Unemployment in local labor markets: empirics and theory

Adrià Morron Salmeron

TESI DOCTORAL UPF / ANY 2017

DIRECTOR DE LA TESI
Jan Eeckhout, Departament d'Economia i Empresa, Universitat Pompeu Fabra

Als meus pares

Acknowledgements

I am deeply thankful to Universitat Pompeu Fabra for the excellent environment in which I have developed my undergraduate studies and my doctoral thesis. I thank all the professors that have shared their enthusiasm for teaching and their passion for getting a better understanding of the world we live in. For their motivation during my undergraduate studies, I particularly thank Mauricio Folchi, Albert Carreras, Stephan Litschig, and Jordi Galí. In my doctoral studies, I am most grateful to Jan Eeckhout for being both a stimulating and a supportive supervisor. I have greatly benefited from being part of a research team under his coordination, and I specially thank Christoph Hedtrich for inspiring and insightful conversations.

Abstract

The existence of transportation costs gives labor markets a local dimension. In particular, the well-documented existence of agglomeration economies creates a positive correlation between a city's size and the productivity of the workers living there. The thesis explores the implications of this stylized fact on local unemployment rates as well as local labor market flows. First, based on the logic of a standard search and matching model of the labor market, I show that one would expect job finding rates to be increasing in city size, job separation rates to be decreasing in city size and, thus, unemployment rates to be decreasing in city size. Second, I show that, in fact, both job finding and separation rates are decreasing in city size, leading to a zero-correlation between unemployment rates and city size. Finally, I develop three theoretical models that attempt to rationalize these stylized facts within the framework of a local labor market governed by a constant-returns-to-scale matching function.

Resum

La presència de costos de transport fa que els mercats laborals tinguin una dimensió local. Concretament, l'existència d'economies d'aglomeració fa que hi hagi una correlació positiva entre la mida d'una ciutat i la productivitat dels treballadors que hi viuen. La tesi explora les implicacions d'aquest fet estilitzat sobre les taxes d'atur urbanes i sobre els fluxes del mercat laboral. En primer lloc, a partir de la lògica d'un model estàndard d'aparellament al mercat laboral, es demostra que caldria esperar que la probabilitat de trobar una feina augmenti amb la mida de la ciutat, que la probabilitat de perdre una feina disminueixi amb la mida de la ciutat i que, per tant, la taxa d'atur sigui menor en ciutats més grans. En segon lloc, es mostra que, segons les dades, tant la probabilitat de trobar una feina com la de perdre-la disminueixen amb la mida de la ciutat, de tal manera que les taxes d'atur no estan correlacionades amb la mida de la ciutat. En darrer lloc, construeixo tres models que racionalitzen aquests fets estilitzats dins del marc d'un mercat laboral local governat per una funció d'aparellament amb retorns constants a escala.

Preface

The existence of agglomeration economies is a well-established fact within the urban economics literature. When thinking about labor markets, this implies that there must exist differences in labor productivity across cities of different sizes. In fact, as shown by Glaeser & Maré (2001), Glaeser & Gottlieb (2009), and Moretti (2011), among others, labor productivity is increasing in the size of a city, which goes hand in hand with nominal wages being increasing in city size. For instance, as I show in chapter 1 with US Census data for 2000, the median hourly wage of a worker in a big city such as New York, NY, (15.3$), Chicago, IL, (14.4$), Washington DC (15.9$), Philadelphia, PA, (14.3$) or San Francisco, CA, (15.9$) was around 50% higher than in a small city such as Gadsden, AL, (10$), Albany, GA, (10.7$) or Glens Falls, NY, (10.7$). Indeed, the reason why big cities are big is simply that higher labor productivity makes them appealing to workers and firms. As a result, the urban economics literature treats city size as a useful proxy for the productivity of a city's workers. However, on the other hand, provided that workers can move from one local labor market to the other one, labor mobility should arbitrage away differences in a worker's welfare. In fact, Moretti (2011) shows that differences in average real hourly wages across metropolitan areas are much smaller than differences in average nominal wages. That is, even if higher productivity makes a city more appealing, a higher cost of living arbitrages away the differences.

This thesis studies the implications of large productivity differences on local labor markets: that is, labor markets at the city level. Empirically, we observe that unemployment rates vary enormously across cities, and this variation is so large that it rivals the one over the business cycle. For instance, when looking at the distribution of unemployment rates across cities in the United States, the ratio between the 90th and the 10th percentile of the distribution is roughly equal to 2, a magnitude similar to the ratio between the national unemployment rate at the trough of the Great Recession (9.6% in 2010) and the one at the peak of the previous expansion (4.6% in 2007). Given that the median nominal hourly wage in the biggest cities in the US can be 50% higher than in smaller cities, one would expect that the dispersion of unemployment rates is highly correlated with city size: such big differences in nominal wages must reflect differences in labor productivity and, hence, must have implications on job finding rates, job separation rates and, ultimately, on unemployment rates. The chapters of my thesis analyze in detail these three elements of local labor markets.

In the first chapter of the thesis, I provide a theoretical framework that guides our interpretation of the data and I present several new stylized facts on local labor markets. In particular, I construct a simple spatial equilibrium model where workers can freely move across local labor markets in order to maximize their welfare.

Each local labor market is endowed with an exogenous level of productivity and it is described by a textbook search and matching model where unemployment is the result of a matching friction, which can be considered as the simplest and most standard model of local labor markets. This simple model correctly produces a positive correlation between city size and labor productivity. Furthermore, it predicts that job finding rates should be increasing in a city's size. As a result, the model also predicts that unemployment rates should be decreasing in city size. Intuitively, everything else equal, workers move towards cities that are endowed with a higher productivity (because workers will be happier when they get higher wages). This is what make a more productive city also a bigger city. Firms are also attracted to more productive cities because, everything else equal, when they match with a worker the match will produce a higher output. Therefore, the model predicts that firms post more vacancies in larger cities, leading to a higher job finding rate and, hence, a lower unemployment rate (again, everything else equal). Finally, because both higher wages and higher job finding rates make some cities more appealing, the cost of living in these cities goes up to make workers equally well-off across locations. Thus, the model also predicts that the cost of living is increasing in the size of a city.

In order to test the predictions of the model, I construct summary statistics for local labor markets in the United States between 1996 and 2015. In particular, within the context of the search and matching literature, a labor market is described by the probability that a worker finds a job (the job finding rate) and the probability that a worker loses a job (the job separation rate), which together determine the unemployment rate. Thus, using micro-data from the Current Population Survey, which is the primary source of labor force statistics for the population of the United States, I compute job finding rates, job separation rates, and unemployment rates for the main 250 cities[1] in the United States. Contrary to the predictions of the simple model, I show that unemployment rates are uncorrelated with city size (which, recall, is a proxy for labor productivity), and that this is a result of both job finding rates and job separation rates being decreasing in city size. The robustness checks show that these findings are not due to differences in demographics nor in the sectorial composition of the labor market.

Given that the data yields counterintuitive results, in the second chapter of the thesis I analyze three theoretical explanations for the stylized facts presented in chapter 1. First, I extend a richer version of the simple model presented in chapter 1 by introducing a friction to the vacancy posting process. Intuitively, in the simple model of chapter 1 there are two forces at play that shape the predictions

[1] In particular, the theoretical concept of a city is mapped in the data to a metropolitan statistical area, which is defined by the Office of Management and Budget of the United States to capture a geographic area with a high degree of economic and social interconnectedness.

of the model. On the one hand, productivity differences trigger migratory movements towards the most productive cities, leading to a smaller pool of job seekers in less productive cities and to a larger pool in more productive cities. Everything else equal, this force tends to depress job finding rates in more productive cities (due to higher competition between job seekers). On the other hand, productivity differences also trigger differences in the vacancy-posting process, whereby firms find it optimal to post more vacancies in higher-productivity cities. Everything else equal, this force tends to depress job finding rates in less productive cities. Therefore, if we observe that job finding rates are decreasing in city size, this line of reasoning suggests the existence of a friction that impends the vacancy-posting process of firms: at the limit, if the amount of vacancies posted was independent of labor productivity, only the force depressing job finding rates in more productive cities would be at play. The first model presented in chapter 2 embeds this mechanism with a spatial equilibrium model with frictional unemployment, endogenous job separations and an endogenous housing market. The model is also estimated using data for a given year (in particular, for 2013, although the empirical results presented in chapter 1 are robust across time).

Second, I explore an alternative explanation based on the concept of specialization (defined as the scarcity of a worker's type). Intuitively, higher specialization is a potential source of a higher productivity, of a higher degree of match-specific investment assets between a worker and a firm, and of a lower matching efficiency. Namely, just as a lower matching efficiency tends to depress job finding rates, a higher match-specific investment between workers and firms tends to depress job separation rates. That is, a higher degree of specialization might work in the right direction for all three variables: productivity, job separation rates, and job finding rates. Hence, I build a model in which workers can choose their preferred degree of specialization and where they take into account its impact on productivity, job finding rates and job separation rates. Based on Adam Smith's old insight that the size of the market allows for greater specialization, within the context of a spatial equilibrium model I analyze the conditions under which the degree of specialization is increasing in city size and, at the same, under which specialization leads to job finding rates and job separation rates being decreasing in city size.

Third, a simpler explanation of the counterintuitive empirical results presented in chapter 1 is that they are a statistical artifact: namely, labor turnover is higher in smaller markets because of the workings of the Law of Large Numbers. Intuitively, turnover is much more likely to be higher in a city with a single firm, where a firm-idiosyncratic shock has large city-wide consequences, than in a city with infinitely many firms, where each firm's idiosyncratic shock has a negligible impact. To explore this line of reasoning, I reproduce the city-size distribution of the United States and shock each employed/unemployed individual with an exogenous probability of switching to unemployment/employment. As one might guess, the resulting dispersion of labor market flows and unemployment rates is higher in smaller cities, precisely because of the workings of the Law of Large Numbers. However, because the Law of Large Numbers produces a symmetric dispersion (there are as many small cities with higher flows as with smaller flows), the average labor market turnover in a small city is not statistically different from the one in a big city. Thus, the Law of Large Numbers does not appear to be a satisfactory explanation of the empirical results presented in chapter 1: economics, not just statistics, seem to be at work.

Finally, I conclude the thesis in chapter 3 with a review of the literature in which the thesis is framed. Three strands of literature are particularly important. First, the urban economics literature has widely documented the presence of agglomeration economies that lead to labor being more productive in bigger cities. In this thesis I take agglomeration economies as an exogenous input, but the urban economics literature discusses several mechanisms that lead to agglomeration economies. Three theories stand out: reduced costs of moving goods across space, labor market pooling, and the diffusion of ideas. Second, the spatial equilibrium literature has shown that labor mobility arbitrages away differences in nominal wages. In particular, in a spatial equilibrium with free mobility, workers must be equally well-off in all locations. Because there exist differences in productivity across cities, in equilibrium the corresponding differences in nominal wages are counterbalanced by differences in the cost of living. Last, the puzzle presented by the data in chapter 1 would be easily resolved if the matching function governing the labor market exhibited decreasing returns to scale: in that case, job finding rates might be decreasing in city size just because of the technology of the market (as opposed to the optimal behavior of firms and workers). However, as I discuss in chapter 3, there is a wide consensus on the finding that matching functions exhibit constant returns to scale. Thus, a constant-returns-to-scale matching function is taken as a constraint in the empirical and theoretical analyzes of chapters 1 and 2.

Contents

List of Figures

List of Tables

Chapter 1

STYLIZED FACTS ON UNEMPLOYMENT IN LOCAL LABOR MARKETS

1.1 Introduction

The local dimension of labor markets matters. Intuitively, transportation costs make the location of workers and firms relevant and, thus, give labor markets a local dimension. Empirically, unemployment rates vary enormously across cities, and this variation is so large that it rivals the one over the business cycle. For example, Figure 1.1 reports metropolitan unemployment rates computed from the American Community Survey. In 2000, the 10th percentile corresponds to Kansas City, MO-KS, with an unemployment rate of 4.08% while the 90th percentile almost doubles this number with an unemployment rate of 7.44% for Spokane, WA. As for 2010, the 10th percentile corresponds to Omaha, NE/IA, with a rate of 7.25% and the 90th percentile is again twice as large with a rate of 14.18% for Gadsden, AL. In turn, in the Great Recession, the national unemployment rate also roughly doubled from 4.6% in 2007 to 9.6% in 2010. These regional differences remain large even after controlling for age, gender, education and race (see Kline & Moretti (2013)). They are also significant after controlling for the different industry composition of cities (see Gan & Zhang (2006)). Furthermore, as Figure 1.2 shows, these differences are not transitory.

As Glaeser & Gottlieb (2009) document, city size is positively correlated with a city's productivity. This comes from the observation that nominal wages –which are a proxy of a worker's productivity– are strongly increasing in city size (see Figure 1.3, which plots median hourly wages computed at the city level from the 2000 US Census against city size).

The link between higher nominal wages, higher labor market productivity and larger city size is well-established in the urban economics literature. Glaeser & Gottlieb (2009) provide an excellent review of the topic, and show that the presence of agglomeration economies leads to higher labor productivity in bigger cities where, as a result, workers end up earning higher nominal wages. Therefore, building on the urban economics literature, in this thesis I take agglomeration economies as given and treat city size as a proxy for a city's productivity.

The first question I address is whether differences in labor productivity across cities (proxied by city size) are translated into systematic differences in local labor markets' unemployment rates. To do so, we need to observe that the unemployment rate of a city (u_c) is the result of two countervailing forces: flows from unemployment to employment and flows from unemployment to employment.[1] That is, if a city has L_c workers, E_c of which are employed and $L_c - E_c$ of which are unemployed, then the unemployment rate evolves according to

$$\Delta u_c = js_c \frac{E_c}{L_c} + jf_c \frac{L_c - E_c}{L_c} = js_c(1 - u_c) + jf_c u_c$$

where js_c and jf_c are the rates at which employed and unemployed workers lose and find jobs, respectively. Evaluating this expression at a steady state with a constant unemployment rate gives us a handy decomposition of the unemployment rate which will be used throughout the thesis:

$$u_c = \frac{js_c}{js_c + jf_c}$$

Thus, beyond looking at local unemployment rates, we need to pay attention to the behavior of job finding and separation rates across cities of different sizes (that is, ultimately, of different labor productivities). This chapter of the thesis is aimed at these questions. However, before looking at the data, the next section presents a simple theoretical framework that gives us a prior with which I will contrast the empirical sections of this chapter.

1.2 A simple spatial model with frictional unemployment

Consider an economy with C local labor markets, each of which is endowed with exogenous city-wide productivity A_c. Each labor market is described by a random search framework with exogenous separations. Unemployed workers can freely

[1]Obviously, flows between not-in-labor-force and unemployment are also relevant for the determination of the unemployment rate. For simplicity, I abstract from these transitions.

move to the city where they enjoy the highest utility and firms can freely post vacancies in any local labor market.

1.2.1 The matching process

Each local labor market is characterized by two homogeneous sets of agents: firms and workers, both of which randomly search for a match. Because of frictions in the matching process, given v vacancies posted by firms and u unemployed workers available for hiring, m matches are created according to:

$$m = m(u, v); \quad m_u, m_v > 0$$

where m exhibits constant returns to scale in u and v.[2] Because of this property, we can define the tightness of the market as

$$\theta = \frac{v}{u}$$

and then define the probability of finding a match as

$$\frac{m}{v} = m\left(\frac{1}{\theta}, 1\right) \equiv q(\theta)$$
$$\frac{m}{u} = \theta q(\theta)$$

for a firm and a worker, respectively. Observe that the probability that an unemployed worker is matched to a vacancy, m/u, is increasing in the tightness θ of the market.

1.2.2 The firm's problem

Firms pay a flow cost κ for posting a vacancy. With probability $q(\theta)$, they meet and match with a worker. An occupied job produces flow output A, which is exogenous and common to all firms within a given city, and pays a wage w. Finally, jobs are destroyed with exogenous probability δ. Letting V and J denote the present-discounted value of expected profit from an empty vacancy and an occupied job, respectively, the behavior of firms is described by:

$$rV_c = -\kappa_c + q(\theta_c)\left(J_c - V_c\right), \tag{1.1}$$
$$rJ_c = A_c - w_c + \delta_c\left(V_c - J_c\right) \tag{1.2}$$

[2] A constant-returns-to-scale matching function is the benchmark in the literature. See Petrongolo & Pissarides (2001).

where c is the index of a given local labor market and r is the continuous-time discount rate. In each local labor market there is free entry of firms, which drives the value of a vacancy to zero. That is,

$$V_c = 0 \tag{1.3}$$

1.2.3 The worker's problem

Within a given local market, workers pay a housing cost p^h_c. For simplicity, I do not microfound the housing market here.[3] Rather, based on the strong empirical link between city size and the cost of housing (see Figure 2.2),[4] I assume housing prices are an increasing function of a city's size:

$$p^h_c = f(L_c), \quad f' > 0 \tag{1.4}$$

Unemployed workers earn unemployment benefits b, search for jobs in the local labor market where they are located, and they find a match with probability $\theta_c q(\theta_c)$. Employed workers earn a wage w and lose their job with probability δ. When a worker loses her job, she can relocate to the local labor market where her utility (as an unemployed) is highest. Letting U and W denote the present-discounted value of being unemployed and employed, respectively, the behavior of workers is described by

$$rU_c = b_c - p^h_c + \theta_c q(\theta_c)\,(W_c - U_c) \tag{1.5}$$

$$rW_c = w_c - p^h_c + \delta\left(\max_{c'} U_{c'} - W_c\right) \tag{1.6}$$

Because unemployed workers are free to relocate, in equilibrium the value of being unemployed must be the same in every local labor market:

$$\max_{c'} U_{c'} - U_c = 0 \Rightarrow U_c = U \;\; \forall c \in C \tag{1.7}$$

1.2.4 Wage setting

Firms and workers split the surplus of the match in constant shares (Nash bargaining). Thus, in each local labor market the wage w_c ensures that workers get a share β of the surplus:

$$W_c - U_c = \beta\,(W_c - U_c + J_c - V_c) \tag{1.8}$$

[3]See chapter 2 for microfoundations for the demand and supply of local housing.

[4]See chapter 2 for details on how housing costs are computed.

1.2.5 Equilibrium

Note that, by imposing free mobility (equation (1.7)) into equation (1.5), the model turns out to be a textbook search and matching model of the labor market, and we can solve for θ_c in each city independently. In particular, plugging (1.6) and (1.2) into (1.8) and then using (1.5), it is easy to obtain the following expression for wages:

$$w_c = (1-\beta)b_c + \beta\left(A_c + \kappa_c\theta_c\right) \tag{1.9}$$

Next, imposing (1.3) into (1.1) and (1.2), combining the two expressions and using (1.9) to substitute for the wage yields the equilibrium for θ_c:

$$\frac{(1-\beta)(A_c-b_c)-\beta\kappa_c\theta_c}{r+\delta_c} = \frac{\kappa_c}{q(\theta_c)} \tag{1.10}$$

Last, given θ_c we can solve for U_c by combining (1.5) and (1.6) and using (1.3) and (1.2) together with (1.8). Thus, we get

$$U_c = b_c - p_c^h + \frac{\theta_c q(\theta_c)\beta(A_c+\kappa_c\theta_c-b_c)}{r+\delta_c+\theta_c q(\theta_c)} = U \tag{1.11}$$

which, from the fact that $p_c^h = f(L_c)$ and together with

$$\sum_{c\in C} L_c = L, \tag{1.12}$$

where L is the exogenous country-wide labor force, pins down the size of every local labor market.

With this simple model, we get the following predictions:

1. From equation (1.10), market tightness, and thus the job finding rate, is increasing in a local labor market's productivity: intuitively, the higher the productivity, the more profitable vacancies are in expected terms.

2. Therefore, unemployment rates are decreasing in a local labor market's productivity:[5]

$$u_c = \frac{\delta_c}{\delta_c + \theta_c q(\theta_c)}$$

[5] This simple model assumes that the job separation rate, δ_c, is independent of a city's productivity. However, extending the model to make δ_c endogenous shows that, everything else equal, higher A_c leads to lower δ_c, which reinforces the negative correlation between A_c and u_c: the higher A_c is, the less likely it is that an idiosyncratic shock to an occupied job is strong enough to break the match. Such a model is presented in the theoretical part of thesis (chapter 2).

