. These points are at $T = 1.59$ in Panel (c) of Figure 1. Contrary to our results, vom Berge (forthcoming) shows that a full agglomeration emerges when the transport costs are low. A detailed discussion of these differences is provided in Section 3.2.

[Table 1 and Figure 1 about here]

3.2 Regional Labor Markets

From our numerical results, we mainly discuss the regional labor market outcomes in a spatial equilibrium.[18] We assume that region 1 has at least half the share of the labor force ($0.5 \leq s_1 < 1$). Panels (a), (b), (c), and (d) of Figure 2 illustrate respectively how the shares

[17] As shown in Pflüger and Tabuchi (2010), a full agglomeration is never a stable spatial equilibrium in a typical Helpman (1998) model. Intuitively, this is because if all the workers gather in one region, the price of land in the other region becomes zero. Consequently, the workers have an incentive to move to the vacant region to enjoy higher utility; thus, a full agglomeration never arises.

[18] The figures for labor market tightness θ_i, wage curve, price index for manufactured goods G_i, land price p_i^H, and cost-of-living index $(G_i)^\mu (p^H)_i^{1-\mu}$, $(i = 1, 2)$, are available on the Web supplement file.

of the employed workers, nominal wages, unemployment rates, and labor market tightness vary depending on the transport costs.

Panel (a) of Figure 2 shows that when the transport costs are high, region 1 has a larger share of the employed than region 2. In that case, we call region 1 an employment cluster, core region, or agglomerated region. Panel (b) of Figure 2 shows that a higher nominal wage is offered in the employment cluster. As the transport costs fall, this wage inequality becomes smaller because the difference in the shares of the employed also becomes smaller. Panel (c) of Figure 2 presents a lower unemployment rate in the employment cluster. Contrary to this result, labor market tightness in the employment cluster takes higher value in Panel (d) of Figure 2, suggesting that the unemployed can easily find jobs thus lowering the unemployment rate in a agglomerated region.

Our model provides some predictions different from vom Berge (forthcoming), who incorporates a search and matching framework into Krugman's (1991) model. vom Berge (forthcoming) shows the a positive relationship between the regional unemployment rates and agglomeration. That is, the unemployment rate in a core region takes a higher value compared to that in a periphery region. However, our model shows a negative relationship, as shown in Panel (c) of Figure 2. This difference arises from the sector that generates a dispersion force.[19] Intuitively, in a Krugman-type model, a full agglomeration emerges and no manufacturing worker lives in the periphery region. Therefore, the unemployment rate in a periphery region virtually becomes zero. By contrast, in a Helpman-type model, a partial agglomeration appears, and therefore the manufacturing workers always live in the periphery region. As a result, a higher nominal wage in the core region generates a higher labor market tightness, which further leads to a lower unemployment rate.[20]

[Figure 2 about here]

[19] Krugman's (1991) model deals with freely tradable agricultural goods, but the agricultural workers are not mobile. Helpman's (1998) model deals with the land sector, whose services are consumed locally.

[20] In vom Berge (forthcoming), the nominal wage in the core region is lower, leading to a lower labor market tightness and a higher unemployment rate in the core region.

4 Empirical Analysis: A Multi-Region Case

In this section, we consider a multi-region case with data. Our attempt in Section 4.1 was to develop the standard NEG empirical framework considering search frictions in the regional labor markets. Besides, we empirically examine the theoretical predictions obtained from Krugman's (1991) and Helpman's (1998) models with a search and matching framework in Section 4.2.

4.1 Structural Estimation Approach

We now structurally estimate the parameters of an NEG model with a search and matching framework. In this estimation, the data of Mexican states are used, and thus, the number of regions R becomes 32. Our empirical strategy is based on the estimation of the wage equation (20). Taking the logarithm of it yields the following specification for regression analysis:

$$\log(w_{i,t}) = \log\Gamma(\theta_{i,t}) + \frac{1}{\sigma}\log\left[\sum_{j=1}^{32}\mu Y_{j,t}G_{j,t}^{\sigma-1}T_{ij}^{1-\sigma}\right], \tag{32}$$

where the transport cost T_{ij} needs to be specified. In this paper, we use the following specification:

$$T_{ij} \equiv B[D_{ij}(1+\varphi C_{ij})]^{\xi}, \tag{33}$$

where B is constant, D_{ij} is a bilateral distance between regions i and j, C_{ij} is a contiguity dummy that takes the value of 1 if regions i and j share the same border and zero otherwise, φ is a parameter measuring adjacent effect, and ξ is a distance decay parameter.

To facilitate the estimation procedure, we approximate $\Gamma(\theta_{i,t})$ as follows:[21]

$$\log\Gamma(\theta_{i,t}) \approx -\frac{\delta_{i,t}\gamma}{q(\theta_{i,t})} = -\gamma\frac{u_{i,t}\theta_{i,t}}{1-u_{i,t}} \quad \text{and} \quad \Gamma(\theta_{i,t})^{\sigma} \approx \exp\left(-\sigma\gamma\frac{u_{i,t}\theta_{i,t}}{1-u_{i,t}}\right),$$

[21] We use the following approximation: $\log(1+x) \approx x$.

where we use the following job destruction rate obtained from (26):

$$\delta_{i,t} = \frac{u_{i,t}\theta_{i,t}q(\theta_{i,t})}{(1-u_{i,t})}.$$

This approximation allows us to estimate our regression model without specifying the matching function in regression analysis.