3. As mentioned in the previous section, wages are increasing in productivity (equation (1.9)).

4. City size is increasing in productivity: equation (1.11) implies that, everything else equal, the value of being unemployed is higher in more productive cities (because of higher wages and higher job finding rates); thus, housing prices (and, therefore, city size) must be increasing in a local labor market's productivity in order to ensure that (1.7) holds and workers in less productive cities are equally happy.

1.3 Data

Based on the theoretical framework of the last section, we are interested in estimating the relationship between city size and the following local labor market statistics: unemployment rates, job finding rates and job separation rates (that is, movements between unemployment and employment).[6] I take metropolitan statistical areas (MSAs) as the unit of observation, which the Office of Management and Budget of the US delineates in order to capture a geographic area with a high degree of economic and social interconnectedness.[7] In more detail, a metropolitan area contains a core urban area of 50,000 or more population. It consists of one or more counties and includes the counties containing the core urban area, as well as any adjacent counties that have a high degree of social and economic integration (as measured by commuting to work) with the urban core.

1.3.1 Data Sources

The results reported below are based on data from the Current Population Survey (CPS). The CPS, sponsored jointly by the U.S. Census Bureau and the U.S. Bureau of Labor Statistics (BLS), is the primary source of labor force statistics for the population of the United States, and it interviews a nationally representative sample of 60,000 households at a monthly frequency. Also, the public-use CPS data contains information on the MSA in which a household is located. Although the exact number varies over time, as the definition of each MSA adjusts to capture changing economic and social linkages, on average I work with monthly data on 250 MSAs from 1996 to 2015.

Another desirable property of CPS is that its methodological design allows the researcher to match individuals across surveys and construct a panel dataset.

[6] I also look at job-to-job transition as well as movements between not-in-labor-force and employment and unemployment. These data are presented in later sections of the chapter.

[7] In particular, we look at Consolidated Basic Statistical Areas (CBSAs).

In particular, the sample is divided into eight representative subsamples called rotation groups, with housing units in each rotation group being interviewed for four consecutive months, followed by an 8-month break, and then by another four months of interviews. In any given monthly sample, approximately one-eight of the sample units will be interviewed for the first time, one-eight for the second time, . . . , and one-eight for the eighth time. Also, in any given month one-eight of the sample will be leaving the sample permanently, and one-eight will be leaving for the next eight months before being reinterviewed. In sum, there is a 75% of the sample that is common from month to month. This 75% is matched across monthly surveys based on unique household and individual identifiers (plus gender and age) to construct a panel dataset. Exploiting the panel dimension of the dataset is crucial to compute job finding and job separation rates.

A potential concern regarding the use of CPS is that the sample size in the smallest MSAs might not be large enough to get a reliable estimate of unemployment rates (given the relatively low incidence of unemployment) and low-frequency labor market transitions. Thus, regarding unemployment rates, I also use data from the American Community Survey (ACS), which surveys annually a nationally representative sample of 3.5 million households. However, the ACS does not have a panel dimension and, hence, cannot be used to construct labor market transition rates. Nevertheless, I address small sample size concerns on job finding and job separation rates in the robustness section.

1.3.2 Alternative Datasets

CPS data allows us to construct gross labor market market flows from a worker's perspective: that is, the frequency with which an unemployed worker finds a job, an employed worker loses her job, etc. . . Alternatively, there are other data sets, such as the Business Dynamics Statistics (BDS) or the Longitudinal Employer Household Dynamics (LEHD), that also look at flows from the firm's perspective. The main reason for not using BDS data is that it offers information on net flows rather than gross flows: that is, it reports net employment growth in expanding and contracting establishments. However, since I am interested in gross transition probabilities, I need information on gross flows. LEHD does provide information to compute gross flows. However, LEHD has a major drawback, as its geographical information is not disaggregated enough in the public-use version, so I am not able to have information on MSAs.

1.3.3 Definning flows

Finally, before moving to the next section, a brief comment on mapping labor market transition rates δ_c and $\theta_c q(\theta_c)$ from the theoretical framework to the data. In the model, these frequencies stand for the probability that an unemployed worker finds a job and an employed worker loses hers between any two periods. Thus, using CPS data I compute these flows as:

$$\theta_c q(\theta_c) \approx ue_t = \frac{\text{Unemployed at } t\text{, Employed at } t+1}{\text{Unemployed at } t}$$
$$\delta_c \approx eu_t = \frac{\text{Employed at } t\text{, Unemployed at } t+1}{\text{Employed at } t}$$

1.4 Stylized facts on local labor markets

Eyeballing the data suggests a surprising no-relationship between city size and unemployment rates (Figure 1.5).[8]

However, if we look at job finding rates and job separation rates we see a clear negative correlation with city size (Figures 1.6 and 1.7).[9]

In fact, these two negative correlations explain why unemployment rates do not vary with city size: the ratio $\frac{eu_c}{ue_c}$ is roughly constant (Figure 1.8).[10]

Furthermore, these correlations are stable over time. To see so, Figures 1.9 to 1.11 show the time series β from

$$u_{ct} = \alpha + \beta \cdot \ln(Laborforce_{ct}) + \epsilon^{u}_{ct}$$
$$flow_{ct} = \alpha + \beta \cdot \ln(Laborforce_{ct}) + \epsilon^{flow}_{ct}$$

where $flow = \{ue, eu\}$. These regressions are estimated at each point in time using annual data from 1996 to 2015 for the cross section of MSAs.

These differences are also economically significant. To put the magnitudes in perspective, let us take 2013 as our reference point, and roughly set $\hat{\beta}^{ue} = -0.035$ and $\hat{\beta}^{eu} = -0.005$. The next table shows descriptive statistics for local labor market flows in 2013:

Table 1.1: Summary statistics of local labor market flows - 2013

Flow	mean	std. dev.	min	max
UE	23.28%	6.83%	12%	47.55%
EU	2.04%	0.84%	0.88%	4.33%

[8]The sample of cities is restricted so that unemployment rates are computed with at least 5 observations. But this is not an issue, as reproducing this exercise with ACS data, where sample size is not a concern, yields the same no correlation. See section 1.5.1 below.

[9]For EU rates, the sample of cities is restricted to cities with at least 40 employed observations. For UE rates, the sample of cities is restricted to cities with at least 5 unemployed observations.

[10]Below, I also document that job-to-job transitions are significantly decreasing in city size, and so are employment-to-not-in-labor-force flows. Instead, not-in-labor-force-to-employment flows are not correlated with city size.

Starting from a city whose flows correspond to the sample average, if we double the size of this city we see a significant drop in flows:

$$\frac{ue_1 - ue_0}{ue_0} = -\frac{0.035\ln(2)}{0.2328} = -10.42\%$$
$$\frac{eu_1 - eu_0}{eu_0} = -\frac{0.005\ln(2)}{0.0204} = -16.99\%$$

Note that in this numerical illustration unemployment rates would decrease in city size as job separation rates drop faster than job finding rates. The reason why this is compatible with unemployment rates being flat in city size is that job finding and job separation rates decline in a nonlinear way. However, on average, the drop in job finding and job separation rates is roughly consistent with flat unemployment rates. To see so I estimate

$$\frac{eu_{ct}}{ue_{ct}} = \alpha + \beta \cdot \ln(Laborforce_{ct}) + \epsilon_{ct}$$

and I plot the time series of $\hat{\beta}$ in Figure 1.12.

Summing up, regarding local labor markets, I have highlighted the following stylized findings:

1. Labor productivity is *increasing* in city size.

2. Unemployment rates do *not* change over city size.

3. Job finding and separation rates are *decreasing* in city size.

Given (1) and a constant returns to scale matching function (which are the common premises in the literature), I have shown that the predictions of the simple standard model are at odds with (2) and (3). Thus, a successful model needs to:

- Break $corr\left(\frac{m(v,u)}{u}, A\right) > 0$; and/or,

- Break $corr\left(\frac{m(v,u)}{u}, \delta\right) < 0$.

1.5 Robustness

In this section I show that the stylized facts presented in the previous section do not seem to be due to city and individual observable characteristics. I also show that the results do not seem to be driven by differences in sample size.

1.5.1 The usual suspects

First, I address two concerns at once: 1) the no-correlation between city size and unemployment does not hold when conditioning on education levels; and 2) small sample size implies that not enough unemployed individuals are surveyed in small cities. Recall that an alternative data source comes from the American Community Survey, which surveys annually a nationally representative sample of 3.5 million households, so that small sample size is not a problem even when conditioning on education levels. Thus, using data from the ACS, I rerun the above regressions on unemployment rates four times: for unemployment rates for the whole population, for unemployment rates for those with no highschool education, for unemployment rates for those with highschool education and for unemployment rates for those with college education (or higher). Figures 1.13 to 1.16 corroborate that, in general, unemployment rates seem to be uncorrelated with city size.

Next, I show that the finding that job separation and job finding rates are decreasing in city size is not due to differences in the age, education or industry composition of cities. To see so, take an individual i at time t and let

$$ue_{it} = \begin{cases} 1 & \text{if } i \text{ is unemployed at } t \text{ and employed at } t+1 \\ 0 & \text{if } i \text{ is unemployed at } t \text{ and } t+1 \end{cases}$$

$$eu_{it} = \begin{cases} 1 & \text{if } i \text{ is employed at } t \text{ and unemployed at } t+1 \\ 0 & \text{if } i \text{ is employed at } t \text{ and } t+1 \end{cases}$$

At each point in time[11] and using the US national sample from the CPS, I estimate the expected probability of transitioning from one employment state to the other one as a function of individual observables X_{it}:

$$E[ue_{it}] = \Phi(X_{it})$$
$$E[eu_{it}] = \Phi(X_{it})$$

where $\Phi(\cdot)$ is the standard normal probability density function and X_{it} is a vector that includes the age of the individual as well as education and industry category dummies.[12] Then I average the predicted transition rates at the city level. This gives us the job finding and separation rates of a city predicted by the observable characteristics of its residents: if the results of the previous sections are due to these observable characteristics, then $\hat{E}[\cdot]$ will be significantly correlated with city size. Finally, I compute the difference between the actual transition rates and the

[11] That is, at a monthly frequency.

[12] The industry category refers to date t if the individual is employed at t, and to date $t+1$ otherwise.

predicted ones: if this residual is not significantly correlated with city size, then observables will be the most likely factor driving the results presented above.

Therefore, in order to check whether the differences in flows between small and large cities are due to observables, I regress the city's predicted probability and the difference with the observed one against city size. That is,

$$E[flow_{it}] = \alpha + \beta \cdot \ln(Laborforce_{ct}) + \epsilon_{ct}$$
$$E[flow_{it}] - flow_{it} = \alpha + \beta \cdot \ln(Laborforce_{ct}) + \epsilon_{ct}$$

where $flow = \{ue, eu\}$. Figures 1.17 to 1.20 plot the time series of the estimated coefficient on city size. They show that observables do not predict that flows should be different across cities of different sizes, and therefore that the observed correlation between transitions and city size is significant after controlling for observables. In particular, $\hat{E}[\cdot]$ is uncorrelated with city size, which means that based on observables flows should not be different across cities of different sizes. However, the fact that $E[flow_{it}] - flow_{it}$ is significantly increasing in city size implies that flows (net of observables) are significantly decreasing in city size.

1.5.2 Addressing sample size

Another potential concern is that the sample in small cities is not large enough to adequately measure low-probability events such as unemployment-to-employment transitions (on average, unemployed individuals transition to employment at relatively high rates, but the issue is that unemployment is a low-probability event). I have addressed this concern regarding unemployment rates by using ACS data. However, ACS data does not have panel dimension and, thus, it cannot be used to check for sample size problems in labor market *flows*. In order to do so, I construct fictitious cities that contain enough observations and rerun the regressions. In particular, at every point in time, I sort individuals according to the size of their city of residence. Then they are grouped in 100 bins according to the city size distribution. Each bin becomes a new fictitious city whose defining characteristic is that all its components live in a city of a similar size. In this way, I make sure that there are enough sample observations across (fictitious) cities of all sizes. Using such fictitious cities, I estimate the following regression for each year from 1996 to 2015:

$$flow_{it} = \alpha + \beta \cdot \ln(Laborforce_{it}) + \epsilon_{it}$$

Figures 1.21 to 1.22 report the time series of $\hat{\beta}$ and its confidence interval. As we can see, the coefficients remain significantly negative and close to the levels observed when using actual cities.

Similarly, with this approach I have enough sample observations in each bin to compute labor market flow for separate educational groups. Thus, I also estimate

β separately for individuals with no highschool eduaction, with at most highschool education, and with at least college educations. As Figures 1.23 to 1.28 show, flows are still decreasing in city size.[13]

1.6 Other stylized facts

1.6.1 Focusing on occupations and education

Zooming into the occupational composition of cities, there are two broad occupational categories whose employment shares most significantly change over city size: finance, insurance and real estate (Figure 1.29), and business and repair services (Figure 1.30). However, the results shown above are robust to dropping individuals belonging to these occupations.

1.6.2 Other flows

Using CPS data, I can also look at other labor market flows, such as job creation and separation due to job-to-job flows and due to transitions between employment and not-in-labor-force. Define

$$ee_t = \frac{\text{Employed at } t \text{ in } j \text{ firm, Employed at } t+1 \text{ in } k \text{ firm}}{\text{Employed at } t}$$

$$nilfe_t = \frac{\text{Not in labor force at } t\text{, Employed at } t+1}{\text{Not in labor force at } t}$$

$$enilf_t = \frac{\text{Employed at } t\text{, Not in labor force at } t+1}{\text{Employed at } t}$$

Just as in a previous section, I estimate

$$flow_{ct} = \alpha + \beta \cdot \ln(Laborforce_{ct}) + \epsilon_{ct}^{flow}$$

where $flow = \{ee, nilfe, enilf\}$ using annual data from 1996 to 2015 for the cross section of MSAs. Figures 1.31 to 1.33 report $\hat{\beta}$. We can see that job-to-job transition rates are consistently decreasing in city size, and so are employment to not-in-labor-force transition rates. However, job creation arising from not-in-labor-force to employment transitions is not significantly correlated with city size.

[13]Here annual flows have been computed as the sum over monthly flows, this is why -compared to the figures above- coefficients are roughy multiplied by 10

1.6.3 Unemployment Duration

The finding that job finding rates and job separation rates are decreasing in city size is consistent with workers in smaller cities having shorter unemployment spells: as turnover is higher in smaller cities, both entrance into and exit from unemployment are higher, so we should expect to see a larger fraction of short unemployment spells in smaller cities. This seems to be present in the data, as shown in Figure 1.34, which depicts the fraction of individuals at different unemployment duration categories in small (bottom 9 deciles) and big cities (cities in top decile).

1.6.4 Productivity shocks

When looking for a theoretical explanation of the decreasing flows, one possibility is that the answer lies in the distribution of idiosyncratic productivities within cities: how often employed workers are shocked with a productivity realization bad enough to break the match between the firm and the worker (which depends on both the arrival rate of shocks and the size of the shock). Based on the link between nominal wages and labor productivity, one way of gathering information on this distribution is by computing the average growth rate over a period of time of a city's average wage as well as its standard deviation over time. The average growth will be indicative of productivity growth while the standard deviation will be indicative of how volatile productivity is (that is, indicative of productivity shocks). Figures 1.35 to 1.38 report these statistics for full-time male workers. As the simple correlations suggest, average individual productivity growth is similar across cities of different sizes. However, its standard deviation is decreasing in city size. Therefore, these correlations suggest that the distribution of productivity growth has fatter tails in smaller cities.

1.6.5 Data on Vacancies and Market Tightness

HelpWanted Online, from the Conference Board, provides data on vacancies for the 50 largest MSAs in the US. This is relevant as the decreasing job finding rate suggests that market tightness might be decreasing in city size. However, when computing market tightness from HelpWanted Online data I do not find a statistically significant relationship with city size. Figure 1.39 illustrates this with data for September 2013.

Furthermore, when computing labor market flows for the subsample of the 50 largest MSAs, I do not find a statistically significant relationship with city size (Figure 1.40).

1.7 Conclusion

The local dimension of labor markets matters. Empirically, this can be illustrated by the large dispersion in productivity and unemployment rates across cities. The logic of a standard model of the labor market where unemployment is the byproduct of frictions in the search for a match between workers and firms suggests that the two should be correlated: higher city-wide productivity should lead to higher job finding rates and, hence, lower unemployment rates. However, this does not seem to be supported by the data, at least when a city's productivity is proxied by its size (another standard assumption in the literature). In fact, I find that unemployment rates are not correlated with city size. The reason is that both job finding and job separation rates are decreasing in city size in such a way that they tend to offset each other. Furthermore, this seems to be a genuine characteristic of local labor markets, and these correlations do not seem to be the spurious result of differences in demographics (education and age) or industry composition. Nor the results seem to be driven by a statistical artifact due to insufficient observations in smaller cities.

Figures for Chapter 1

Figure 1.1: Metropolitan Unemployment Rates in 2000 and 2010

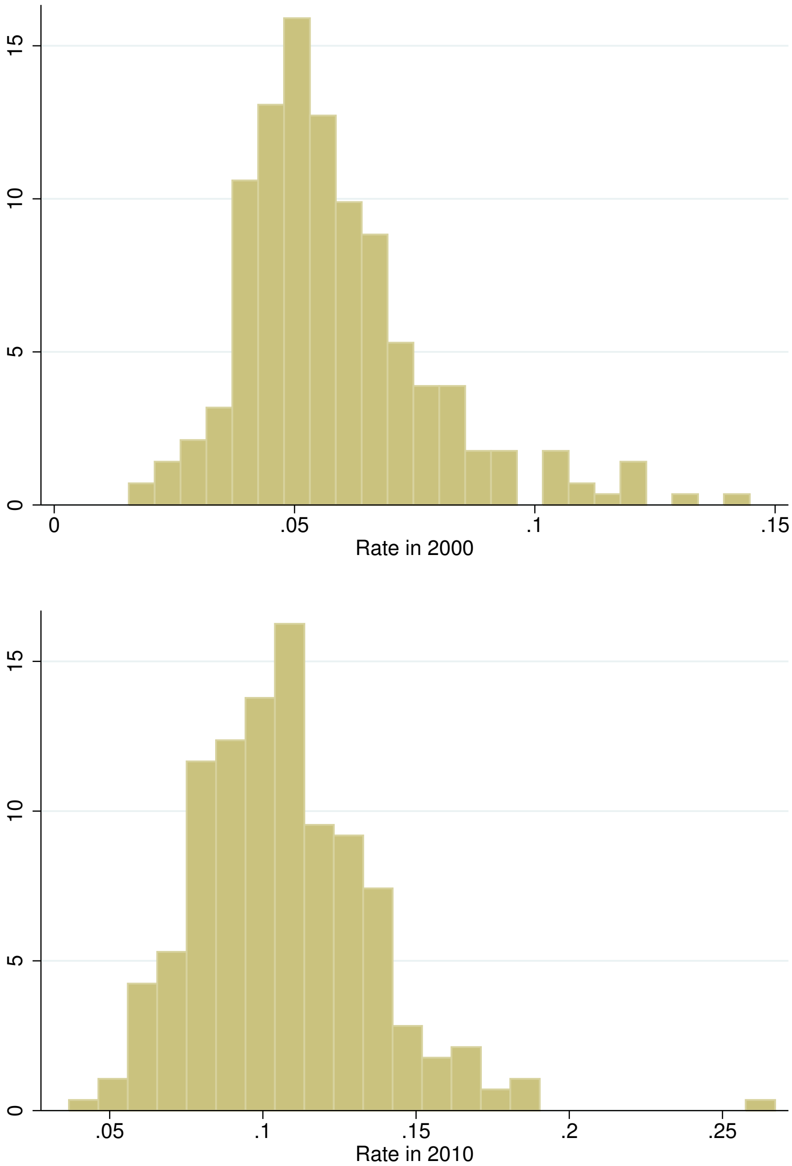


Figure 1.2: Metropolitan Unemployment Rates in 2000, 2005 and 2010

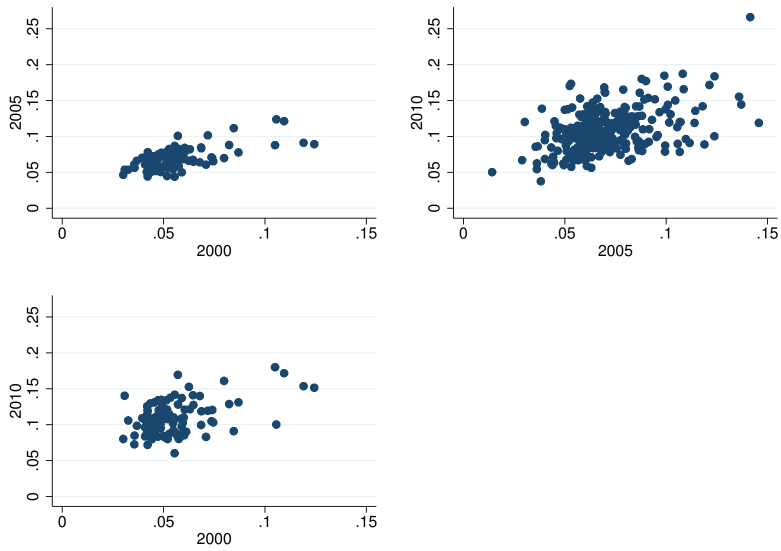


Figure 1.3: Metropolitan (log) hourly wage in 2000

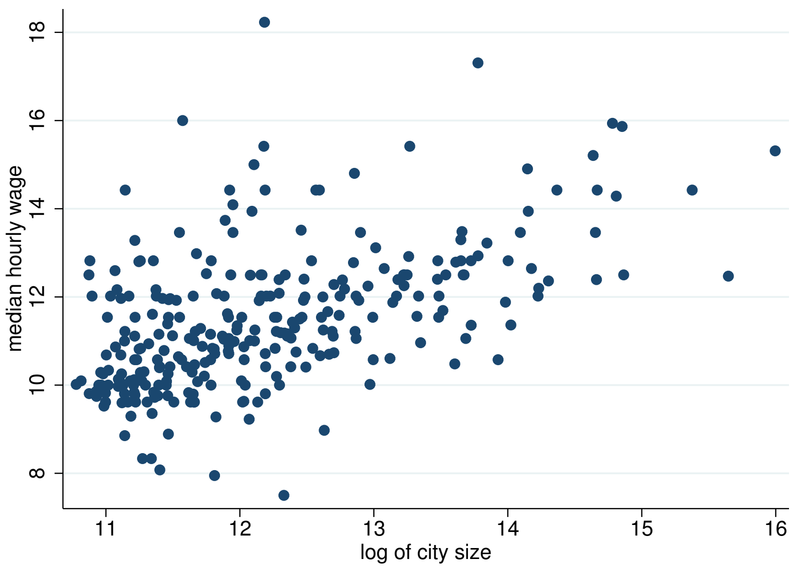


Figure 1.4: Housing prices and city size

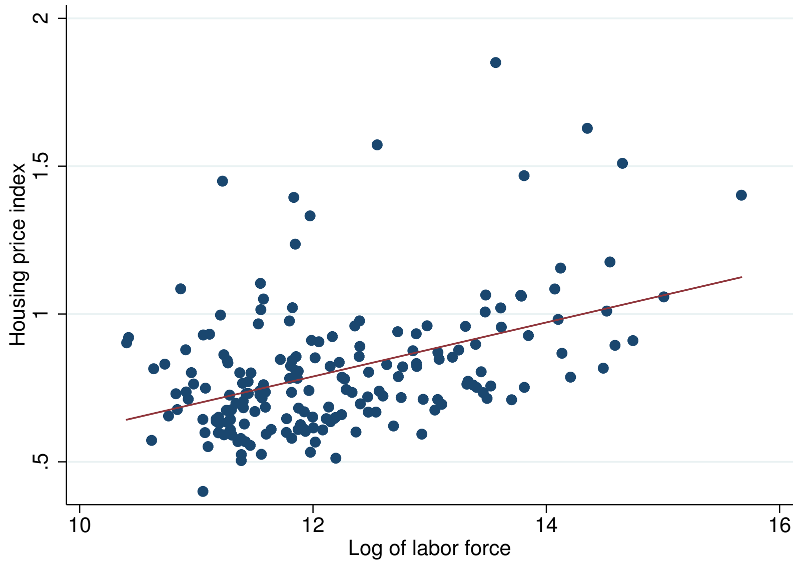


Figure 1.5: Metropolitan Unemployment Rates in 2013

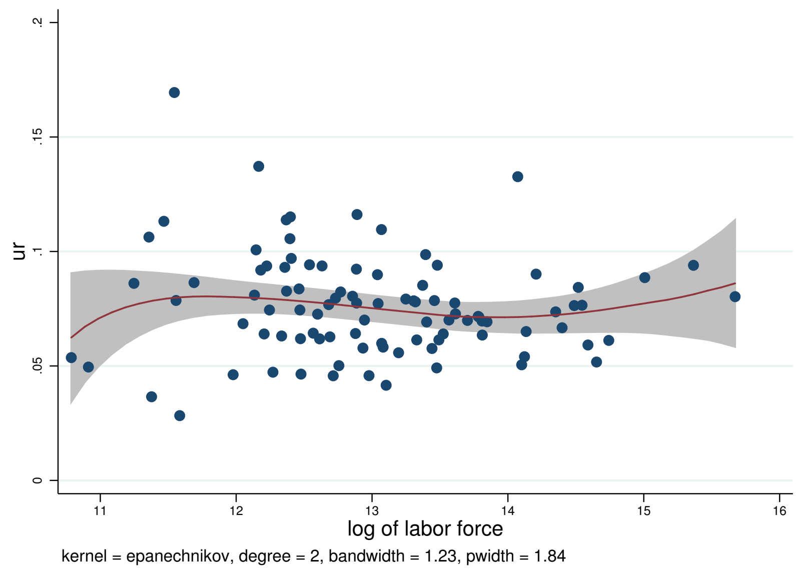


Figure 1.6: Metropolitan Job Finding (UE) Rates in 2013

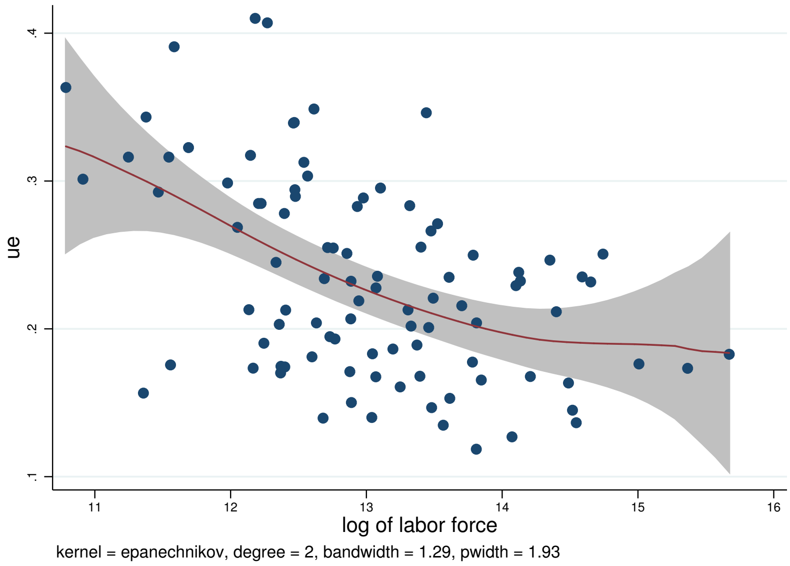


Figure 1.7: Metropolitan Job Separation (EU) Rates in 2013

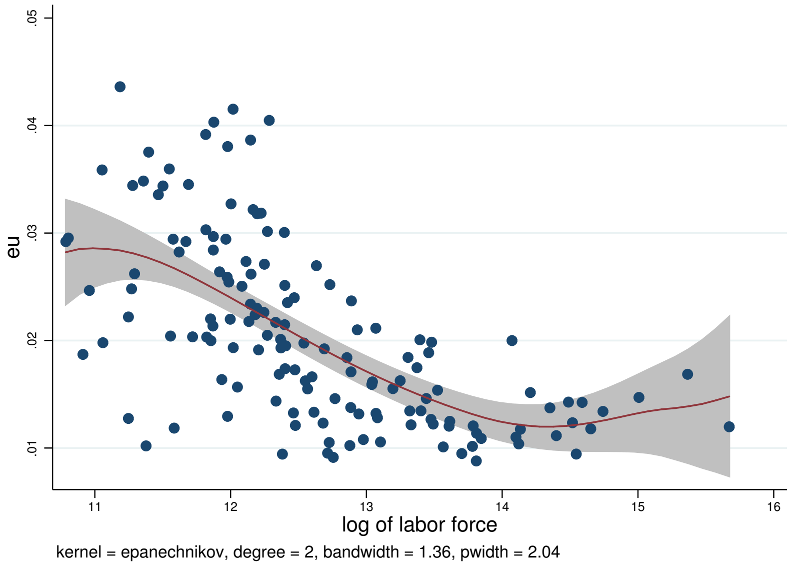


Figure 1.8: EU over UE in 2013

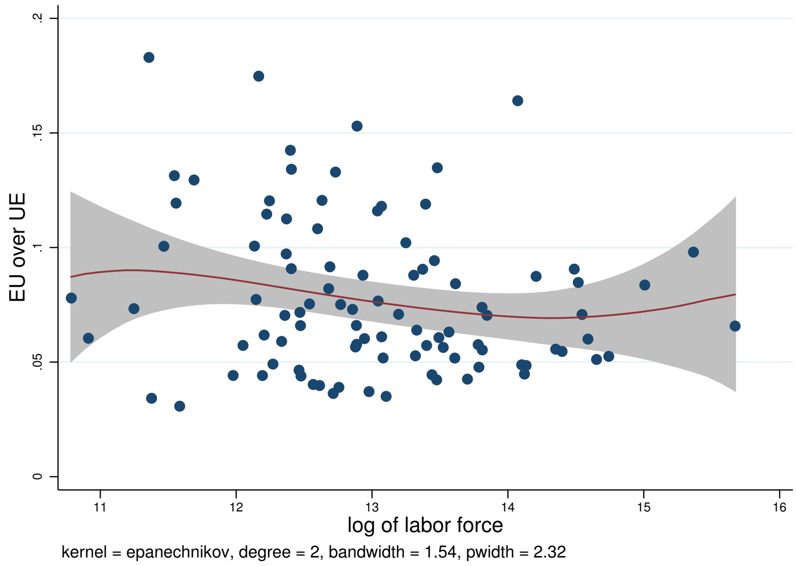


Figure 1.9: Unemployment rates and city size

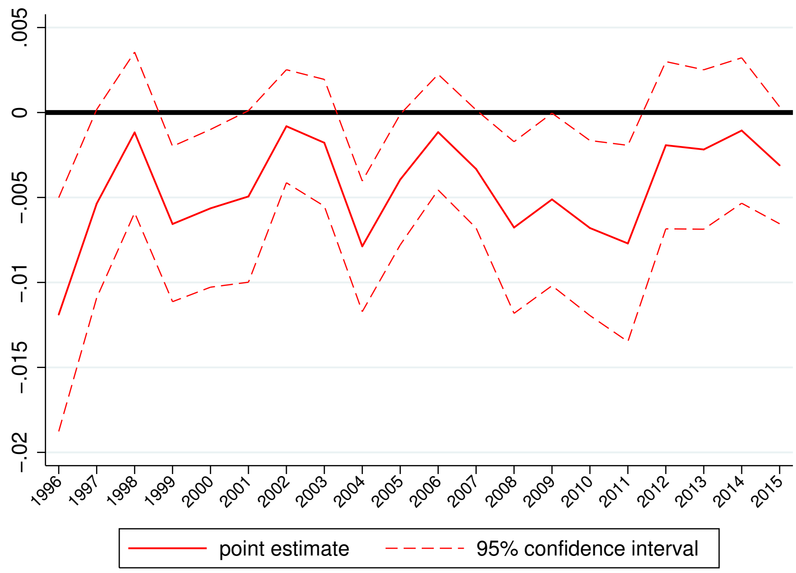


Figure 1.10: UE transition rates and city size

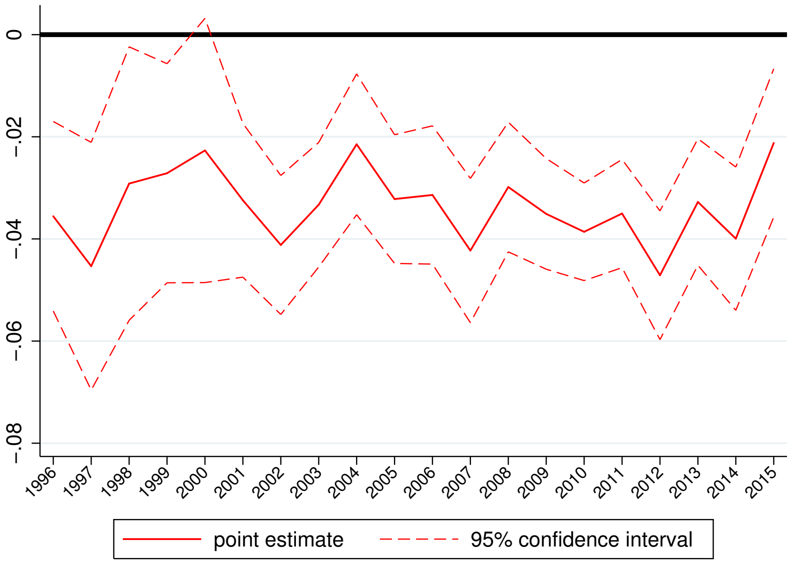


Figure 1.11: EU transition rates and city size

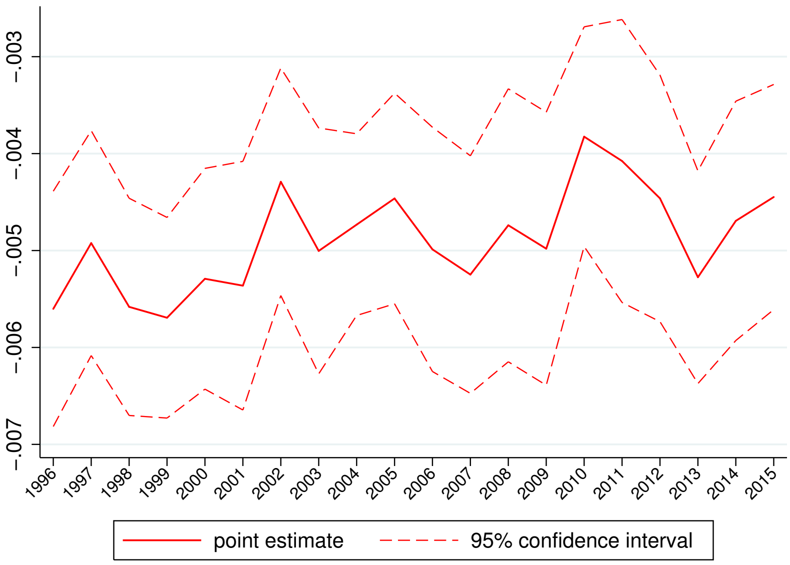


Figure 1.12: EU/UE and city size

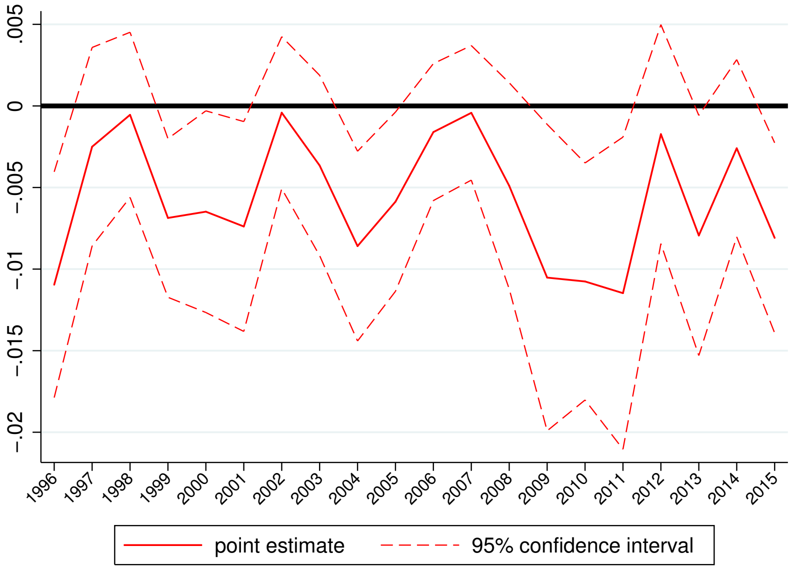


Figure 1.13: Unemployment rates and city size - ACS

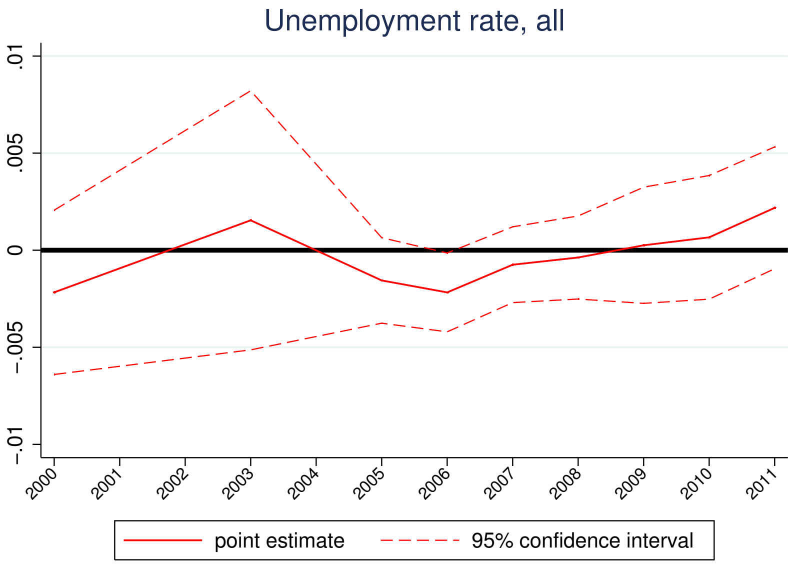


Figure 1.14: Unemployment rates and city size, no highschool - ACS

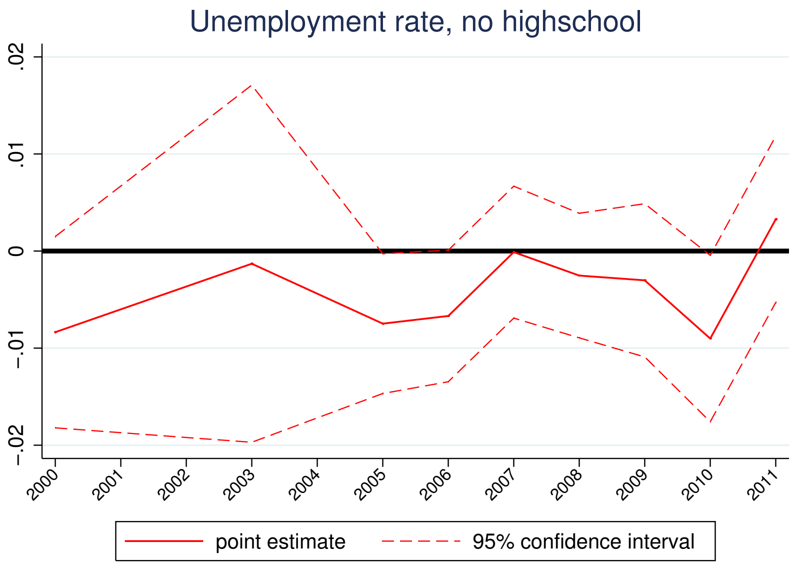


Figure 1.15: Unemployment rates and city size, highschool - ACS

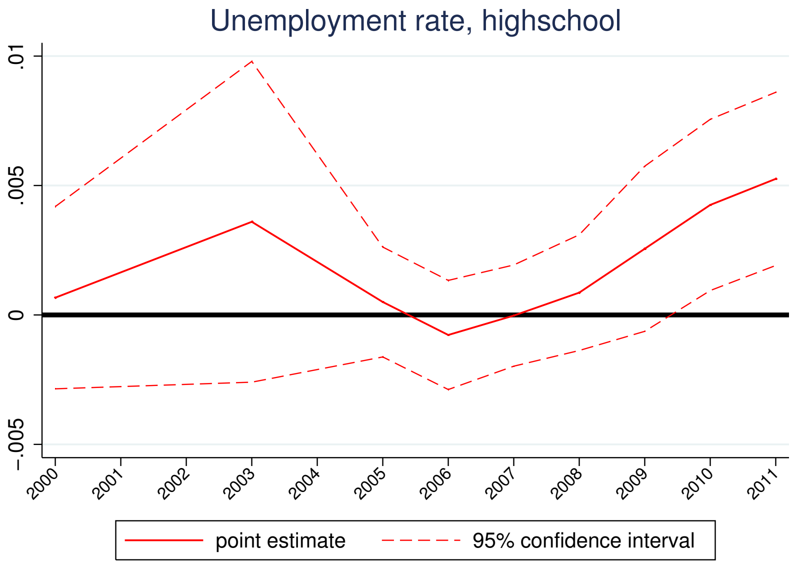