For the estimation of equation (32), we need to consider three estimation issues. First, the omitted variable bias should be considered. In general, wage is determined on the basis of not only the RMP but also human capital stock. Thus, we need to introduce control variables on human capital, $\boldsymbol{Z}_{i,t}$, into the regression model. In the educational economics literature, the Mincerian wage equation is often estimated to examine the returns to education. We follow the standard manner of the Mincerian wage equation and therefore a vector of $\boldsymbol{Z}_{i,t}$ includes years of education, age, and age squared.[22]

Second, we need to pay attention to the regional fixed effects. When unobservable regional heterogeneities are related to explanatory variables, the parameter estimates include bias. Following Hanson (2005), we takethe first difference of (32) to eliminate the state fixed effect. Thus, the regression model is given by

$$\begin{aligned} \mathit{\Delta}\log(w_{i,t}) &= -\gamma\mathit{\Delta}\frac{u_{i,t}\theta_{i,t}}{1-u_{i,t}} + \frac{1}{\sigma}\mathit{\Delta}\log\left[\sum_{j=1}^{32} Y_{j,t}G_{j,t}^{\sigma-1}\left[D_{ij}(1+\varphi C_{ij})\right]^{\xi(1-\sigma)}\right] + \mathit{\Delta}\boldsymbol{Z}_{i,t}\boldsymbol{\eta} + \mathit{\Delta}\varepsilon_{i,t}, \\ G_{j,t} &= \left[\sum_{k=1}^{32}(1-u_{k,t})L_{k,t}\exp\left(-\sigma\gamma\frac{u_{k,t}\theta_{k,t}}{1-u_{k,t}}\right)w_{k,t}^{1-\sigma}\left[D_{kj}(1+\varphi C_{kj})\right]^{\xi(1-\sigma)}\right]^{1/(1-\sigma)}, \end{aligned} \tag{34}$$

where $\mathit{\Delta}$ represents the first difference, $\boldsymbol{\eta}$ a parameter vector of control variables, and $\varepsilon_{i,t}$ error terms. We additionally control for changes in the share of workers by industry and year fixed effects as well. Unlike Hanson (2005), this model does not include μ in the regression model. The parameters of our interest and the expected signs are $\sigma > 1$, $\gamma > 0$, $\xi > 0$, and $\varphi < 0$. As a benchmark estimation, we estimate (34) by using the nonlinear least squares (NLS). From Thompson (2011), we calculate the heteroskedasticity-consistent standard errors clustered

[22]We use age instead of work experience.

by state and year.

Third, the parameter estimates suffer from a simultaneity bias because the RMP includes the regional income, which depends on the wage. In addition, the first term, the approximated term for $\Gamma(\theta_{i,t})$, is also an endogenous variable. Therefore, our NLS estimates of the structural parameters might be biased. For robustness, we rely on instrumental variable (IV) method, and thus our estimates are obtained by using nonlinear instrumental variable (NLIV) method. Our instrumental variables are given in Table 2. We use the distance-based weighed sums of lagged values for regional incomes, wages, labor force, unemployment rates, and labor market tightness and the lagged value of the approximated $\Gamma(\theta_{i,t})$. We take the first differences of these values.

[Table 2 about here]

4.2 Regional Unemployment Rates and Agglomeration

Here, we attempt to examine the relationship between regional unemployment rates and agglomerations. In this paper, we use the labor force density as a proxy for agglomeration. Our theoretical predictions show the negative relationship between the regional unemployment rate and agglomeration, whereas vom Berge (forthcoming) obtains a positive relationship between them. Thus, we empirically test two contradictory results.

Instead of state data, we use municipal data to mitigate the problems arising from the natural environment and avoid misleading results. This is because the area by state differs considerably in terms of inhabitable area. Thus, our regression model for unemployment rates is give by

$$\log(u^s_{i,t}) = \psi \log(\text{Dens}^s_{i,t}) + \boldsymbol{Z}^s_{i,t}\boldsymbol{\phi} + e^s_{i,t}, \tag{35}$$

where $u^s_{i,t}$ is the spatially smoothed unemployment rate of municipality i at year t, ψ the key parameter of our interest, $\text{Dens}^s_{i,t}$ the log of spatially smoothed labor force density, $\boldsymbol{Z}^s_{i,t}$ a vector of spatially smoothed control variables, $\boldsymbol{\phi}$ a vector of parameters for the control variables, and $e^s_{i,t}$ the error terms. Note that the raw municipal data are not appropriate because commuting flows are not negligible at the municipality level and the local labor markets do not necessarily coincide with the administrative areas. Therefore, we use spatially smoothed municipal data concerning the neighboring municipalities. See Section 5.2 for calculation of the spatially smoothed variables. The control variables include the average years of schooling, rates of male and female labor force participation, and shares of the population aged 15–24, 25–59, and 60 and above. To control for the endogeneity problem of labor force density, we estimate equation (35) by using the IV method.

5 Data

5.1 Data for NEG Wage Equation

For the estimation of wage equation (34), we need the data on wage ($w_{i,t}$), unemployment rate ($u_{i,t}$), labor market tightness ($\theta_{i,t}$), regional income ($Y_{i,t}$), labor force ($L_{i,t}$), distance (D_{ij}), and contiguity (C_{ij}). In this paper, we use Mexican state panel data.[23] Mexico has 31 states and the Federal District, and we use the annual data of these states are used. Our data are limited to the period 2005–2010 because the National Occupation and Employment Survey (*Encuesta Nacional de Ocupación y Empleo*, ENOE) offers the 2005–2010 data based on the 2005 Population Census.[24] Since ENOE provides quarterly data on the labor market outcomes by state, we calculate the annual values based on average.

Table 3 shows the descriptive statistics used for the estimation of the NEG wage equation (34). ENOE offers the state data based on average wage (in peso), total labor force, and unemployment rates. In the estimation, the average wages by state are adjusted by consumer price index with the base year 2003$(=100)$.[25] The National Employment Service

[23] Since the municipal data on wages, unemployment rate, labor market tightness, and regional income are not available at the same time, we use state data for estimating the NEG wage equation.