Figure 1.16: Unemployment rates and city size, college - ACS

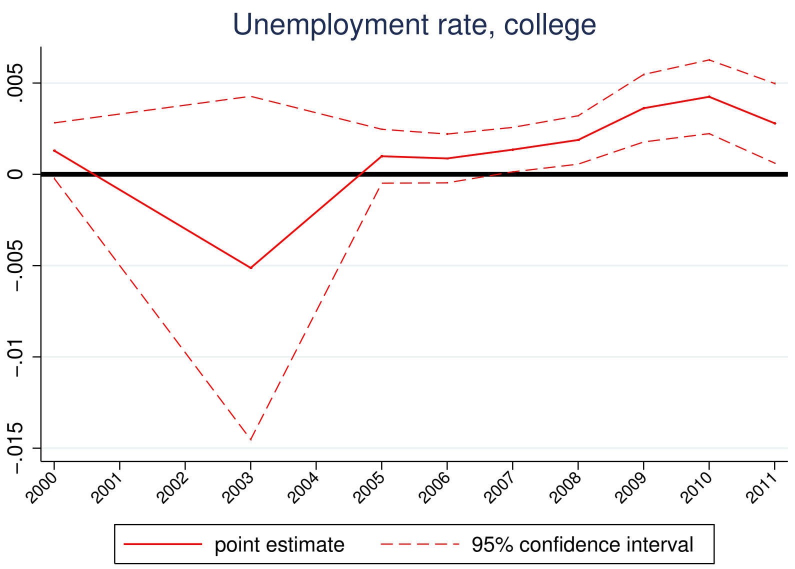


Figure 1.17: UE as from observables and city size

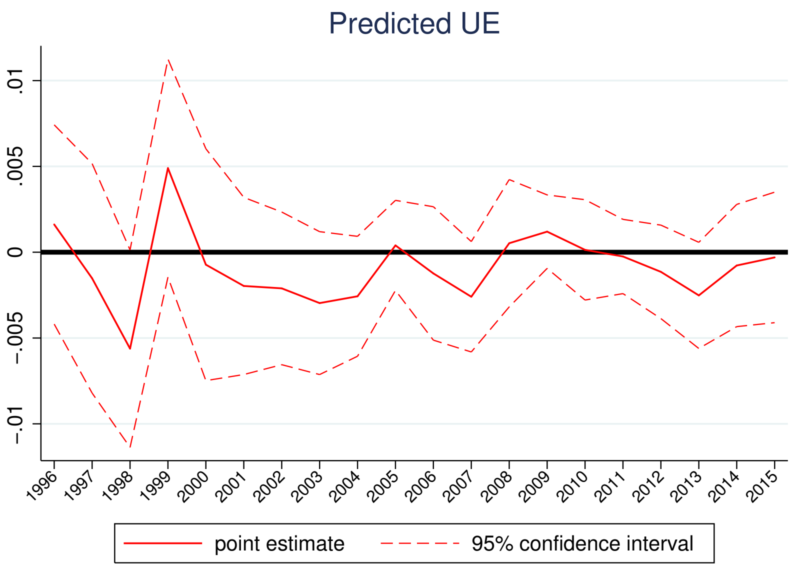


Figure 1.18: UE residual and city size

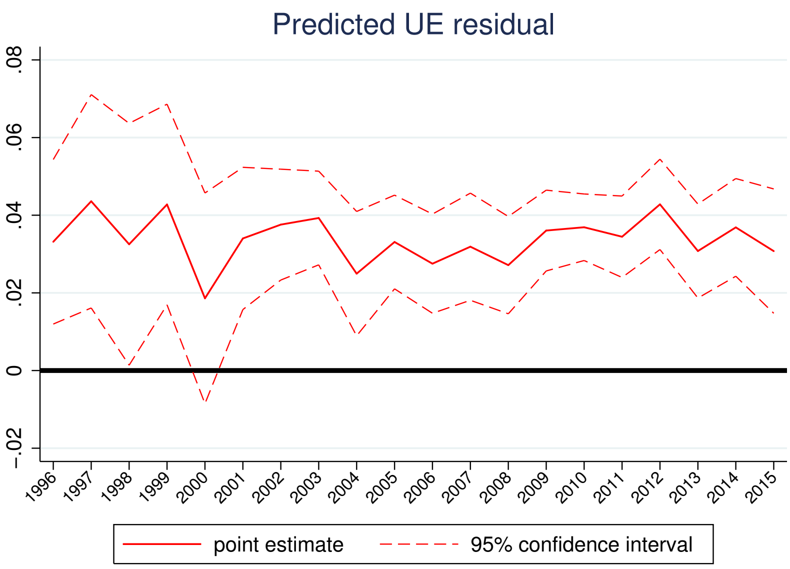


Figure 1.19: EU as from observables and city size

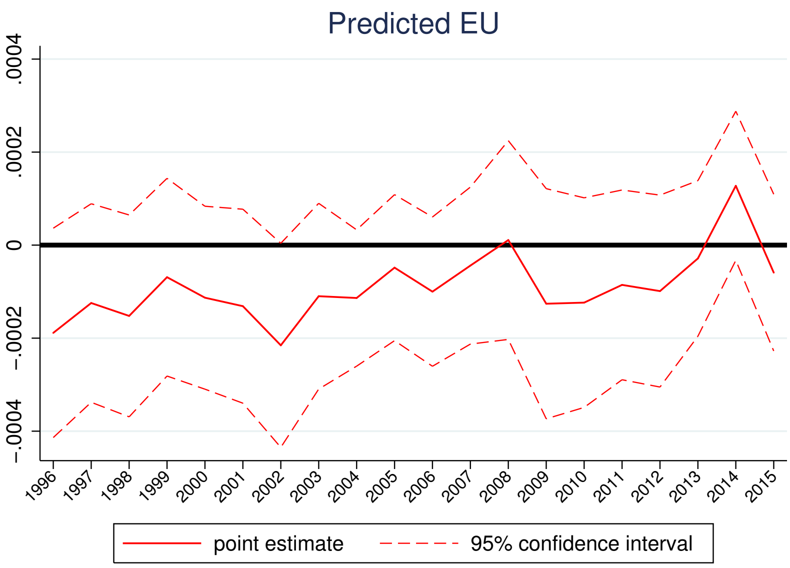


Figure 1.20: EU residual and city size

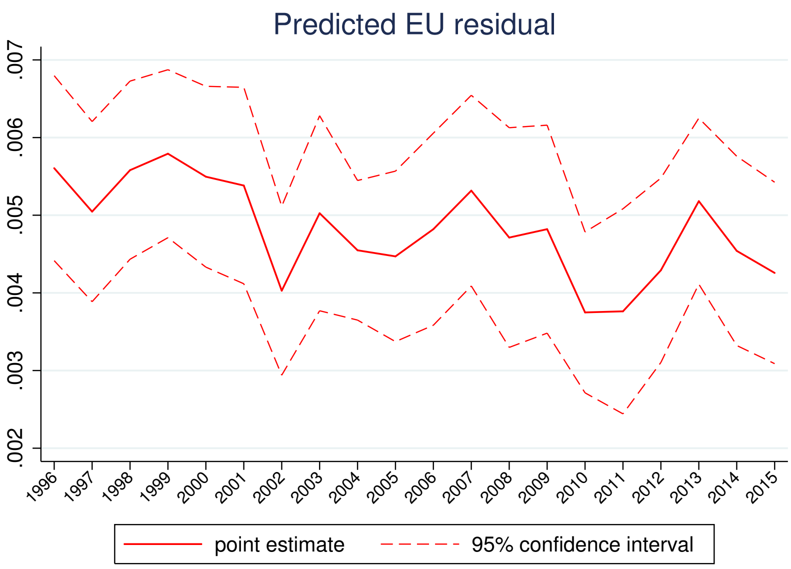


Figure 1.21: UE transition rates and city size in fictitious cities

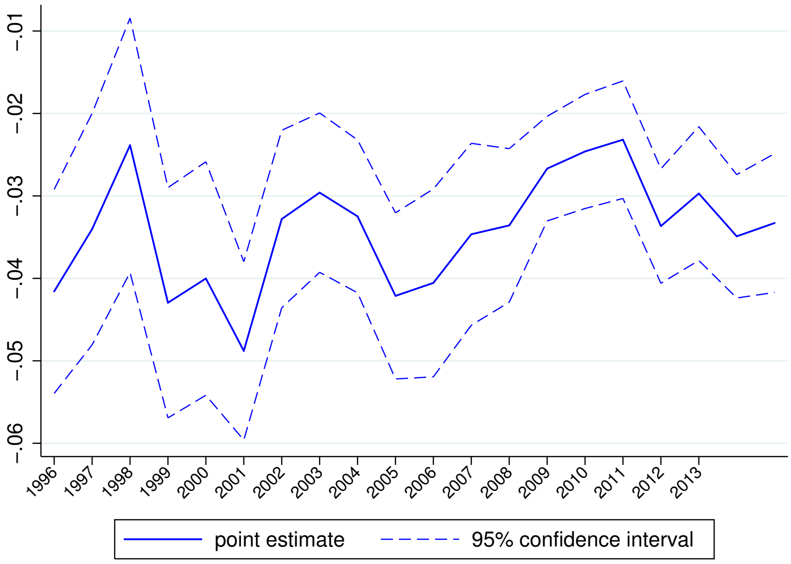


Figure 1.22: EU transition rates and city size in fictitious cities

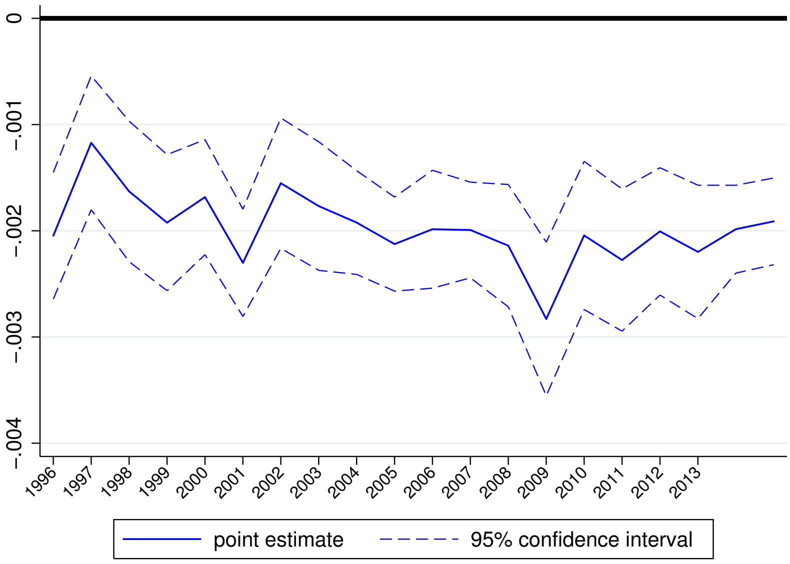


Figure 1.23: UE transition rates and city size in fictitious cities - no highschool

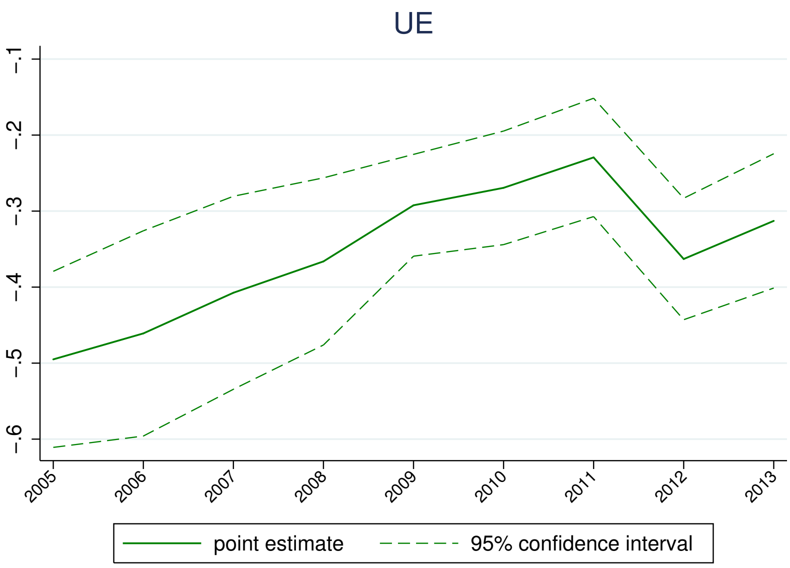


Figure 1.24: UE transition rates and city size in fictitious cities - highschool education

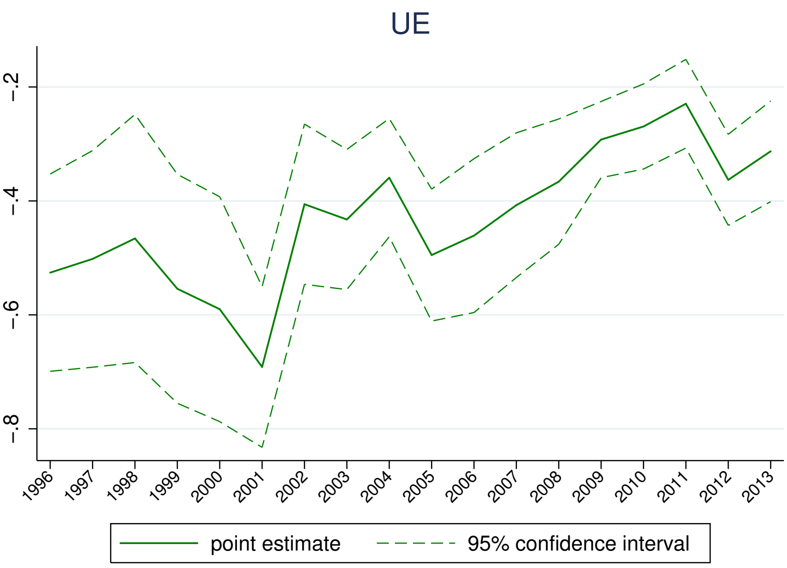


Figure 1.25: UE transition rates and city size in fictitious cities - college education

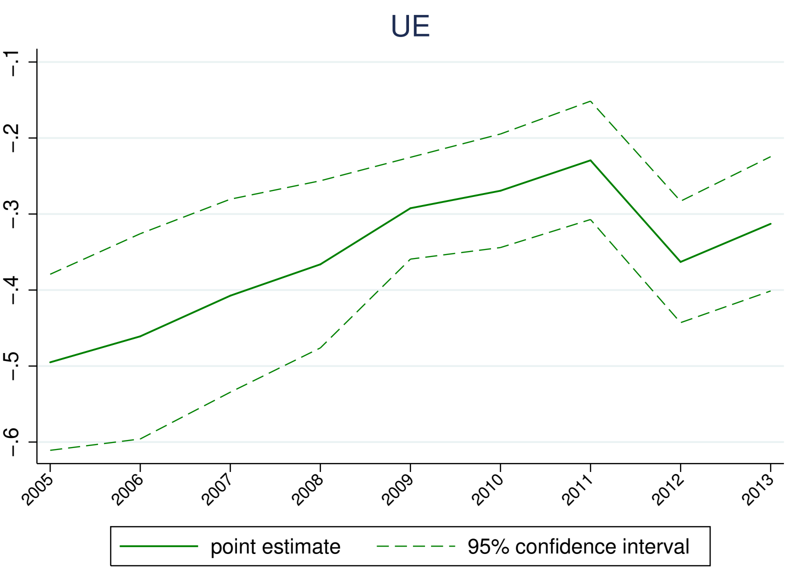


Figure 1.26: EU transition rates and city size in fictitious cities - no highschool

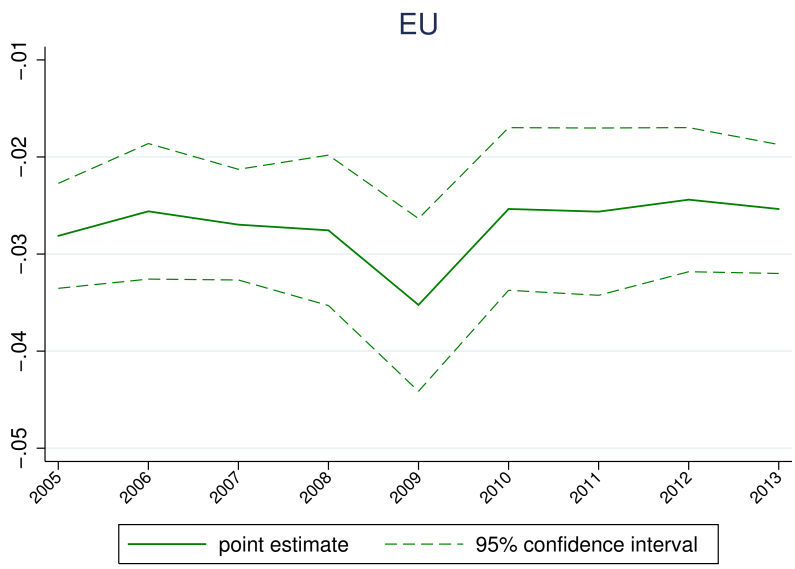


Figure 1.27: EU transition rates and city size in fictitious cities - highschool education

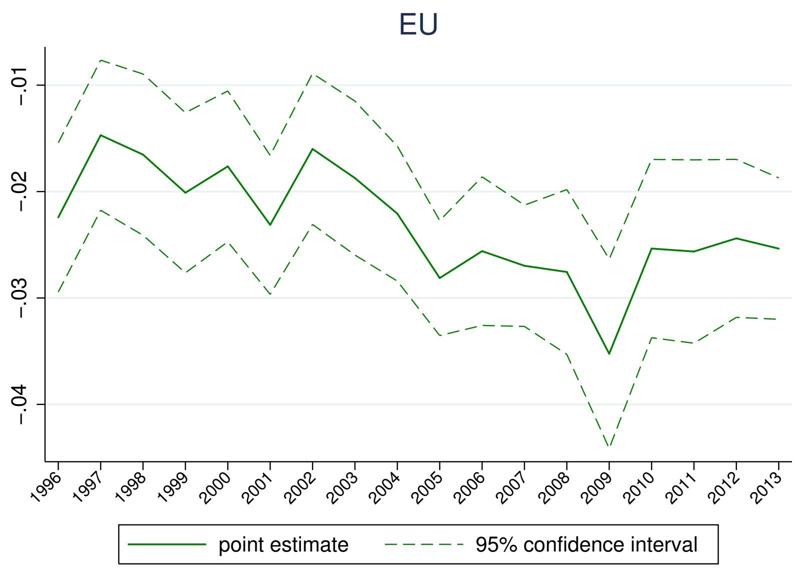


Figure 1.28: EU transition rates and city size in fictitious cities - college education

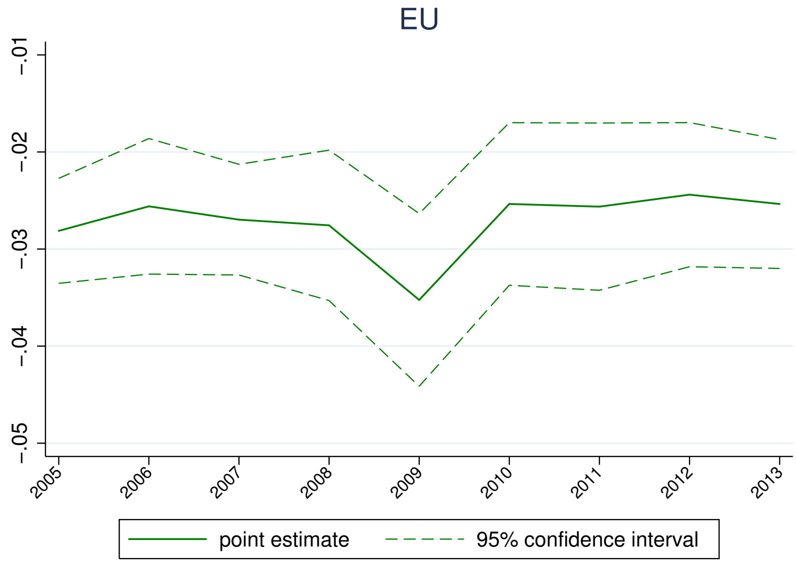


Figure 1.29: Financial occupations and city size

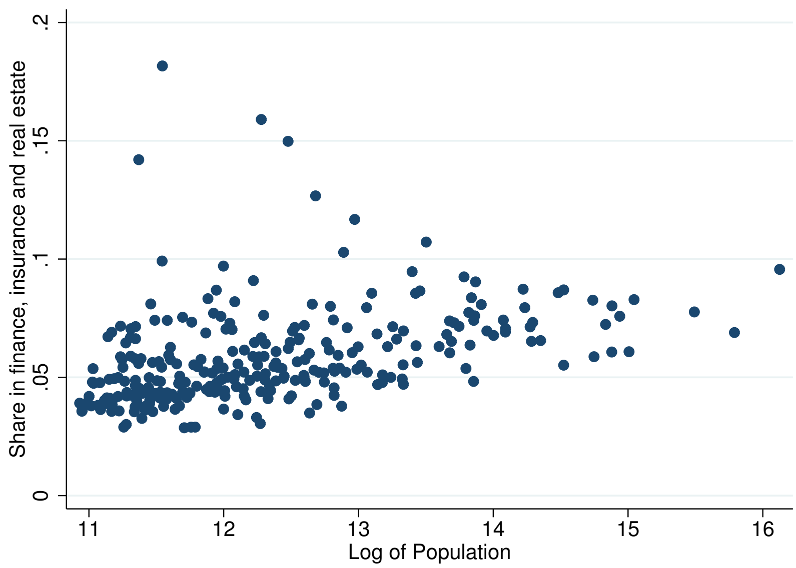


Figure 1.30: Business and repair services and city size

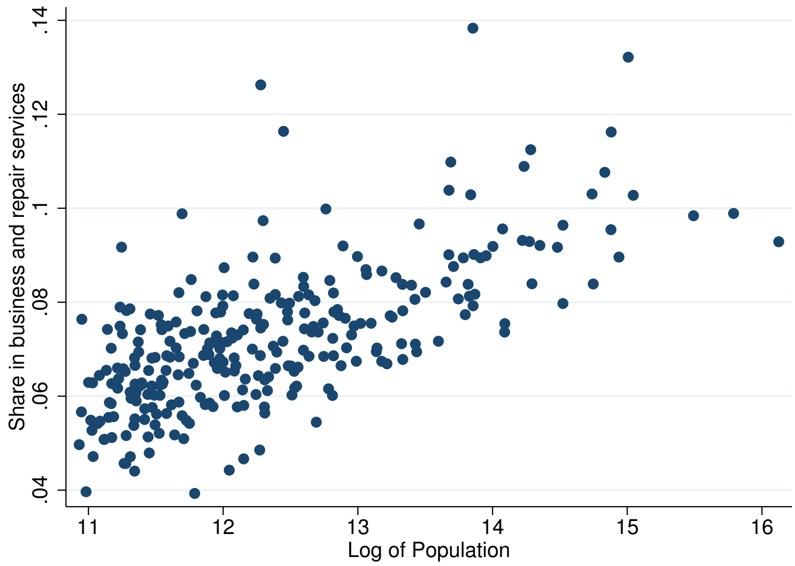


Figure 1.31: Job-to-job transition rates and city size

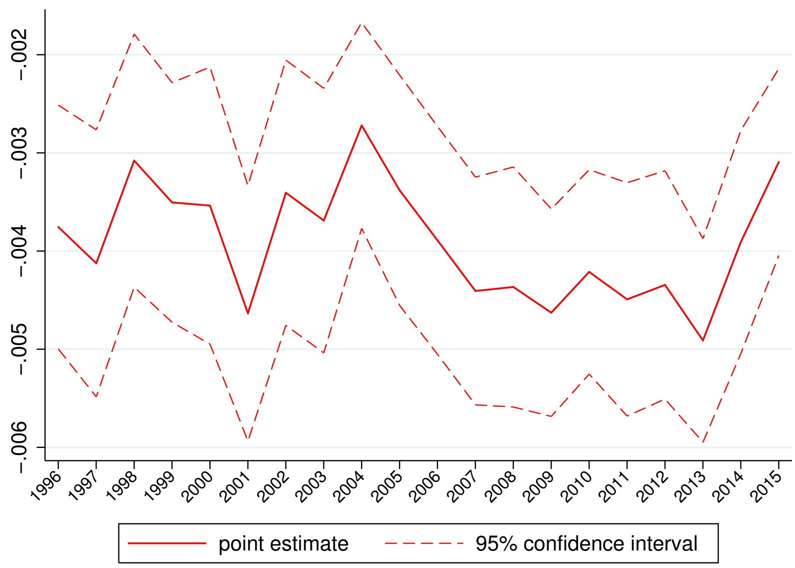


Figure 1.32: Nilf to E transition rates and city size

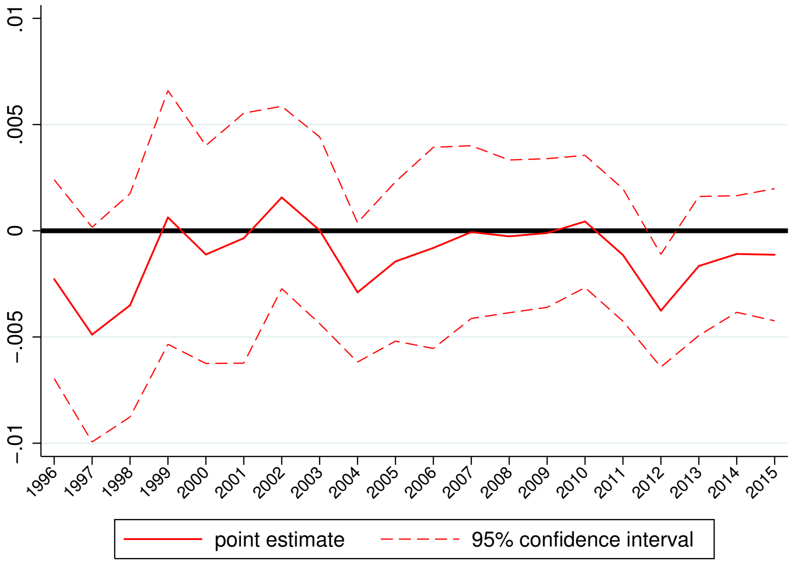


Figure 1.33: E to Nilf transition rates and city size

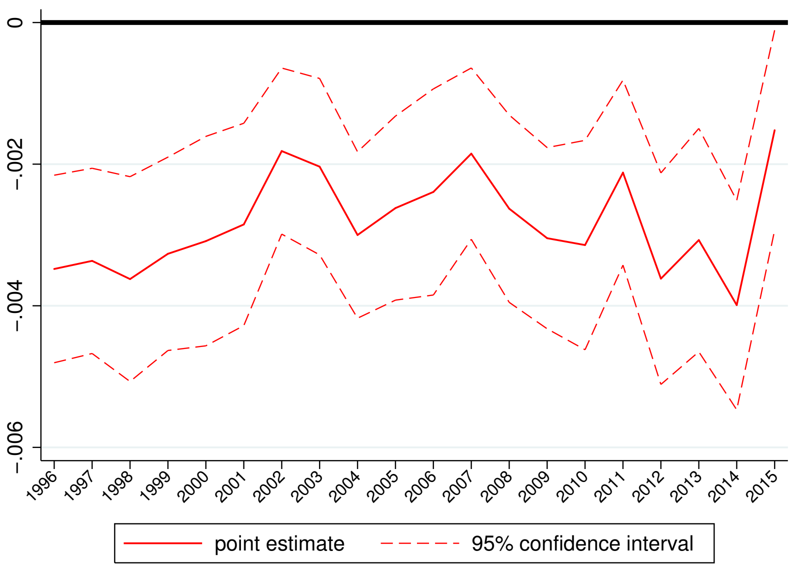


Figure 1.34: Duration of unemployment and city size, average 1994-2010

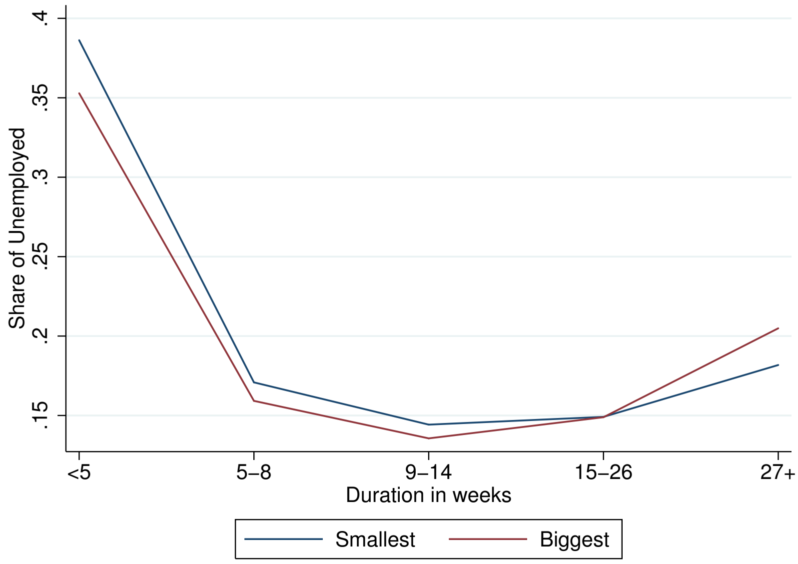


Figure 1.35: Growth rate of average weekly earnings and city size, average 2005-2013

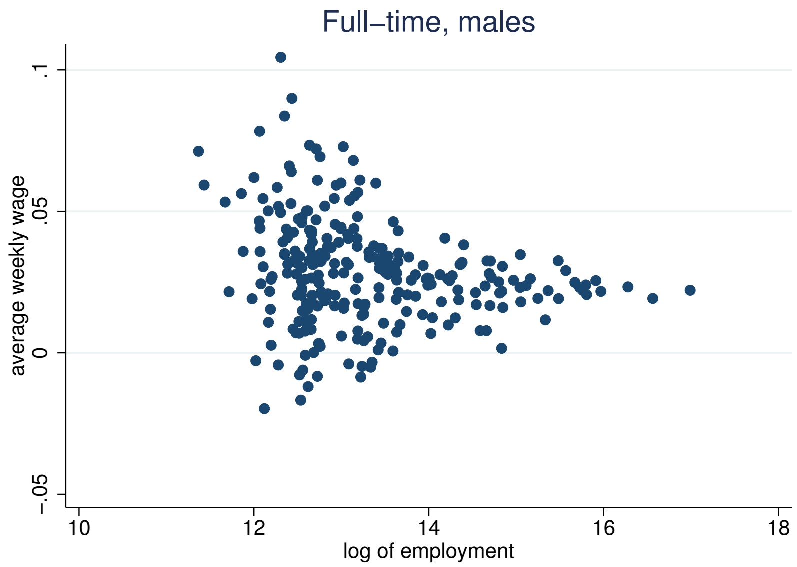


Figure 1.36: Growth rate of average hourly wages and city size, average 2005-2013

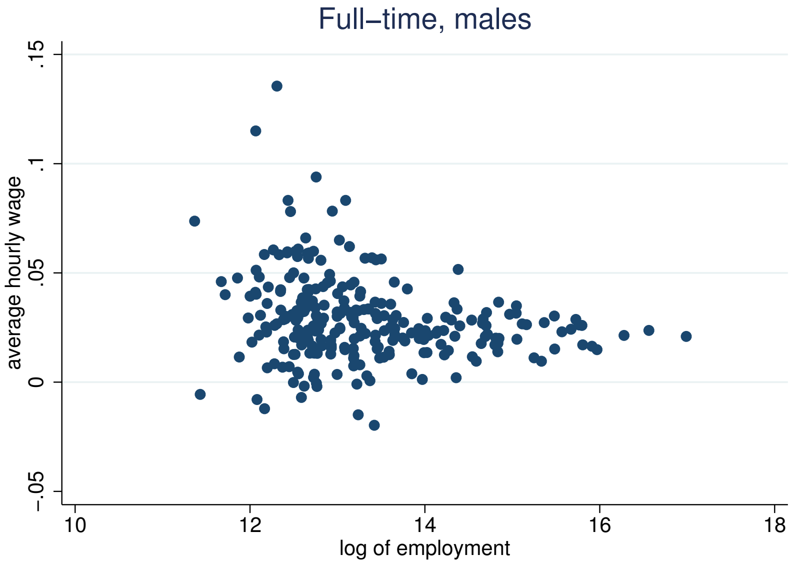


Figure 1.37: Growth rate of average weekly earnings and city size, standard deviation 2005-2013

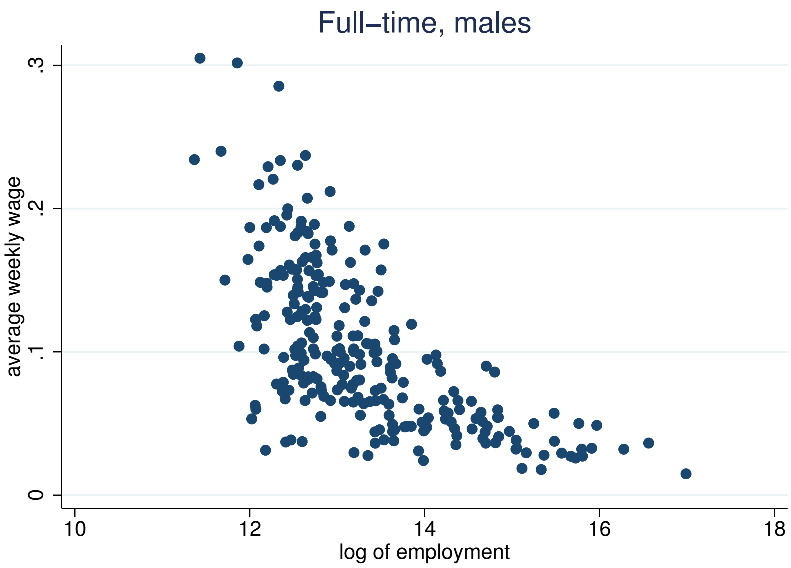


Figure 1.38: Growth rate of average hourly wages and city size, standard deviation 2005-2013

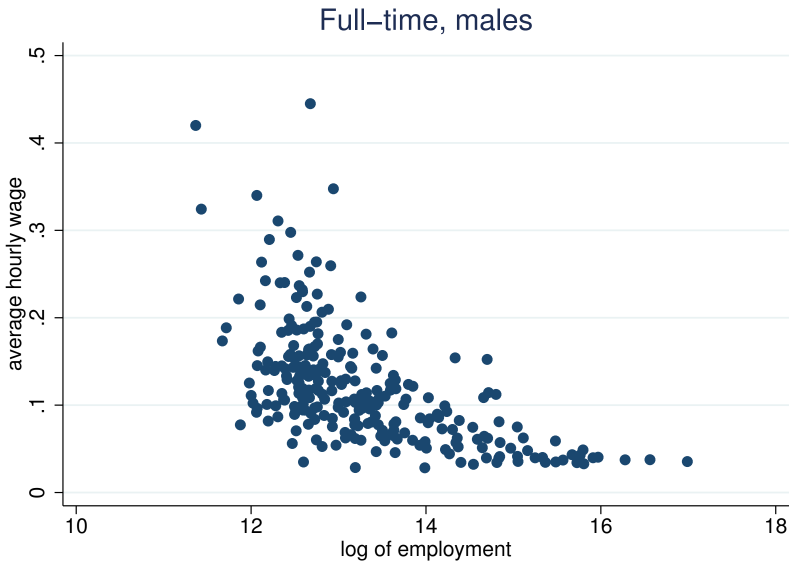


Figure 1.39: Market tightness and city size

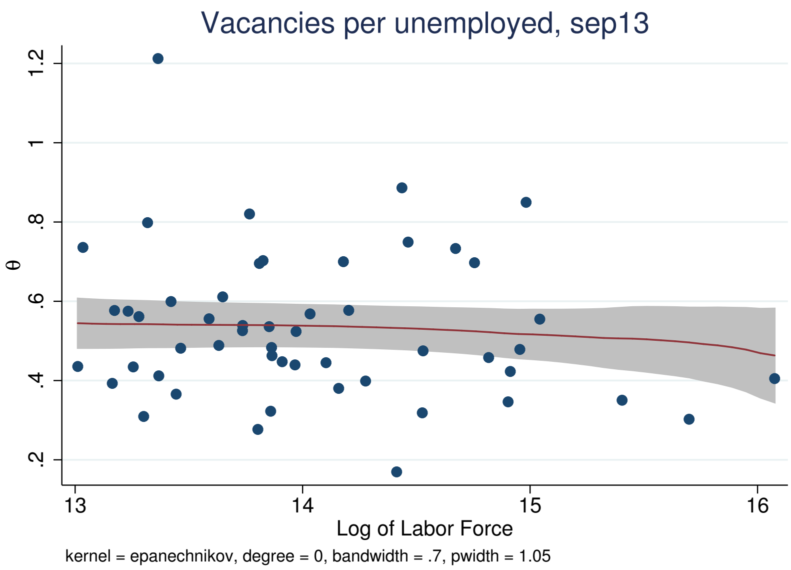
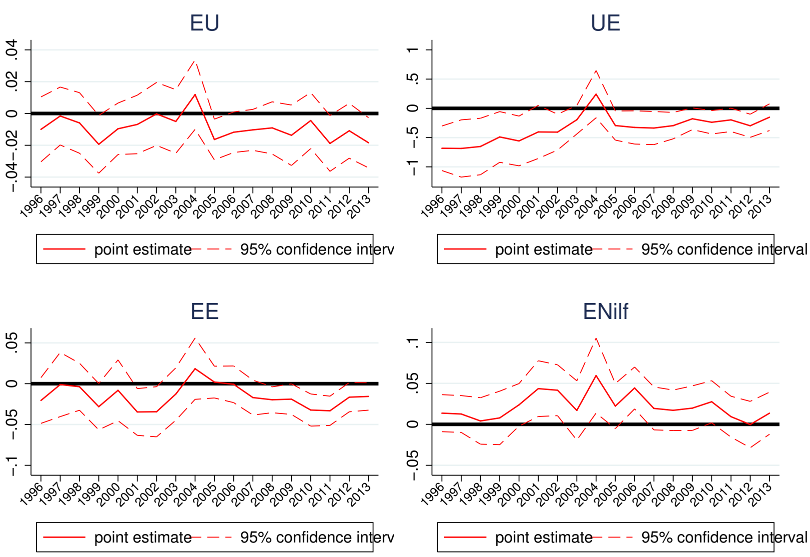


Figure 1.40: Labor market flows and city size



Chapter 2

MODELING LOCAL LABOR MARKETS WITH FRICTIONAL UNEMPLOYMENT

2.1 Introduction

There are two well-known stylized facts in the literature on local labor markets: 1) Labor productivity is increasing in city size (see, for instance, Glaeser & Gottlieb (2009) and Moretti (2011)); and 2) The matching function that governs labor market matches between firms and workers exhibits constant returns to scale (see, for instance, Petrongolo & Pissarides (2001)). In the first chapter of the thesis, I have documented three additional stylized facts on local labor markets: 1) Unemployment rates are uncorrelated with city size; 2) Job finding rates are decreasing in city size; and 3) Job separation rates are decreasing in city size. In this chapter I present three theoretical rationalizations of these five stylized facts:

1. Frictions in vacancy-posting.

2. Specialization.

3. The law of large numbers.

The logic for pursuing each explanation is as follows. First, one of the reasons that the simple model presented in chapter 1 predicts that job finding rates are decreasing in city size is that firms are free to post as many vacancies as they want. In practice, this means that they are infinitely sensitive to productivity differences. However, if there exists a friction that dampens the vacancy-posting process, then we also dampen the correlation between labor productivity and vacancy posting (at the limit, if vacancy-posting were exogenously given, this correlation would be zero). In fact such an assumption is not implausible: as I show below, the fact that firms need to pay a cost for settling up in a city (that is independent of the amount of vacancies posted) already impends the vacancy-posting process. Crucially, if this cost is related to the housing market (think of renting an office building), then it is plausible that this cost is increasing in city size. The implications of this mechanism are explored below in detail.