[24] The new series started in 2010, based on the 2010 Population Census. Although we tried to combine the two series, there were some problems about data connection between them. Therefore, we limit our data to the period 2005–2010.

[25] The monthly national CPI data are available from the INEGI. We calculate the annual CPI by averaging the monthly data for individual years.

(*Servicio Nacional de Empleo*), which does the job matching between job seekers and vacancies, is managed by the Ministry of Labor and Social Welfare (*Secretaría de Trabajo y Previsión Social*). One of its wings, the Job Bank (*Bolsa de Trabajo*), reports the number of job applications and vacancies by state, from which we calculate vacancies to job applications ratio as labor market tightness $\theta_{i,t}$. Regional income is substituted by the gross state product (GSP), which is available from the National Institute of Statistic and Geography (*Instituto Nacional de Estadística y Geografía*, INEGI) database. We use the real GSP (in thousands of pesos) evaluated at the 2003 price. The bilateral geographic distances (in km) are measured by great-circle distances using the formula of Vincenty (1975).[26] By following the standard method used in the literature (e.g., Redding and Venables, 2004), the internal distance is taken int account by using $D_{ii} = 2/3\sqrt{\text{Area}_i/\pi}$, where π is the circular constant. The contiguity dummy takes the value of 1 if the two states share the same border and 0 otherwise. We introduce the vector of control variables $\boldsymbol{Z_{i,t}}$, which includes the average years of schooling, age, and age squared, which are available in the ENOE database.

For the construction of instrumental variables, we used the lagged values of GSP, nominal wage, labor force, unemployment rate, and labor market tightness. We also use the nominal wage, labor force, and unemployment rate from ENOE, conducted from 2005. However, the National Employment Survey (*Encuesta Nacional de Empleo*, ENE) offers the corresponding state data for 2002–2004. Thus, we calculate the annual average values from the quarterly ENE data.

5.2 Data for Unemployment Analysis

For our analysis of unemployment rates and agglomeration, we use the 2000 and 2010 Mexican population censuses.[27] Based on the censuses, the National System of Municipal In-

[26]The data on latitude and longitude of each state capital are available from the *Annual Statistics of United Mexican States: Edition 2005* (*Anuario Estadístico de los Estados Unidos Mexicanos, Edicíon 2005*), published by INEGI.

[27]In the population censuses, labor data are available for every ten years. The data on the 1990 population census are also used for the instrumental variables. We drop Nicolás Ruíz in the Chiapas state in 2000 because of the lack of labor data.

formation (*Sistema Nacional de Información municipal*, SNIM) provides its summarized municipal data on area, labor force (the employed and unemployed), average years of schooling, labor force participation rate by gender, and the population aged 15–24, 25–59, 60 and above.[28]

We construct our data set as follows. Let $z^s_{i,t}$ denote the spatially local sum data of municipality i at year t, calculated as $z^s_{i,t} = \sum_{j=1}^{R} \mathbf{1}_{ij}(d) z_{j,t}$, where R stands for the number of municipalities, $z_{j,t}$ the raw data of municipality j, and $\mathbf{1}_{ij}(d)$ the ijth element of the indicator matrix, in which the ijth element takes the value of 1 if the distance between municipalities i and j is less than $d$km and 0 otherwise.[29] We set $d = 50$km. Thus, the spatially smoothed unemployment rate of municipality i is calculated as $u^s_{i,t} = U^s_{i,t}/L^s_{i,t}$, where $U^s_{i,t}$ and $L^s_{i,t}$ are the spatially local sum of the unemployed and the labor force, respectively, of municipality i at year t. In the same manner, we calculate the spatially smoothed labor force density as $\text{Dens}^s_{i,t} = L^s_{i,t}/\text{Area}^s_{i,t}$. Further, the other variables are also calculated following the same method.[30] Table 4 shows the descriptive statistics of the spatially smoothed municipal data by year.

[Tables 3 and 4 about here]

6 Empirical Results

6.1 NEG Wage Equation

Table 5 reports the estimation results for wage equation (34).[31] Column (1) of Table 5 gives the benchmark estimation result, and Column (2) presents the estimation result after controlling for human capital stock and industry structure by state. The estimates of key

[28] The data are available in the following Web site (URL: `http://www.snim.rami.gob.mx/`).

[29] SNIM also offers the latitude and longitude of municipalities, from which the bilateral distances between any two municipalities can be calculated by using the formula of Vincenty (1975).

[30] The average years of schooling is calculated as the spatially local sum of years of schooling divided by the number of municipalities within a $d$km radius of municipality i.

[31] Nonlinear estimations are conducted using Ox Console 6.21 (Doornik and Ooms, 2006).

structural parameters (σ, ξ, γ, and φ) show statistical significance at the 1% level except for $\hat{\gamma}$ in Column (2) and further show the theoretically expected signs. As mentioned in Hering and Poncet (2010), the estimates of elasticity of substitution tend to lie between 5 and 10. Our point estimates, however, somehow take higher values.[32] The value of $1/\hat{\sigma}$ can be interpreted as the impact of RMP on wage. From our estimation result in Column (2), an increase of RMP by 1% leads to an increase of wage by 0.08%. Although the economic impact is small, this result gives an important implication—goodness of geographical accessibility raises the regional nominal wages. This is a well-known finding in the literature (e.g., Hanson, 2005; Redding and Venables, 2004; Mion, 2004; Brakman et al., 2004; Hering and Poncet, 2010; Head and Mayer, 2011). However, this paper shows that the same results can be obtained even when we take into account the search frictions in regional labor markets.