Second, a worker's degree of specialization is a plausible candidate to explain why she is more productive. In fact, following Adam Smith's insight that specialization is increasing in the size of the market, it is reasonable to consider a model in which a worker's degree of specialization is increasing in the size of the city in which she lives. Crucially, the degree of specialization might have important implications for her changes of finding a job (if she is unemployed) or of losing her job (if she is employed). In particular, in a match with a highly specialized employee, both the firm and the worker are likely to have invested heavily on match-specific assets (this might be the reason why the worker is that much specialized), thereby depressing the incentives to break up the match. Similarly, a highly specialized worker might have fewer chances of finding a suitable match in the labor market –provided that there is a high enough degree of randomness in her job seeking process. This framework is explored in more detail below.

Finally, a simpler explanation might come from the Law of Large Numbers: decreasing job finding and separation rates (i.e. lower turnover) might be the natural process of convergence towards the 'true' process as the size of the population gets larger. This more mechanical hypothesis is the last one explored below.

2.2 Frictional Vacancy-Posting: an Illustration

2.2.1 Intuition

Higher productivity in a given location makes it appealing to workers, so they move to that location; at the same time, higher productivity gives firms an incentive to post more vacancies. Thus, there are two forces governing market tightness: migration towards higher-productivity cities (which, everything else equal, tends to depress job finding rates for workers), and higher vacancy-posting in higher-productivity cities (which, everything else equal, tends to lead to higher job finding rates for workers). These ingredients are explored within a spatial model with frictional unemployment to assess whether the existence of a friction impending the vacancy-posting process provides a good rationalization of the stylized facts.

2.2.2 Setup

Consider a city c that is endowed with city-wide productivity A_c. Its local labor market is described by a simple matching model with endogenous separation. The salient characteristic of the market is that the behavior of firms is exogenous: at every point in time, the stock of vacancies is exogenously given by v_c, so that there is no endogenous vacancy-posting. Thus, workers are the only relevant agents. When settled in city c, workers can be either unemployed or employed. In either case, they need to pay a fixed cost p for housing.[1] If unemployed, they earn unemployment benefits b and find a job with probability $\theta q(\theta)$, where $\theta \equiv v/u$, v is the number of vacancies and u is the number of unemployed. If they find a job, they are endowed with the highest productivity, which is assumed to be 1. Employed workers are tied to a stochastic productivity x, and they earn all the output they produce, which is Ax where A is city-specific and x is job-specific. With probability λ, they are shocked and a new job-specific productivity is drawn from G. Given the new productivity, workers decide whether to destroy the match. In particular, if the new productivity is below a threshold x_D they are better-off in unemployment and the match is destroyed. Before reentering unemployment, workers choose which city they want to be located in.

In other words,

$$\begin{aligned} \theta_c &= \frac{v_c}{u_c}, \text{ where } v_c \text{ is given} \\ rU_c &= b_c - p_c + \theta_c q(\theta_c)\left[W_c(1) - U_c\right] \\ rW_c(x) &= A_c x - p_c + \lambda\left[\int_{x_{Dc}}^{1} W_c(s)\,\mathrm{d}G(s) + G(x_{Dc})\max_{c'\in C}\{U_{c'}\} - W_c(x)\right] \\ W_c(x_{Dc}) &= U_c \end{aligned}$$

where U_c and W_c represent the value of being unemployed and employed in city c, respectively.

In equilibrium flows into and out of unemployment must be equalized. That is,

$$u_c\theta_c q(\theta_c) - \lambda G(x_{Dc})(L_c - u_c) = 0$$

[1] Housing is assumed to be equivalent to a lump sum tax. That is, given income y, workers solve the following utility maximization problem:

$$\begin{aligned} &\max_c u(c) = c \\ &\text{s.t. } c = y - p \end{aligned}$$

Because of free mobility of the unemployed, in equilibrium the value of unemployment must be the same everywhere. That is,

$$U_c = \bar{U} \text{ for all } c$$

Housing prices are assumed to be increasing in the size of the market:

$$p_c = p(L_c),\ p' > 0$$

Finally, the aggregate labor force is exogenously given and it is allocated across all cities:

$$\sum_{c \in C} L_c = \bar{L}$$

2.2.3 Equilibrium

The equilibrium is characterized by a bundle $\{L_c, u_c, x_{Dc}\}_{c \in C}$. To derive it, first evaluate $W_c(x)$ at $x = x_{Dc}$ and use utility equalization to obtain

$$\int_{x_{Dc}}^{1} W_c(s)\,\mathrm{d}G(s) = -A_c x_{Dc} + p_c + [r + \lambda(1 - G(x_{Dc}))]\,\bar{U}$$

Then,

$$\begin{aligned}(r+\lambda)W_c(x) &= A_c(x - x_{Dc}) + [r + \lambda(1 - G(x_{Dc}))]\,\bar{U} + \lambda G(x_{Dc})\bar{U} = \\ &= A_c(x - x_{Dc}) + (r+\lambda)\bar{U}\end{aligned}$$

Now evaluate this expression at $x = 1$, solve for $W_c(1) - \bar{U}$ and plug this into $r\bar{U}$ to obtain:

$$r\bar{U} = b_c - p_c + \frac{\theta_c q(\theta_c)}{r+\lambda} A_c(1 - x_{Dc})$$

Hence, for any two cities B and S, in equilibrium:

$$b_B - p(L_B) + \frac{\theta_B q(\theta_B)}{r+\lambda} A_B(1 - x_{DB}) = b_S - p(L_S) + \frac{\theta_S q(\theta_S)}{r+\lambda} A_S(1 - x_{DS})$$

which pins down L_B and L_S given $L_B + L_S = \bar{L}$, and also given $\{u_c, x_{Dc}\}_{c=B,S}$. However, note that since

$$u_c \theta_c q(\theta_c) - \lambda G(x_{Dc})(L_c - u_c) = 0$$

we have that u_c is simply a function of L_c and x_{Dc}. Thus, we are only missing x_{Dc}.

Next, plug the expression we have derived for $W_c(x)$ into its Bellman equation:

$$
\begin{aligned}
(r+\lambda)W_c(x) &= A_c x - p_c + \lambda\left[\int_{x_{Dc}}^{1} \frac{A_c(s-x_{Dc}) + (r+\lambda)\bar{U}}{r+\lambda}\,\mathrm{d}G(s) + G(x_{Dc})\bar{U}\right] = \\
&= A_c x - p_c + \lambda\left[\int_{x_{Dc}}^{1} \frac{A_c(s-x_{Dc})}{r+\lambda}\,\mathrm{d}G(s) + \bar{U}\right]
\end{aligned}
$$

Evaluate it at $x = x_{Dc}$ to obtain

$$
\begin{aligned}
x_{Dc} &= \frac{p(L_c)}{A_c} - \frac{\lambda}{r+\lambda}\int_{x_{Dc}}^{1} s - x_{Dc}\,\mathrm{d}G(s) + \frac{r\bar{U}}{A_c} = \\
&= \frac{b_c}{A_c} + \frac{\theta_c q(\theta_c)}{r+\lambda}(1-x_{Dc}) - \frac{\lambda}{r+\lambda}\int_{x_{Dc}}^{1} s - x_{Dc}\,\mathrm{d}G(s)
\end{aligned}
$$

which pins down x_{Dc} as a function of θ_c.

The mechanism of the model is the following. Everything else equal, $A_B > A_S$ makes city B more appealing to workers than city S because of higher labor income. Thus, individuals have an incentive to move from S to B. This lowers θ_B while raising θ_S. As a result, x_{DB} goes down and x_{DS} goes up because of the positive correlation between market tightness and the separation bound (higher market tightness raises the value of unemployment and, therefore, workers become pickier about x_D). Finally, the increase in L_B raises housing prices in B while the drop in L_S lowers housing prices in S, which depresses the incentives to migrate.

Note that given $A_B > A_S$, it is most likely that $L_B > L_S$, which also implies $\theta_B < \theta_S$ and, in turn, $x_{DB} < x_{DS}$. If $L_B < L_S$, people in B would be enjoying higher incomes and lower housing prices together with higher job finding rates. Clearly, this would be against utility equalization, unless the response of x_{Dc} to θ_c is so large that it offsets all other effects. In what follows, I will assume that this response is not that large.

2.2.4 Simulation

In order to illustrate the predictions of the model, I simulate it with two cities $\{S, B\}$. Assume the following functional forms:

$$
\begin{aligned}
p(L) &= L^{\eta} \\
q(\theta) &= \theta^{-\alpha} \\
x &\sim Uniform[0,1]
\end{aligned}
$$

The model is calibrated as follows:[2]

Table 2.1: Exogenous vacancy-posting model: Calibration

	A_c	v_c	b	η	α	r	λ	$\bar{L}$
S	1	0.0018	0.2	0.5	0.5	0.05	0.1	1
B	1.5	0.0018	0.2	0.5	0.5	0.05	0.1	1

The model is simulated as follows:

1. Guess L_B^0 and $L_S^0 = \bar{L} - L_B^0$.

2. Given this guess, find $\{x_{Dc}, u_c\}_{c\in\{B,S\}}$ that satisfy the equilibrium conditions.

3. Check that $U_B = U_S$. If abs$(U_B - U_S) < \tau$, the equilibrium has been found. Otherwise,

   - If $U_B > U_S$, update your guess with $L_B^{n+1} = L_B^n + \epsilon$.
   - If $U_B < U_S$, update your guess with $L_B^{n+1} = L_B^n - \epsilon$.
   - With your new guess, go back to step 2.

Figure 2.1 depicts the output of the simulation.

That is,

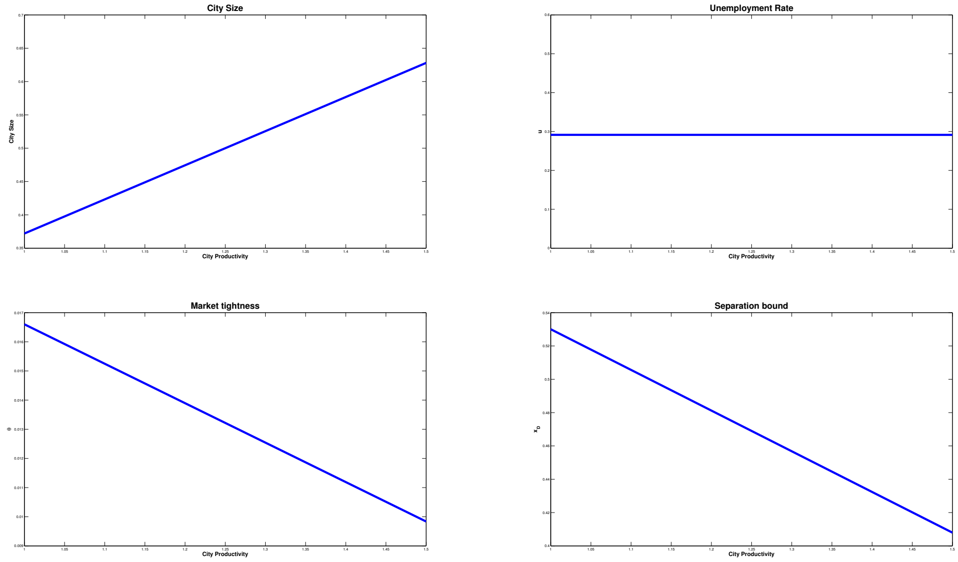
- City size is increasing in A.

- Market tightness is decreasing in A: the job finding rate is lower in the biggest city.

- The separation bound is decreasing in A: the job separation rate is lower in the biggest city.

[2]The value chosen for v_c is such that, given all other parameters, the ratio of the job separation rate over the job finding rate implies a constant unemployment rate across the two cities.

Figure 2.1: Simulation of the simple model



2.3 Frictional Vacancy-Posting with Micro-foundations

The previous section has shown that introducing frictions to vacancy posting into a spatial model with frictional unemployment can lead us to reproduce the stylized facts on local labor markets from which I set off at the beginning of the chapter. In this section, I develop a richer version of the model and take it to the data presented in the first chapter of the thesis.

2.3.1 The setup

Assume that workers have preferences over a consumption good c, whose price is normalized to 1, and housing h, with price p. Given an income y_{ic}, worker i living in city c solves the following problem:

$$\max_{c_{ic}, h_{ic}} u = a_c c_{ic}^{1-\delta} h_{ic}^{\delta}$$
$$\text{s.t. } c_{ic} + p_c h_{ic} = y_{ic}$$

where a_c is a city-specific amenity. The optimal behavior given y_{ic} is:

$$c(y_{ic}) = (1-\delta) y_{ic},$$
$$h(y_{ic}, p_c) = \delta \cdot \frac{y_{ic}}{p_{ic}}$$

which implies the following indirect utility $v(y_{ic}, p_{ic})$:

$$v(y_{ic}, p_{ic}) = a_c(1-\delta)^{1-\delta}\delta^{\delta}\frac{y_{ic}}{p_c^{\delta}}$$

Housing supply is perfectly inelastic and given by $\bar{H}_c$. Housing prices are in charge of clearing the market:

$$\int_0^{L_c} h(y_{ic}, p_c)\,\mathrm{d}i = \bar{H}_c$$

Free mobility of the unemployed means that the value of being unemployed, U_c, must be the same everywhere. Thus, in equilibrium free mobility implies that

$$U_c = U \text{ for all } c$$

Finally, the national supply of labor is exogenously given by $\bar{L}$, which in equilibrium must be equal to the sum over each city's labor force, L_c. That is,

$$\sum_{c\in C} L_c = \bar{L}$$

2.3.2 The local labor market

Within a city, unemployed workers and vacancies meet randomly, and the total number of matches in a given period is given by

$$m_c = m(v_c, u_c)$$

where m exhibits constant returns with respect to v_c and u_c. Defining $\theta_c \equiv v_c/u_c$, the firm's probability of finding a worker and the worker's probability of finding a job are given by

$$\frac{m_c}{v_c} \equiv q(\theta_c),\; q' < 0$$
$$\frac{m_c}{u_c} \equiv p(\theta_c) = \theta_c q(\theta_c),\; p' > 0$$

Unemployed workers receive unemployment benefits b and randomly search for a job. If they find one, they are endowed with the highest match-specific productivity, $\bar{x}$. Employed workers endowed with idiosyncratic productivity x earn a wage $w_c(x)$ and next period they are shocked with a new idiosyncratic productivity, which is drawn from a distribution G, with probability λ. After observing the new idiosyncratic productivity, they decide whether to stay in the job or switch to unemployment. Let x^w_{Dc} be the smallest productivity with which they are willing to stay in the job. Clearly, at this point they are indifferent between working or being unemployed. If they become unemployed, they migrate to the city where they get the highest value. Analytically the behavior of workers is described by

$$
\begin{aligned}
rU_c &= v(b_c, p_c) + \theta_c q(\theta_c) \left[W_c(\bar{x}) - U_c \right] \\
rW_c(x) &= v(w_c(x), p_c) + \lambda \left[\int_{x^w_{Dc}}^{\bar{x}} W_c(s) \, \mathrm{d}G(s) + G(x^w_{Dc}) \max_{c' \in C} \{U_{c'}\} - W_c(x) \right] \\
W_c(x^w_{Dc}) &= U_c
\end{aligned}
$$

Firms post vacancies by paying a flow cost κ. When a vacancy gets filled, it is allocated the highest productivity. Filled jobs produce output, pay wages and get shocked with a new idiosyncratic productivity with probability λ. If the new idiosyncratic productivity is lower than x^f_{Dc}, firms decide to break the match and the job turns to a new vacancy, where x^f_{Dc} makes the firm indifferent. The output produced by a firm depends both on the idiosyncratic productivity of the match and on the city-specific productivity A_c. Thus, the behavior of firms is described by

$$
\begin{aligned}
rV_c &= -\kappa + q(\theta_c) \left[J(\bar{x}) - V_c \right] \\
rJ_c(x) &= A_c x - w_c(x) + \lambda \left[\int_{x^f_{Dc}}^{\bar{x}} J_c(s) \, \mathrm{d}G(s) + G(x^f_{Dc}) V_c - J_c(x) \right] \\
J_c(x^f_{Dc}) &= V_c
\end{aligned}
$$

where V and J the value of an unoccupied and and occupied job, respectively. Just as workers pay for housing in order to live in city c, firms need to pay an entry cost to be located in city c. This entry cost is paid only once, and it is assumed to be a function f of the city's housing price. Intuitively, before posting vacancies and producing, firms need to rent a spot in the outskirts[3] of the city where employees work. Since there is free entry of firms, they locate in city c until

$$rV_c = f(p_c)$$

Finally, wages split the surplus of the match in constant shares:

$$W_c(x) - U_c = \beta \left[W_c(x) - U_c + J_c(x) - V_c \right]$$

Thus, firms and workers always agree on whether to break or keep the match. That is,

$$x^w_{Dc} = x^f_{Dc} = x_{Dc}$$

[3]That is, they will not influence the housing market of workers.

The main difference with respect to a textbook frictional labor market with endogenous separation (such as the one in Pissarides (2000)) is the city entry cost for firms. Its function is to dampen vacancy posting and make it less responsive to productivity differences. The intuition is as follows. Everything else equal, workers move to cities with higher city-specific productivity, where they will earn higher wages. If firms were not able to adjust the amount of vacancies they post, worker mobility would drive market tightness -and hence the job finding rate- down. Given that housing prices go up as workers flow into a city, the fact that firms need to buy a unit of land whose price depends on housing prices makes it costlier for them to adjust the amount of vacancies posted.