The estimates of distance decay parameter ξ take the range of 1.66–1.67 in Columns (1) and (2) of Table 5. These values seem to be quite high, which means that the transport costs between the Mexican states are quite-costly. Compared with the empirical estimates of the models taking the same or similar specifications of the transport costs in equation (33), for example, Bosker et al. (2010) estimate the standard NEG wage equation and obtain 0.102 for the point estimate of distance decay parameter using the NUTS-II region data. Using the Chinese province and prefecture data, Bosker et al. (2012) obtain the range 0.578–0.632 for the estimate of the distance decay parameter. Since the contiguity dummy coefficient estimate φ shows significant negative values, if we consider an adjacent effect between the states that share the same border, the transport costs become lower.

Unlike the standard NEG models, our model has another key structural parameter γ. Obtaining all the estimates of structural parameters enables us to calculate the real market potentials and price indices.[33]

In addition, the NEG contributes to the literature on education and wage. The NEG wage equation can be interpreted as an extended version of the Mincerian wage equation although

[32]Note that the standard errors are large; therefore, the interval estimates take a wide range.
[33]See the Web supplement file.

we use regional data, rather than micro data.[34] Thus, the coefficient parameter of years of schooling η_1 shows the rate of returns to education from a regional average perspective. The estimate in Column (2) shows a significantly positive value, and we obtain 0.051. While the period of our state panel data is 2005–2010, the estimate takes a value very close to that obtained in the existing literature. For example, Chiquiar (2008) estimates the Mincerian wage equation using the Mexican micro data, gathered from the 1990 and 2000 population censuses. According to his estimation results with full control variables, the estimates are 0.040 for 1990 and 0.051 for 2000.

[Table 5 about here]

6.2 Lower Unemployment Rates in Higher Dense Regions

Table 6 shows the estimation results for equation (35). Columns (1) and (2) of Table 6 show the ordinary least squares (OLS) and IV estimates for 2000. In Column (1), labor force density has a significantly negative impact on unemployment rates at the 10% level. As shown in Column (2), the IV estimate also shows a significantly negative sign at the 1% level. Columns (3) and (4) show the OLS and IV estimates for 2010. The OLS estimate of labor force density is negative but not significant. In Column (4), the IV estimate shows a significantly negative sign at the 1% level.[35] Therefore, the coefficient of labor force density consistently shows significantly negative sign after controlling for the endogeneity problems arising from the omitted variables and simultaneity.

Our important finding is that the unemployment rates are lower in agglomerated regions, as expected in our model. As shown in vom Berge (forthcoming), the aggregate relationship between regional unemployment rates and population (labor force) density are positive, especially in developed countries. However, our evidence from using Mexican municipal

[34]Using Chinese micro data, Hering and Poncet (2010) estimate the Mincerian wage equation involving the RMP term.

[35]We also implement the fixed and random effect estimations controlling for municipal fixed effects. As shown in Table 6, however, the parameter estimates are not identical between 2000 and 2010. Thus, we should report the estimation results separately. See the Web supplement file for the fixed and random effects estimation results.

data shows negative relationship after controlling for the endogeneity bias that arises from omitted variables and simultaneity. Another key point is that we paid more attention to job search behaviors and the timing of migration. Most of workers in developed countries would search for jobs before migration to other regions, which violates our theoretical assumption. To more fit our theoretical framework, we used the Mexican municipal data. In summary, our empirical results suggest that the agglomeration economies play a key role in reducing the regional unemployment rates.

[Table 6 about here]

7 Concluding Remarks

This paper theoretically and empirically analyzed the relationship between regional wages, unemployment rates, and agglomerations. In the theoretical part of our analysis, we extended a multi-region Helpman (1998) model by incorporating job search frictions in regional labor markets. To understand model properties, we conducted our numerical analysis under the assumption of two symmetric regions. We then compared these results with those obtained from Krugman's (1991) model with a search and matching framework of vom Berge (forthcoming). In the empirical part of our analysis, by using Mexican state panel data, we structurally estimated the NEG wage equation augmented by the search and matching framework. In addition, we examined the relationship between the regional unemployment rates and agglomeration (expressed by labor force density) by using Mexican municipal data.

Our theoretical and empirical results show that in the NEG model with search and matching, geographic accessibility across regional markets on average increases the regional nominal wages. Thus, our paper confirmed that the well-known implication on the positive relationship between RMPs and nominal wages holds even if frictional labor markets are taken into account. However, there are two contradictory predictions about the relationship between regional unemployment rates and agglomeration between our model and vom Berge (forthcoming): our model predicts a lower unemployment rate in agglomerated region by using a Helpman-type model, while vom Berge (forthcoming) predicts a higher unemployment rate in an agglomerated regions by using a Krugman-type model. From our empirical results obtained by using Mexican municipal data, we found that the elasticity of the labor force density on unemployment rate is significantly negative after controlling for endogeneity problem, implying that the unemployment rates in agglomerated regions are comparatively lower. To sum up, our findings suggest that the agglomeration of economic activities leads to higher nominal wages and lower unemployment rates.

Finally, it would be interesting to investigate how job search behaviors and the timing of migration affect the relationship between region unemployment rates and agglomeration in further studies.

References

[1] Blanchflower, David G. and Andrew J. Oswald (1994) *The Wage Curve*, Cambridge, MA: MIT Press.

[2] Bosker, Maarten, Steven Brakman, Harry Garretsen, and Marc Schramm (2010) "Adding geography to the new economic geography: Bridging the gap between theory and empirics," *Journal of Economic Geography* 10(6), pp. 793–823.

[3] ——— (2012) "Relaxing Hukou: Increased labor mobility and China's economic geography," *Journal of Urban Economics* 72(2–3), pp. 252–266.

[4] Brakman, Steven, Harry Garretsen, and Marc Schramm (2004) "The spatial distribution of wages: Estimating the Helpman-Hanson model for Germany," *Journal of Regional Science* 44(3), pp. 437–466.

[5] Chiquiar, Daniel (2008) "Globalization, regional wage differentials and the Stolper-Samuelson theorem: Evidence from Mexico," *Journal of International Economics* 74(1), pp. 70–93.

[6] Combes, Pierre-Philippe, Thierry Mayer, and Jacques-François Thisse (2008) *Economic Geography: The Integration of Regions and Nations*, New Jersey: Princeton

University Press.

[7] Doornik, Jurgen A. and Marius Ooms (2006) *Introduction to Ox*, London: Timberlake Consultants Press. (URL: `http://www.doornik.com/`).

[8] Epifani, Paolo and Gino A. Gancia (2005) "Trade, migration and regional unemployment," *Regional Science and Urban Economics* 35(6), pp. 625–644.

[9] Francis, John (2009) "Agglomeration, job flows and unemployment," *Annals of Regional Science* 43(1), pp. 181–198.

[10] Fujita, Masahisa, Paul Krugman, and Anthony J. Venables (1999) *The Spatial Economy: Cities, Regions, and International Trade*, Cambridge, MA: MIT Press.

[11] Hanson, Gordon H. (1998) "North American economic integration and industry location," *Oxford Review of Economic Policy* 14(2), pp. 30–44.

[12] ——— (2005) "Market potential, increasing returns and geographic concentration," *Journal of International Economics* 67(1), pp. 1–24.

[13] Head, Keith and Thierry Mayer (2006) "Regional wage and employment responses to market potential in the EU," *Regional Science and Urban Economics* 36(5), pp. 573–594.

[14] ——— (2011) "Gravity, market potential and economic development," *Journal of Economic Geography* 11(2), pp. 281–294.

[15] Helpman, Elhanan (1998) "The size of regions," in Pines, David, Efraim Sadka, and Itzhak Zilcha eds. *Topics in Public Economics: Theoretical and Applied Analysis*, Cambridge: Cambridge University Press, Chap. 2, pp. 33–54.

[16] Hering, Laura and Sandra Poncet (2010) "Market access impact on individual wages: Evidence from China," *Review of Economics and Statistics* 92(1), pp. 145–159, February.

[17] Krugman, Paul (1991) "Increasing returns and economic geography," *Journal of Political Economy* 99(3), pp. 483–499.

[18] Krugman, Paul and Raul Livas-Elizondo (1996) "Trade policy and the Third World metropolis," *Journal of Development Economics* 49(1), pp. 137–150.

[19] Marshall, Alfred (1890) *Principles of Economics*, London: Macmillan.

[20] Mion, Giordano (2004) "Spatial externalities and empirical analysis: The case of Italy," *Journal of Urban Economics* 56(1), pp. 97–118.

[21] Petrongolo, Barbara and Christopher A. Pissarides (2001) "Looking into the black box: A survey of the matching function," *Journal of Economic Literature* 39(2), pp. 390–431.

[22] Pflüger, Michael and Takatoshi Tabuchi (2010) "The size of regions with land use for production," *Regional Science and Urban Economics* 40(6), pp. 481–489, November.

[23] Pissarides, Christopher A. (2000) *Equilibrium Unemployment Theory*, Cambridge, MA: MIT Press, 2nd edition.

[24] Redding, Stephen and Anthony J. Venables (2004) "Economic geography and international inequality," *Journal of International Economics* 62(1), pp. 53–82.

[25] Rogerson, Richard, Robert Shimer, and Randall Wright (2005) "Search-theoretic models of the labor market: A survey," *Journal of Economic Literature* 43(4), pp. 959–988.

[26] Sato, Yasuhiro (2000) "Search theory and the wage curve," *Economics Letters* 66(1), pp. 93–98.

[27] Thompson, Samuel B. (2011) "Simple formulas for standard errors that cluster by both firm and time," *Journal of Financial Economics* 99(1), pp. 1–10.

[28] Vincenty, Thaddeus (1975) "Direct and inverse solutions of geodesics on the ellipsoid with application of nested equations," *Survey Review* 23(176), pp. 88–93.

[29] vom Berge, Philipp (forthcoming) "Search unemployment and new economic geography," *Annals of Regional Science* Online First.

[30] Zierahn, Ulrich Theodor (forthcoming) "Agglomeration, congestion, and regional unemployment disparities," *Annals of Regional Science* Online First.

[31] Ziesemer, Thomas (2005) "Monopolistic competition and search unemployment," *Metroeconomica* 56(3), pp. 334–359.

Appendix A Derivation of Land Rent

The aggregate income of all the regions is equal to the sum of their disposable labor incomes and incomes from land services:

$$\sum_{j=1}^{R} Y_j = \sum_{j=1}^{R} [(w_i - \tau)(1 - u_i)L_i + (z - \tau)u_i L_i] + (1 - \mu) \sum_{j=1}^{R} Y_j.$$

Thus, the aggregate income from land services in the economy becomes

$$(1 - \mu) \sum_{j=1}^{R} Y_j = \frac{1 - \mu}{\mu} \sum_{j=1}^{R} [(w_i - \tau)(1 - u_i)L_i + (z - \tau)u_i L_i]$$

Dividing this by the regional share of labor force, the aggregate land rent in region i can be given by

$$\frac{L_i}{\sum_{j=1}^{R} L_j}(1 - \mu) \sum_{j=1}^{R} Y_j = \frac{L_i}{\sum_{j=1}^{R} L_j} \frac{1 - \mu}{\mu} \sum_{j=1}^{R} [(w_i - \tau)(1 - u_i)L_i + (z - \tau)u_i L_i] \, .$$

Furthermore, dividing it by the workers living in region i, the land rent that individuals receive can be given by

$$h = \frac{1}{\sum_{j=1}^{R} L_j}(1 - \mu) \sum_{j=1}^{R} Y_j = \frac{1}{\sum_{j=1}^{R} L_j} \frac{1 - \mu}{\mu} \sum_{j=1}^{R} [(w_i - \tau)(1 - u_i)L_i + (z - \tau)u_i L_i] \, .$$

See also Helpman (1998) for more details.