2.3.3 Equilibrium

First, we solve for the wage. Using $rW_c(x)$ and $rJ_c(x)$ into the surplus-sharing equation one gets

$$(1-\beta)v(w_c(x), p_c) + \beta w_c(x) = \beta A_c x + (1-\beta)rU - \beta r V_c$$

Subsituting for $v(\cdot)$, U and V_c, we find that the wage is given by

$$w_c(x) = \frac{a_c(1-\beta)(1-\delta)^{1-\delta}\delta^{\delta}b + \beta p_c^{\delta}\left[A_c x + \theta_c \kappa + f(p_c)(\theta_c - 1)\right]}{a_c(1-\beta)(1-\delta)^{1-\delta}\delta^{\delta} + \beta p_c^{\delta}}$$

Second, we need to find the job creation and destruction equations (that is, the solution for θ_c and x_{Dc}). To do so, evaluate the value of a filled job at x_{Dc} and plug the resulting expression back into the value of a filled job to get

$$(r+\lambda)J_c(x) = A_c(x - x_{Dc}) + w_c(x_{Dc}) - w_c(x) + (r+\lambda)V_c$$

Substituting for the wage gives us

$$J_c(x) - V_c = \frac{a_c(1-\beta)(1-\delta)^{1-\delta}\delta^{\delta}A_c(x - x_{Dc})}{(r+\lambda)\left[a_c(1-\beta)(1-\delta)^{1-\delta}\delta^{\delta} + \beta p_c^{\delta}\right]}$$

At the same time, imposing free entry into the value of a vacancy gives us

$$J_c(\bar{x}) - V_c = \frac{f(p_c) + \kappa}{q(\theta_c)}$$

Combining the two expressions gives us the job creation equation, which is an equation in x_{Dc} and θ_c (given p_c):

$$\frac{f(p_c) + \kappa}{q(\theta_c)} = \frac{a_c(1-\beta)(1-\delta)^{1-\delta}\delta^{\delta}A_c(\bar{x} - x_{Dc})}{(r+\lambda)\left[a_c(1-\beta)(1-\delta)^{1-\delta}\delta^{\delta} + \beta p_c^{\delta}\right]}$$

To find the job destruction equation, note that we can rewrite the Bellman equation for the value of a filled job as

$$rJ_c(x) = A_c x - w_c(x) + \lambda \left[\int_{x_{Dc}}^{\bar{x}} J_c(s) - V_c \, \mathrm{d}G(s) + V_c - J_c(x) \right]$$

Plugging in the expression for $J_c(x) - V_c$ into the integral and evaluating everything at $x = x_{Dc}$ we get

$$rV_c = A_c x_{Dc} - w_c(x_{Dc}) + \frac{\lambda}{r+\lambda} \int_{x_{Dc}}^{\bar{x}} \frac{a_c(1-\beta)(1-\delta)^{1-\delta}\delta^\delta A_c \left[s - x_{Dc}\right]}{a_c(1-\beta)(1-\delta)^{1-\delta}\delta^\delta + \beta p_c^\delta} \, \mathrm{d}G(s)$$

Finally, plug in the wage and rearrange terms to obtain the job destruction equation, which is also an equation in x_{Dc} and θ_c (given p_c):

$$x_{Dc} = \frac{b + f(p_c)}{A_c} + \frac{\beta p_c^\delta}{a_c(1-\beta)(1-\delta)^{1-\delta}\delta^\delta} \frac{(\kappa + f(p_c))\theta_c}{A_c} - \frac{\lambda}{r+\lambda} \int_{x_{Dc}}^{\bar{x}} s - x_{Dc} \, \mathrm{d}G(s)$$

Third, we need to pin down housing prices. Because workers can be in two income states, employment and unemployment, we deal with two types of consumers of housing. However, this means that workers constantly readjust their consumption of housing as they switch across labor market states. In order to avoid this, I assume that there is perfect income sharing at the city level. That is, the local government imposes a 100% tax on income that is then fully distributed in equal shares to every worker in the city. Therefore, everyone in city c has the same income

$$y_{ic} = y_c = \frac{u_c}{L_c} b + \left(1 - \frac{u_c}{L_c}\right) \int_{x_{Dc}}^{\bar{x}} w_c(s) \, \mathrm{d}G_{x_D}(s)$$

where G_{x_D} is the truncated distribution:

$$G_{x_D} = P(x < X | x > x_D) = \frac{G(x)}{1 - G(x_D)}$$

Note that I derived the wage equation assuming different incomes. But if all workers receive the same flow income one might think that there is no incentive for them to secure a good deal with their matching firm. However, we can think of individuals as living in families, within which some individuals work and some are unemployed. Then we can rephrase the income-pooling assumption as saying that individuals maximize family income, and the family distributes it equally among its members. Under this assumption, the equilibrium in the housing market is given by

$$\delta \left[u_c \frac{b}{p_c} + (L_c - u_c) \int_{x_{Dc}}^{\bar{x}} \frac{w_c(s)}{p_c} \, \mathrm{d}G_{x_D}(s) \right] = \bar{H}_c$$

where

$$\frac{u_c}{L_c} = \frac{\lambda G(x_{Dc})}{\lambda G(x_{Dc}) + \theta_c q(\theta_c)}$$

Finally, we need to find the spatial allocation of workers that satisfies the aggregate resource constraint,

$$\sum_{c \in C} L_c = \bar{L},$$

and utility equalization

$$U_c = U \text{ for all } c$$

Note that with income pooling both unemployed and employed workers of all productivity types get the same flow payment. As a result, the *ex post* present-discounted values of every labor market state must be the same. That is,

$$W_c(x) = U_c \;\; \forall x$$

Therefore, there is not only perfect spatial equalization of the value of being unemployed but also of the value of being employed, regardless of one's type and location:

$$W_c(x) = U_c = U \;\; \forall x, c$$

Given that the present-discounted value of being located in city c is given by

$$rU_c = v(y_c, p_c),$$

the spatial equilibrium requires that flow utilities are equalized across cities. That is,

$$v(y_c, p_c) = v(y_{c'}, p_{c'}) \;\; \forall c, c' \in C$$

or, substituting:

$$a_c \left[\frac{u_c}{L_c} \frac{b}{p_c^\delta} + \left(1 - \frac{u_c}{L_c}\right) \int_{x_{Dc}}^{\bar{x}} \frac{w_c(s)}{p_c^\delta} \, \mathrm{d}G_{x_{Dc}}(s) \right] =$$
$$= a_{c'} \left[\frac{u_{c'}}{L_{c'}} \frac{b}{p_{c'}^\delta} + \left(1 - \frac{u_{c'}}{L_{c'}}\right) \int_{x_{Dc'}}^{\bar{x}} \frac{w_{c'}(s)}{p_{c'}^\delta} \, \mathrm{d}G_{x_{Dc'}}(s) \right] \forall c, c' \in C$$

2.3.4 Discussion

The standard textbook frictional labor market has a strong and intuitive connexion between productivity and vacancy posting: the more productive a market, the higher the surplus, so firms post more vacancies, which implies a higher job finding rate for workers. However, this is not what we see in the data when we compare small (low productivity) cities and large (high productivity) cities. The mechanisms that reconcile the frictional labor market with the data are labor mobility and housing prices. The key intuition of the model presented here is that workers need to be more sensitive to productivity differences across cities than firms. Thanks to higher housing prices, the firm's response to productivity differences is dampened so that labor mobility becomes more sensitive to productivity differences than vacancy posting.

2.3.5 Estimation

Data

In order to estimate the model, we use data on job finding and separation rates, which are computed as unemployment- to- employment and employment- to- unemployment transition frequencies, respectively, using microdata from the Current Population Survey (CPS). Unemployment rates and city size (that is, labor force) are also computed from CPS microdata.[4]

Wages and housing prices are computed as in Eeckhout et al. (2014). In particular, wages are computed using microdata from the CPS merged outgoing rotation groups as provided by the NBER. I restrict the sample to full-time workers in identified metropolitan statistical areas (MSAs), I drop each year's lowest 0.5% (weekly) wage earnings (as a way of eliminating likely misreported wages close to zero) and compute each MSA's year average weekly earnings. As for housing prices, data comes from the 2012-2013 American Community Survey (ACS) as provided by the Minnesota Population Center in its Integrated Public Use Microdata Series (IPUMS). I restrict the sample to housing units in identified MSAs (excluding units in group quarters, farmhouses, mobile homes, trailers, boats, tents and vans). The ACS provides information on the monthly contract rent for rental units and several housing characteristics of the unit (the number of rooms, the units in structure, and the age of structure). Using this information I run hedonic regressions with MSA fixed effects. The MSA's housing price index is computed as the estimated MSA fixed effect, which is standarized so that its weighted (by housing units) mean is equal to one. Finally, data on land comes from the 2013 U.S. Gazetteer Files provided by the US Census information on land area in square meters at the county level (counties are matched to MSAs using the 2013 delineation fixed by the Office of Management and Budget).

Note that the model is static. Thus, I estimate it using data for a given year (in particular, 2013).

[4]See chapter 1 of the thesis for more details on these data.

Algorithm

The model is described by

$$\frac{f(p_c)+\kappa}{q(\theta_c)} = \frac{a_c(1-\beta)(1-\delta)^{1-\delta}\delta^\delta A_c(\bar{x}-x_{Dc})}{(r+\lambda)\left[a_c(1-\beta)(1-\delta)^{1-\delta}\delta^\delta + \beta p_c^\delta\right]} \tag{JC}$$

$$x_{Dc} = \frac{b+f(p_c)}{A_c} + \frac{\beta p_c^\delta}{a_c(1-\beta)(1-\delta)^{1-\delta}\delta^\delta}\frac{(\kappa+f(p_c))\theta_c}{A_c} -$$

$$-\frac{\lambda}{r+\lambda}\int_{x_{Dc}}^{\bar{x}} s - x_{Dc}\,\mathrm{d}G(s) \tag{JD}$$

$$\delta\left[u_c\frac{b}{p_c} + (L_c-u_c)\int_{x_{Dc}}^{\bar{x}}\frac{w_c(s)}{p_c}\,\mathrm{d}G_{x_D}(s)\right] = \bar{H}_c \tag{H}$$

$$a_c\left[\frac{u_c}{L_c}\frac{b}{p_c^\delta} + \left(1-\frac{u_c}{L_c}\right)\int_{x_{Dc}}^{\bar{x}}\frac{w_c(s)}{p_c^\delta}\,\mathrm{d}G_{x_D}(s)\right] = \bar{U}\ \ \forall c\in C \tag{U}$$

$$\sum_{c\in C} L_c = \bar{L} \tag{L}$$

where

$$w_c(x) = \frac{a_c(1-\beta)(1-\delta)^{1-\delta}\delta^\delta b + \beta p_c^\delta\left[A_c x + \theta_c\kappa + f(p_c)(\theta_c-1)\right]}{a_c(1-\beta)(1-\delta)^{1-\delta}\delta^\delta + \beta p_c^\delta} \tag{W}$$

$$\frac{u_c}{L_c} = \frac{\lambda G(x_{Dc})}{\lambda G(x_{Dc}) + \theta_c q(\theta_c)}$$

Assume the following functional forms:

$$f(p_c) = \psi p_c^\xi$$
$$m(v_c,u_c) = \phi v_c^{1-\alpha}u_c^\alpha \Rightarrow q(\theta_c) = \phi\theta^{-\alpha},$$
$$G(x) = \frac{x-\underline{x}}{\bar{x}-\underline{x}}$$

where $\underline{x}$ is normalized to 0.

There are 6 city-specific variables:

$$\{a_c, A_c, p_c, L_c, \theta_c, x_{Dc}\}$$

and I have data on

$$\{w_c, p_c, L_c, ue_c, eu_c, \bar{H}_c\}$$

where ue_c and eu_c are linked to θ_c and x_{Dc} by

$$ue_c = \theta_c q(\theta_c) \tag{UE}$$
$$eu_c = \lambda G(x_{Dc}) \tag{EU}$$

I calibrate the following parameters:

$$\{\beta, \delta, r\}$$

To ensure utility equalization, I focus on utilities relative to city 1 and normalize $a_1 = 1$. That is,

$$\frac{U_c}{U_1} = a_c \left[\frac{\frac{u_c}{L_c}\frac{b}{p_c^\delta} + \left(1 - \frac{u_c}{L_c}\right)\int_{x_{Dc}}^{\bar{x}} \frac{w_c(s)}{p_c^\delta}\,\mathrm{d}G_{x_{Dc}}(s)}{\frac{u_1}{L_1}\frac{b}{p_1^\delta} + \left(1 - \frac{u_1}{L_1}\right)\int_{x_{D1}}^{\bar{x}} \frac{w_1(s)}{p_1^\delta}\,\mathrm{d}G_{x_{D1}}(s)} \right] = 1$$

I estimate the following parameters

$$\{\lambda, \bar{x}, \alpha, \kappa, b, \phi, \psi, \xi\}$$

Denote data-based variables with a d superscript and model-based variables with a m superscript. The algorithm is as follows:

1. Back out θ_c as a function of α and ϕ from

$$ue_c = \phi\theta_c^d(\alpha, \phi)^{1-\alpha}$$

2. Given that we normalize $\underline{x}$, back out $x_{Dc}(\lambda, \bar{x})$ as a function of $\{\lambda, \bar{x}\}$ from

$$eu_c = \lambda \cdot \frac{x_{Dc}^d(\lambda, \bar{x}) - \underline{x}}{\bar{x} - \underline{x}}$$

3. Given $a_1 = 1$, compute U_1 as a function of b using data on u_1, p_1, L_1 and w_1 from

$$U_1 = \left[\frac{u_1^d}{L_1^d}\frac{b}{p_1^{d\delta}} + \left(1 - \frac{u_1^d}{L_1^d}\right)\frac{w_1^d}{p_1^{d\delta}} \right]$$

and, then, compute a_c^d as a function of b using data on u_c, p_c, L_c and w_c from utility equalization:

$$a_c(b) \equiv a_c^d : a_c(b)\frac{\frac{u_c^d}{L_c^d}\frac{b}{p_c^{d\delta}} + \left(1 - \frac{u_c^d}{L_c^d}\right)\frac{w_c^d}{p_c^{d\delta}}}{U_1(b)} = 1$$

4. Now we can back out A_c as a function of $\{\lambda, \bar{x}, b, \kappa, \phi, \alpha\}$ by imposing that the model's expected wage, given $\theta_c^d(\phi, \alpha)$ and $x_{Dc}^d(\lambda, \bar{x})$, must be equal to the data-based wage of each city:

$$A_c(\lambda, \bar{x}, b, \kappa, \phi, \alpha) \equiv A_c^d :$$

$$w_c^d = w_c(x) = \frac{a_c^d(1-\beta)(1-\delta)^{1-\delta}\delta^\delta b + \beta p_c^{d\delta}\left[A_c^d E[x|x > x_{Dc}^d] + \theta_c^d\kappa + f(p_c^d)\left(\theta_c^d - 1\right)\right]}{a_c^d(1-\beta)(1-\delta)^{1-\delta}\delta^\delta + \beta p_c^{d\delta}}$$

where note that we also use data on housing prices, p_c^d.

5. Given A_c^d and a_c^d, solve the model as a function of $\{\lambda, \bar{x}, b, \kappa, \phi, \alpha, \psi, \xi\}$. That is, find $\{x_{Dc}^m, \theta_c^m, p_c^m, L_c^m\}$, which are a function of $(\lambda, \bar{x}, b, \kappa, \phi, \alpha, \psi, \xi)$, such that

$$\frac{f(p_c^m)+\kappa}{q(\theta_c^m)} = \frac{a_c^d(1-\beta)(1-\delta)^{1-\delta}\delta^\delta A_c^d(\bar{x}-x_{Dc}^m)}{(r+\lambda)\left[a_c^d(1-\beta)(1-\delta)^{1-\delta}\delta^\delta + \beta p_c^{m\delta}\right]}$$

$$x_{Dc}^m = \frac{b+f(p_c^m)}{A_c^d} + \frac{\beta p_c^{m\delta}}{a_c^d(1-\beta)(1-\delta)^{1-\delta}\delta^\delta}\frac{[\kappa+f(p_c^m)]\theta_c^m}{A_c^d} - \frac{\lambda}{r+\lambda}\int_{x_{Dc}^m}^{\bar{x}} s - x_{Dc}^m \,\mathrm{d}G(s)$$

$$\delta\left[u_c^m \frac{b}{p_c^m} + (L_c^m - u_c^m)\int_{x_{Dc}^m}^{\bar{x}} \frac{w_c^m(s)}{p_c^m}\,\mathrm{d}G_{x_D}(s)\right] = \bar{H}_c^d$$

$$a_c^d\left[\frac{\frac{u_c^m}{L_c^m}\frac{b}{p_c^{m\delta}} + \left(1-\frac{u_c^m}{L_c^m}\right)\int_{x_{Dc}^m}^{\bar{x}}\frac{w_c^m(s)}{p_c^{m\delta}}\,\mathrm{d}G_{x_{Dc}}(s)}{\frac{u_1^m}{L_1^m}\frac{b}{p_1^{m\delta}} + \left(1-\frac{u_1^m}{L_1^m}\right)\int_{x_{D1}^m}^{\bar{x}}\frac{w_1^m(s)}{p_1^{m\delta}}\,\mathrm{d}G_{x_{D1}}(s)}\right] = 1 \;\; \forall c \in C$$

$$\frac{u_c^m}{L_c^m} = \frac{\lambda G(x_{Dc}^m)}{\lambda G(x_{Dc}^m) + \theta_c^m q(\theta_c^m)}$$

where L is known, L_1 is derived from

$$\sum_{c\in C} L_c^m(\lambda, \bar{x}) = L$$

and the wage is given by

$$w_c^m(x) = \frac{a_c^d(1-\beta)(1-\delta)^{1-\delta}\delta^\delta b + \beta p_c^{m\delta}\left[A_c^d x + \theta_c^m\kappa + f(p_c^m)\left(\theta_c^m - 1\right)\right]}{a_c^d(1-\beta)(1-\delta)^{1-\delta}\delta^\delta + \beta p_c^{m\delta}}$$

6. Find $\{\lambda, \bar{x}, b, \kappa, \phi, \alpha, \psi, \xi\}$ such that the following loss functions are minimized:

$$\frac{\sum_{c\in C}(L_c^d - L_c^m)^2}{var(L_c^d)}$$
$$\frac{\sum_{c\in C}(p_c^d - p_c^m)^2}{var(p_c^d)}$$
$$\frac{\sum_{c\in C}(w_c^d - w_c^m)^2}{var(w_c^d)}$$
$$\frac{\sum_{c\in C}(\theta_c^d - \theta_c^m)^2}{var(\theta_c^d)}$$
$$\frac{\sum_{c\in C}(x_{Dc}^d - x_{Dc}^m)^2}{var(x_{Dc}^d)}$$
$$\frac{\sum_{c\in C}(u_c^d - u_c^m)^2}{var(u_c^d)}$$

Estimation output

I have run this algorithm successfully with fake data provided that the initial guess of the algorithm is equal to the estimation's solution. Thus, the algorithm works. However, I have failed in successfully mapping the model to real-world data. This is either the model's or the estimation algorithm's fault. Thus, next I proceed to estimate a simplified version of the model.

A simplified estimation

Given that the full model has trouble in matching the data, I also estimate a much simplified version of the model that preserves its main mechanisms. First, I assume that $\delta = 0$ but that housing is paid as a lump-sum tax. That is,

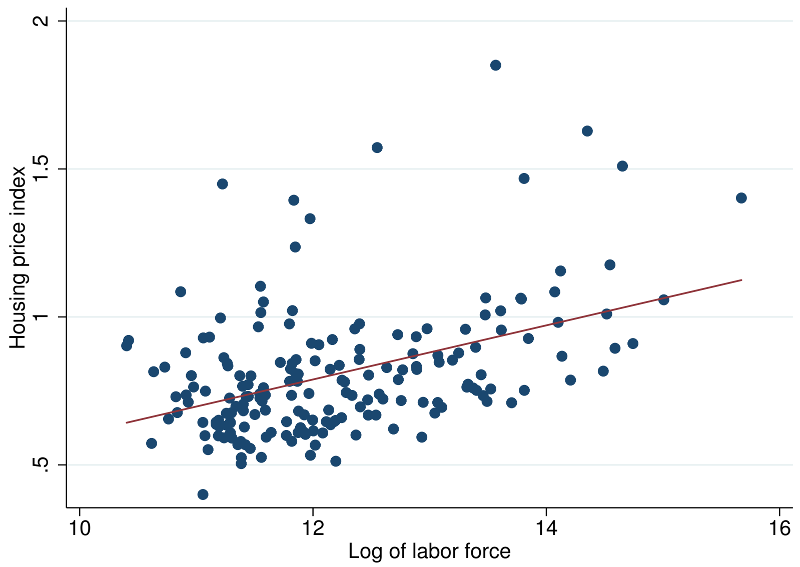
$$\max_{c_{ic}} u = a_c + c_{ic}$$
$$\text{s.t. } c_{ic} + p_c = y$$

Second, I exogenize the housing market and assume that housing prices are given by

$$p_c = \delta_0 + \delta_1 \ln(L_c)$$

which, as Figure 2.2 shows, generally has a good fit.

Figure 2.2: Housing prices and city size



Therefore, in the estimation L_c is inputed as data and p_c is inputed as fitted data.