Table 1: Parameter Setting for Numerical Analysis

Parameter	Explanation
$1 \leq T \leq 2$	Transport Cost
$\sigma = 7$	Elasticity of Substitution among Varieties
$\mu = 0.93$	Expenditure Share for Manufactured Goods
$\delta_i = 0.03$	Job Destruction Rate ($i = 1, 2$)
$\gamma = 0.5$	Marginal Labor Input for Recruiter per Vacancy
$\beta = 0.5$	Bargaining Power of Worker
$\bar{S}_i = 1$	Land Endowment ($i = 1, 2$)
$r = 0.01$	Interest Rate
$z = 0.4$	Unemployment Benefit
$A = 0.6$	Matching Efficiency
$\alpha = 0.5$	Matching Elasticity

Notes: The matching function is $m(u_i L_i, v_i L_i) = A(u_i L_i)^{\alpha}(v_i L_i)^{1-\alpha}$.

Table 2: Instrumental Variables

Explanation	IV
Weighted Sum of Regional Incomes	$\Delta \log\big[\sum_{j=1}^{32} Y_{j,t-2}\big[D_{ij}(1+\hat{\varphi}_{\mathrm{NLS}} C_{ij})\big]^{\hat{\xi}_{\mathrm{NLS}}(1-\hat{\sigma}_{\mathrm{NLS}})}\big]$
Weighted Sum of Nominal Wages	$\Delta \log\big[\sum_{j=1}^{32} w_{j,t-2}\big[D_{ij}(1+\hat{\varphi}_{\mathrm{NLS}} C_{ij})\big]^{\hat{\xi}_{\mathrm{NLS}}(1-\hat{\sigma}_{\mathrm{NLS}})}\big]$
Weighted Sum of Labor Forces	$\Delta \log\big[\sum_{j=1}^{32} L_{j,t-2}\big[D_{ij}(1+\hat{\varphi}_{\mathrm{NLS}} C_{ij})\big]^{\hat{\xi}_{\mathrm{NLS}}(1-\hat{\sigma}_{\mathrm{NLS}})}\big]$
Weighted Sum of Unemployment Rates	$\Delta \log\big[\sum_{j=1}^{32} u_{j,t-2}\big[D_{ij}(1+\hat{\varphi}_{\mathrm{NLS}} C_{ij})\big]^{\hat{\xi}_{\mathrm{NLS}}(1-\hat{\sigma}_{\mathrm{NLS}})}\big]$
Weighted Sum of Labor Market Tightness	$\Delta \log\big[\sum_{j=1}^{32} \theta_{j,t-2}\big[D_{ij}(1+\hat{\varphi}_{\mathrm{NLS}} C_{ij})\big]^{\hat{\xi}_{\mathrm{NLS}}(1-\hat{\sigma}_{\mathrm{NLS}})}\big]$
Approximated $\Gamma(\theta_{i,t})$	$\Delta(u_{i,t-2}\theta_{i,t-2})/(1-u_{i,t-2})$

Notes: The endogenous variables in the regression model (34) are the first differences of the RMP $\Delta \log\big[\sum_{j=1}^{32} Y_{j,t} G_{j,t}^{\sigma-1}\big[D_{ij}(1+\varphi C_{ij})\big]^{\xi(1-\sigma)}\big]$ and the approximated $\Gamma(\theta_{i,t})$. All the above IVs are expressed in first difference. The subscript NLS denotes the NLS estimates obtained as a benchmark estimation. The other exogenous variables are also included in the IVs.

Table 3: Descriptive Statistics for NEG Wage Equation

Variable	Mean	Std. Dev.	Min	Max
Model Variable:				
Wage ($w_{i,t}$)	22.849	4.570	12.831	37.762
Unemployment Rate ($u_{i,t}$)	3.974	1.573	1.088	8.421
Labor Market Tightness ($\theta_{i,t}$)	0.607	0.253	0.267	1.501
GSP ($Y_{i,t}$)	211,281,866	229,783,065	33,181,924	1,305,152,782
Labor Force ($L_{i,t}$)	1,340,918	1,155,003	218,166	5,943,401
Other Variable:				
Years of Schooling	8.866	0.887	6.483	11.082
Age	37.255	0.905	34.895	39.581

Notes: The number of observations is 192 ($R = 32$, $T = 6$). The wages and GSP are in 2003 price. The wage is expressed in peso. THe GSP is expressed in thousands of pesos.

Table 4: Descriptive Statistics for Unemployment Analysis

Variable	Mean	Std. Dev.	Min	Max
2000				
Unemployment Rate (%)	1.050	0.365	0.031	4.878
Labor Force Density (person/km^2)	59.887	142.640	0.053	963.833
Years of Schooling	5.401	1.117	2.910	9.020
Male Labor Force Participation Rate (%)	68.670	5.883	37.641	84.692
Female Labor Force Participation Rate (%)	25.737	6.142	7.756	40.138
Share of Population Aged 15–24 (%)	19.168	1.221	13.225	23.186
Share of Population Aged 25–59 (%)	35.224	3.656	23.463	43.216
Share of Population Aged 60 and above (%)	8.226	1.935	2.589	19.013
2010				
Unemployment Rate (%)	4.072	1.427	1.010	14.079
Labor Force Density (person/km^2)	75.831	172.067	0.059	1146.309
Years of Schooling	6.665	1.090	4.387	10.150
Male Labor Force Participation Rate (%)	72.784	3.349	49.424	84.537
Female Labor Force Participation Rate (%)	27.886	7.745	4.212	48.474
Share of Population Aged 15–24 (%)	18.823	1.005	13.865	22.312
Share of Population Aged 25–59 (%)	39.647	3.565	29.212	46.773
Share of Population Aged 60 and above (%)	10.246	2.351	3.278	26.198

Notes: The numbers of observations are 2442 in 2000 and 2456 in 2010. These municipal data are spatially smoothed. See Section 4.2 for more details.

Table 5: Estimation Results for NEG Wage Equation

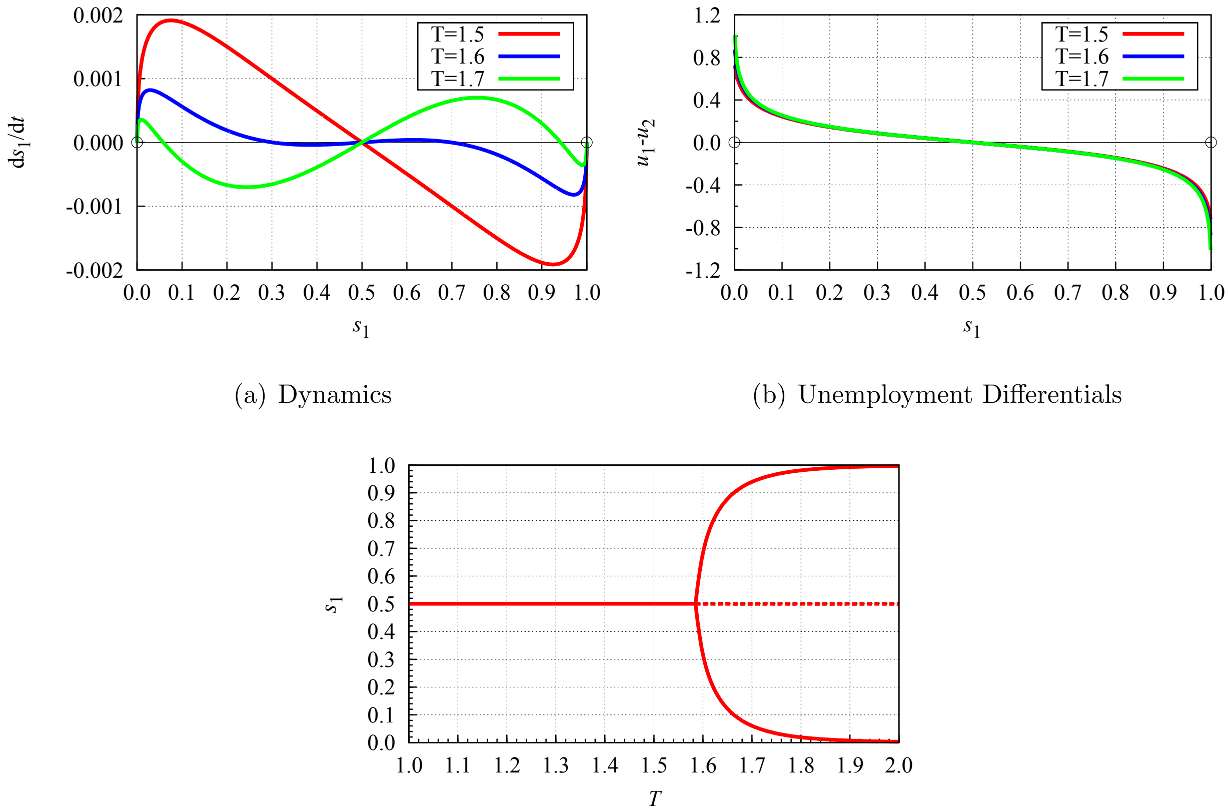
	Dependent Variable: $\Delta \log(w_{i,t})$			
	NLS		NLIV	
Parameter	(1)	(2)	(3)	(4)
σ **(Elasticity of Substitution)**	13.016***	12.311***	14.456	15.157
	(4.523)	(3.555)	(22.956)	(38.880)
ξ **(Elasticity of Distance)**	1.663***	1.667***	1.502	1.039
	(0.595)	(0.496)	(2.519)	(2.142)
γ **(Marginal Labor Input for Recruiting)**	0.428***	0.338*	0.560	0.536
	(0.150)	(0.174)	(0.797)	(1.401)
φ **(Contiguity)**	−0.549***	−0.549***	−0.513***	−0.505***
	(0.011)	(0.009)	(0.101)	(0.137)
η_1 (Years of Schooling)		0.051**		0.039
		(0.025)		(0.034)
η_2 (Age)		0.273		0.294
		(0.296)		(0.610)
η_3 (Age Squared)		−0.004		−0.004
		(0.004)		(0.008)
η_4 (Constant)	0.002	−0.007	0.002	−0.007
	(0.005)	(0.007)	(0.004)	(0.012)
Industry Control	No	Yes	No	Yes
Fixed Effects Control	Yes	Yes	Yes	Yes
Year Dummy Control	Yes	Yes	Yes	Yes
Number of Observations	160	160	160	160
Sum of Squred Residuals	0.069	0.055		
H_0: $\sigma = 1$, H_1: $\sigma > 1$ (p-value)	0.000	0.000	1.000	1.000
Overidentification Test (p-value)			0.897	0.994

Notes: Heteroskedasticity-consistent standard errors clustered by state and year are in the parenthesis. * denotes statistical significance at the 10% level, ** at the 5% level and *** at the 1% level.

Table 6: OLS and IV Estimations for Regional Unemployment Rates and Agglomeration

	Dependent Variable: $\log(u^s_{i,t})$			
	2000		2010	
	OLS	IV	OLS	IV
Explanatory Variable	(1)	(2)	(3)	(4)
Log of Labor Force Density	−0.019*	−0.033***	−0.016	−0.026***
	(0.011)	(0.010)	(0.010)	(0.010)
Years of Schooling	0.042***	0.042***	−0.015	−0.012
	(0.010)	(0.010)	(0.013)	(0.013)
Log of Male Labor Force Participation Rate	−2.521***	−2.508***	−3.023***	−3.043***
	(0.149)	(0.143)	(0.176)	(0.176)
Log of Female Labor Force Participation Rate	−0.102**	−0.068	−0.216***	−0.202***
	(0.043)	(0.041)	(0.052)	(0.051)
Share of Population Aged 15–24	0.055***	0.056***	0.013	0.009
	(0.008)	(0.008)	(0.013)	(0.013)
Share of Population Aged 25–59	0.067***	0.067***	0.037***	0.037***
	(0.004)	(0.004)	(0.006)	(0.006)
Share of Population Aged 60 and above	−0.035***	−0.037***	−0.030***	−0.033***
	(0.005)	(0.005)	(0.004)	(0.005)
Constant	7.570***	7.273***	13.941***	14.276***
	(0.603)	(0.550)	(0.736)	(0.743)
State Dummy	Yes	Yes	Yes	Yes
Number of Observations	2442	2402	2456	2442
R^2	0.706	0.720	0.653	0.652
Dubin-Wu-Hausman Test (p-value)		0.001		0.000

Notes: Heteroskedasticity-consistent standard errors are in the parenthesis. Spatially smoothed municipal data are used. The instrumental variable for log of labor force density is the 10-year lagged log of spatially smoothed labor force density. * denotes statistical significance at the 10% level, ** at the 5% level and *** at the 1% level.



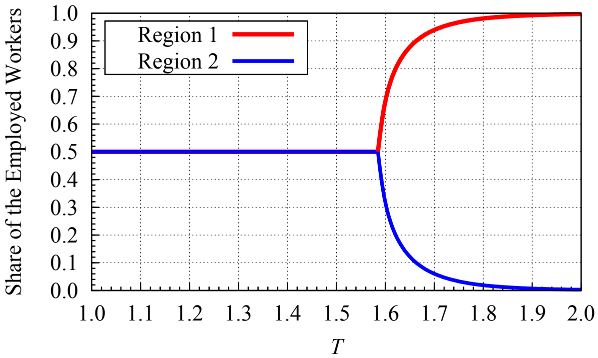
(a) Dynamics

(b) Unemployment Differentials

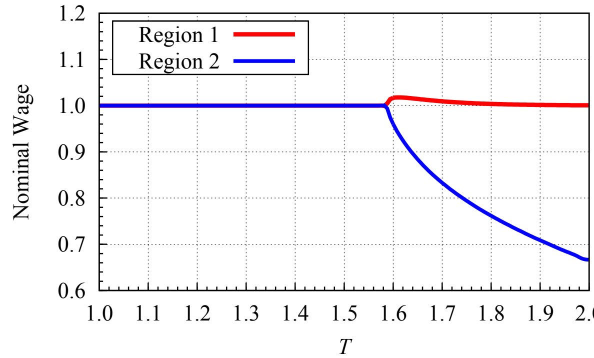
(c) Spatial Equilibrium

Figure 1: Results from Numerical Analysis

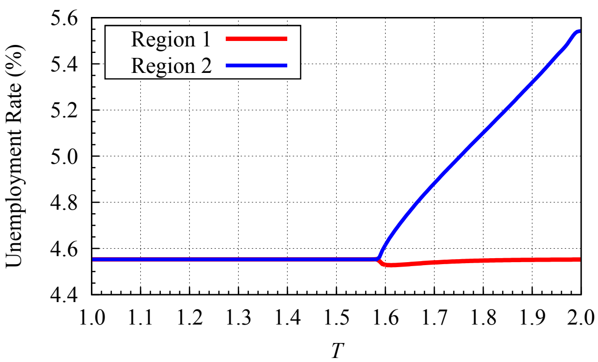
Notes: The solid and dashed lines in Panel (b) denote stable and unstable equilibrium, respectively. The parameters used in this numerical analysis are shown in Table 1.



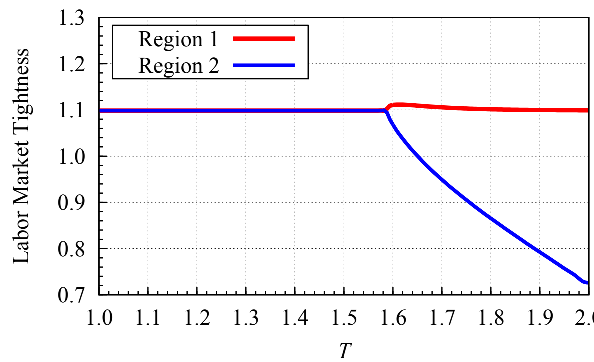
(a) Share of the Employed Workers



(b) Nominal Wage, w_i



(c) Unemployment Rate, u_i



(d) Labor Market Tightness, θ_i

Figure 2: Numerical Simulation in Spatial Equilibrium

Notes: The parameters used in this numerical analysis are in shown Table 1.