Deriving the model just as before, I obtain the following equilibrium characterization:

$$\frac{f(p_c)+\kappa}{q(\theta_c)} = \frac{(1-\beta)A_c(\bar{x}-x_{Dc})}{r+\lambda} \tag{JC}$$

$$x_{Dc} = \frac{b+f(p_c)}{A_c} + \frac{(\kappa+f(p_c))\theta_c\beta}{(1-\beta)A_c} - \frac{\lambda}{r+\lambda}\int_{x_{Dc}}^{\bar{x}} s - x_{Dc}\,\mathrm{d}G(s) \tag{JD}$$

$$p_c = \delta_0 + \delta_1 \ln(L_c)$$

$$b - p_c + a_c + \frac{\beta\theta}{1-\beta}(f(p_c)+\kappa) = \bar{U} \;\; \forall c \in C$$

$$\sum_{c\in C} L_c = \bar{L}$$

where

$$w_c(x) = (1-\beta)b + \beta\left[A_c x + \theta_c\kappa + f(p_c)(\theta_c - 1)\right]$$

$$\frac{u_c}{L_c} = \frac{\lambda G(x_{Dc})}{\lambda G(x_{Dc}) + \theta_c q(\theta_c)}$$

To estimate the model, I assume

$$G(x) = \frac{x-\underline{x}}{\bar{x}-\underline{x}}$$

$$q(\theta) = \phi\theta^{-\alpha}$$

$$f(p) = \psi p^{\xi}$$

I calibrate the following parameters:[5]

Table 2.2: Endogenous frictional vacancy posting: Calibration

r	$\underline{x}$	ϕ	δ_0	δ_1	ψ	$\bar{L}$
0.012	0	1.355	-0.2282	0.0851	1	1

where δ_0 and δ_1 are taken from the regression of the housing price index on the (log) of the MSAs labor force. As for the remaining $\{\alpha, \xi, \beta, \bar{x}.\lambda, b, \kappa\}$ parameters, I set a large grid $\{\alpha_i, \xi_i, \beta_i, \bar{x}_i.\lambda_i, b_i, \kappa_i\}_{i=1}^{N}$. This is a large grid, so I set

[5] ϕ and r come from Shimer (2005).

$N = 5$ and define the grid as

$$\begin{aligned}
\alpha &= \{0.1, \ldots, 0.9\} \\
\xi &= \{1, \ldots, 3\} \\
\beta &= \{0.1, \ldots, 0.95\} \\
\bar{x} &= \{1, \ldots, 5\} \\
\lambda &= \{0.1, \ldots, 0.9\} \\
b &= \{0.1, \ldots, 0.9\} \\
\kappa &= \{0.1, \ldots, 0.9\}
\end{aligned}$$

Then, for each point in the grid, the algorithm is as follows:

1. Get θ_c and x_{Dc} implied by the data and the functional form assumptions for $G(\cdot)$ and $q(\cdot)$.

2. Get A_c implied by the data (i.e. using the wage equation).

3. Given A_c, find $\{\theta_c, x_{Dc}\}$ that solve JC and JD (recall that L_c, p_c are data).

4. Find a_c as the residual that ensures utility equalization.

5. Compute model-data discrepancy for θ_c, x_{Dc}, w_c, given by:

$$L(y) \equiv \frac{\sum_{c=1}^{C} \left(y_c^{model} - y_c^{data}\right)^2}{\sum_{c=1}^{C} \left(y_c^{data} - \bar{y}^{data}\right)^2}$$

   for $y_c = \{\theta_c, x_{Dc}, w_c\}$

Finally, to reduce noise, the data on job finding and separation rates, housing prices, wages and labor force used to discipline the model come from 185 on-the-regression-line cities: that is, fictitious cities that are on the regression line when regressing each variable on the log of labor force.

Figures 2.3 to 2.4 plot the model-predicted job finding and separation rates against the (log) of city size when minimizing the sum of $L(\theta)$, $L(x_D)$ and $L(w)$.

Clearly, the model does not do a good job at matching both rates. In fact, at most it can replicate one of the flows. For instance, Figures 2.5 to 2.6 plot the estimation output when when minimizing $L(x_D)$.

Figure 2.3: Predicted unemployment-to-employment frequency - full loss

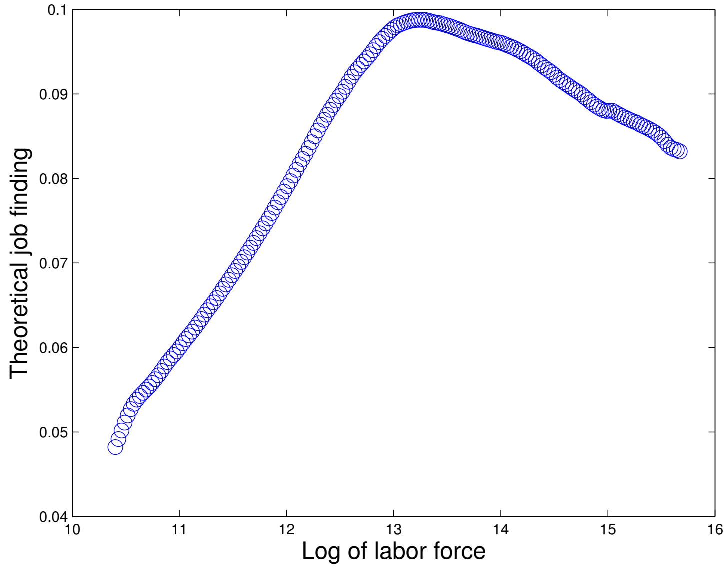


Figure 2.4: Predicted employment-to-unemployment frequency - full loss

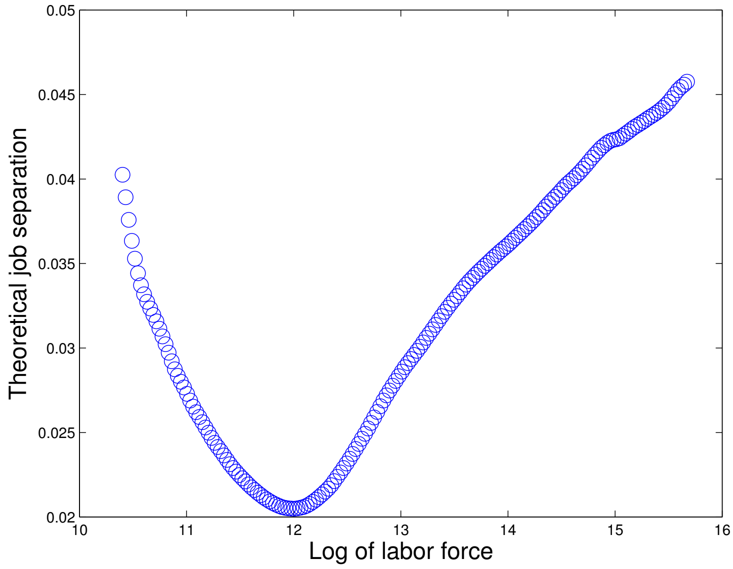


Figure 2.5: Predicted unemployment-to-employment frequency - $L(x_D)$

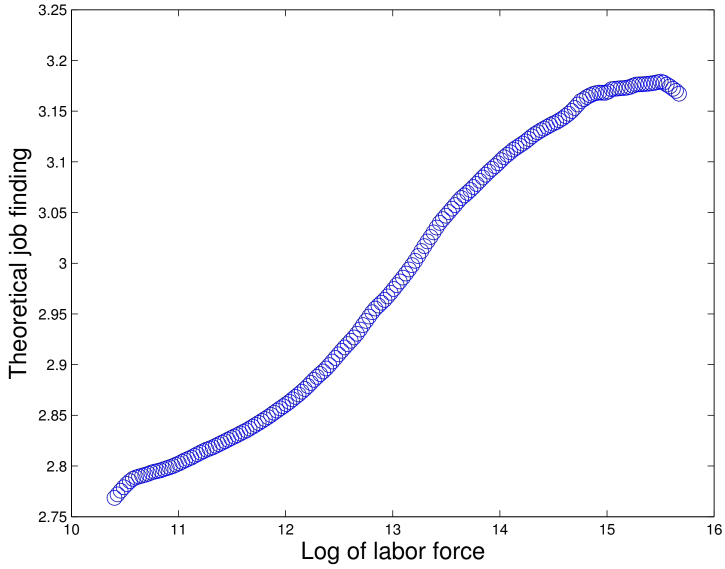
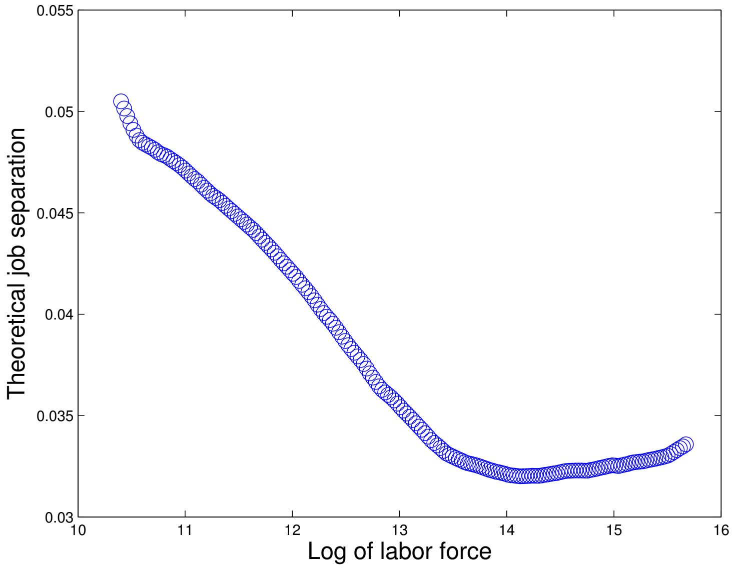


Figure 2.6: Predicted employment-to-unemployment frequency - $L(x_D)$



2.4 Specialization

2.4.1 Intuition

A potential explanation for labor productivity being increasing in city size is that jobs have a higher degree of specialization bigger cities. Greater specialization potentially has two implications that could help rationalize the decreasing-in-city-size labor market flows: greater specialization might make it more difficult to find a match (see, for instance, the search model of Kiyotaki & Wright (1993) in the context of monetary economics) and it might also increase the quality of the match, which in turn would reduce separation rates. To assess these mechanisms and their implications, I develop a spatial equilibrium model with frictional unemployment and specialization of workers. In particular, I extend a simplified version of Postel-Vinay & Robin (2002a) by allowing for endogenous vacancy posting. The motivation for working with an environment close to the one in Postel-Vinay & Robin (2002a) is that in this environment it is simple to derive implications on job-to-job flows (recall that in chapter 1 of thesis I documented that job-to-job flows are also decreasing in city size).

2.4.2 Setup

In each local labor market, all firms can post vacancies and all firms can hire employed and unemployed workers. The number of matches m_i depends on a common matching function m (which takes as an input the number of vacancies v, and the number of unemployed u and employed e workers) and a market-specific matching efficiency λ_i:

$$m_i = \lambda_i \cdot m(v, u + e),\ i = \{0, 1\} \tag{2.1}$$

where 0 stands for unemployed workers and 1 stands for employed workers. That is, on-the-job offers and first-job offers share the same pool of workers but they might have different matching efficiencies. Define:

$$\theta \equiv \frac{v}{u+e},\ q(\theta) \equiv m\left(1, \frac{u+e}{v}\right) \tag{2.2}$$

The evolution of the unemployment rate[6] and the steady state unemployment rate are given by:

$$u_{t+1} = u_t + (1 - u_t)\delta - u_t \cdot \lambda_0 \theta q(\theta) \tag{2.3}$$

$$\Rightarrow u = \frac{\delta}{\delta + \lambda_0 \theta q(\theta)} \tag{2.4}$$

[6] I assume a population of mass 1.

where δ is the exogenous probability with which employed workers transition to unemployment.

2.4.3 Notation

Following Postel-Vinay & Robin (2002a), firms have heterogeneous productivities, which are distributed over $[\underline{p}, \bar{p}]$ according to a cumulative distribution function Γ. Also, define $\bar{\Gamma} = 1 - \Gamma$. Unemployed workers get unemployment benefits equal to b. The lifetime utility of being unemployed is denoted by V_0. The optimal wage offer made by a p-firm to an unemployed worker is denoted by $\phi_0(b)$. Similarly, employed workers in a productivity-p firm get paid w and their lifetime utility is denoted by $V(b, w, p)$. Employed workers get offers from other firms. Thus, denote by $\phi(p, p')$ the optimal wage offer made by a p'-firm to a worker employed in a p-firm such that the worker is willing to accept it. At most, a p-firm is able to offer a wage equal to its productivity. Denote by $s(w, p)$ the productivity of a firm such that the optimal wage offer of such s-firm to a worker earning w in a p firm is given by

$$\phi(s(w, p), p) = w$$

Observe that when $s < p' < p$, the offer from the p'-firm will grant a wage rise to the worker, who will stay in the p-firm. Instead, when $p < p'$ the worker will also get a wage rise, but now she will switch to the p'-firm.

2.4.4 The problem of employees

At each point in time, employees earn a wage that was bargained over when they got hired. Their status can change in three directions: 1) they might become unemployed, 2) they might earn a wage rise within the firm they are already working for (thanks to receiving an external offer that gives them bargaining power), or 3) they might find a new job (where they get offered a wage good enough to make them indifferent between staying in the old job or switching jobs). Thus, the lifetime value of being employed in a p-firm earning w, $V(w, p)$, is

$$\begin{aligned}
&[r + \delta + \lambda_1 \theta q(\theta) \bar{\Gamma}(s(w, p))] V(w, p) = \\
&= w + \lambda_1 \theta q(\theta) \left[\Gamma(p) - \Gamma(s(w, p))\right] \cdot E_{p'}[V(p', p') | s(w, p) < p' \leq p] + \quad (2.5) \\
&+ \lambda_1 \theta q(\theta) \bar{\Gamma}(p) V(p, p) + \delta V_0 \quad (2.6)
\end{aligned}$$

where r is the discount rate. Evaluate this expression at $w = p$ to obtain:

$$V(p, p) = \frac{p + \delta V_0}{r + \delta} \tag{2.7}$$

since $s(p,p) = p$. Now plug it back:

$$(r + \delta + \lambda_1\theta q(\theta)\bar{\Gamma}(s(w,p))]V(w,p) =$$

$$= w + \lambda_1\theta q(\theta)\int_{s(w,p)}^{p}\frac{x+\delta V_0}{r+\delta}\mathrm{d}\Gamma(x) + \lambda_1\theta q(\theta)\bar{\Gamma}(p)\left(\frac{p+\delta V_0}{r+\delta}\right) + \delta V_0 \quad (2.8)$$

Next note that:

$$V(w,p) = V(s(w,p), s(w,p))$$

and hence

$$V(w,p) = \frac{s(w,p) + \delta V_0}{r+\delta}$$

Plugging it into (2.8) one can show that:

$$s(w,p) = w + \frac{\lambda_1\theta q(\theta)}{r+\delta}\int_{s(w,p)}^{p}\bar{\Gamma}(x)\mathrm{d}x \quad (2.9)$$

Then one can show that:

$$\phi(p,p') = p - \frac{\lambda_1\theta q(\theta)}{r+\delta}\int_{p}^{p'}\bar{\Gamma}(x)\mathrm{d}x \quad (2.10)$$

$$\phi_0(p) = b - \frac{\lambda_1\theta q(\theta)}{r+\delta}\int_{b}^{p}\bar{\Gamma}(x)\mathrm{d}x \quad (2.11)$$

As Postel-Vinay & Robin (2002a) point out, unemployed workers are willing to accept a flow wage lower than the unemployment benefits they receive: by accepting such an offer, they also gain the option of starting climbing up the wage ladder as on-the-job offers arrive.

2.4.5 The problem of the unemployed

Unemployed workers earn unemployment benefits but their situation might change if they get a job offer. Thus, the lifetime value of being unemployed is:

$$(r + \lambda_0\theta q(\theta))V_0 = b + \lambda_0\theta q(\theta)E_p[V(\phi_0(p),p)] \quad (2.12)$$

Firms have all the bargaining power. Thus, if a wage offer arrives, a firm will offer a wage that makes the worker indifferent between working or not working. That is, they make an offer $\phi_0(p)$ such that

$$V_0 = V(\phi_0(p),p) \quad (2.13)$$

which implies that:

$$V_0 = \frac{b}{r} \quad (2.14)$$

2.4.6 The problem of firms

Firms open vacancies at a flow cost κ to hire unemployed and currently employed workers. Search is random. Filled vacancies get a productivity $p \in [\underline{p}, \bar{p}]$ from Γ, and their value is denoted by J. Thus, the value F of posting a vacancy is given by:

$$
\begin{aligned}
&[r + (\lambda_0 + \lambda_1)q(\theta)]F = -\kappa + \\
&+ q(\theta)\left\{\lambda_0 E_p[J(p, \phi_0(p))] + \lambda_1 E_{p,w}[J(p, \phi(p', p))]\right\}
\end{aligned} \tag{2.15}
$$

Because there is free entry of firms,

$$F = 0$$

Thus:

$$\lambda_0 E_p[J(p, \phi_0(p))] + \lambda_1 E_{p,w}[J(p, \phi(p', p))] = \frac{\kappa}{q(\theta)} \tag{2.16}$$

where

$$
\begin{aligned}
E_p[J(p, \phi_0(p))] &= \int_{\underline{p}}^{\bar{p}} J(x, \phi_0(x)) \mathrm{d}\Gamma(x) \\
E_{p,w}[J(p, \phi(p', p))] &= \int_{\underline{p}}^{\bar{p}} \int_{\underline{p}}^{x} J(x, \phi(y, x)) \mathrm{d}\Gamma(y) \mathrm{d}\Gamma(x)
\end{aligned}
$$

A firm with a filled job can experience a change in its status because of three reasons: 1) the match gets destroyed, 2) the firm must raise the worker's wage to prevent her from switching employers, or 3) the firm cannot prevent its employee to switch employers. Thus, the value J of a filled job with productivity p and paying a wage w is:

$$
\begin{aligned}
&[r + \delta + \lambda_1 \theta q(\theta) \bar{\Gamma}(s(w, p))] J(p, w) = p - w + \\
&+ \lambda_1 \theta q(\theta) \left[\Gamma(p) - \bar{\Gamma}(s(w, p))\right] \cdot E_{p'}\left[J(p, \phi(p', p)) | s < p' \leq p\right]
\end{aligned} \tag{2.17}
$$

where

$$
w = \begin{cases} \phi_0(p) & \text{if hired from unemployment} \\ \phi(p', p) & \text{if hired on the job} \end{cases}
$$

$$
\begin{aligned}
&\left[\Gamma(p) - \bar{\Gamma}(s(w, p))\right] \cdot E_{p'}\left[J(p, \phi(p', p)) | s < p' \leq p\right] = \\
&= \int_{s(w,p)}^{p} J(p, \phi(x, p)) \mathrm{d}\Gamma(x)
\end{aligned}
$$

2.4.7 Simplification: one type of firms

I will solve a simplified version of this model. In particular, I assume that there is only one type p of firms. In this case, it is easy to see that the value of posting a vacancy is

$$[r + (\lambda_0 + \lambda_1)q(\theta)]F = -\kappa + q(\theta)\left[\lambda_0 J(\phi_0) + \lambda_1 J(\phi(p,p))\right]$$

Note that the wage offered to an unemployed worker is now:

$$\phi_0(p) = \phi_0 = b - \frac{\lambda_1 \theta q(\theta)}{r+\delta} \cdot [p-b]$$

Also note that hiring a worker from a rival firm implies that all surplus must go to the worker. That is, $\phi(p,p) = p$. Then it must be the case that $J(\phi(p,p)) = 0$ and thus free entry ($F = 0$) implies:

$$J(\phi_0) = \frac{\kappa}{\lambda_0 q(\theta)}$$

Clearly, the value of a filled job is:

$$\begin{aligned}
&[r + \delta + \lambda_1 \theta q(\theta)]\, J(w) = p - w + \lambda_1 \theta q(\theta) J(\phi(p,p)) = \\
&= p - w
\end{aligned}$$

since $J(\phi(p,p)) = 0$. Then,

$$J(\phi_0) = \frac{p - \phi_0}{r + \delta + \lambda_1 \theta q(\theta)}$$

Substituting for ϕ_0 and combining the whole expression with free entry:

$$\frac{p - b + \frac{\lambda_1 \theta q(\theta)}{r+\delta} \cdot [p-b]}{r + \delta + \lambda_1 \theta q(\theta)} = \frac{\kappa}{\lambda_0 q(\theta)}$$

Simplifying:

$$J(\phi_0) = \frac{p-b}{r+\delta} = \frac{\kappa}{\lambda_0 q(\theta)}$$

Solving for $q(\theta)$:

$$q(\theta) = \frac{\kappa}{\lambda_0} \cdot \frac{r+\delta}{p-b}$$

The model is now solved. However, if we want to talk about cities this model is problematic. The reason is that$J(\phi_0)$ is increasing in p, which implies that θ is also increasing in p. That is, higher productivity implies higher job finding rates, both for employed and unemployed workers. Since we know from Glaeser & Gottlieb (2009) that labor is more productive in bigger cities, this implies that bigger cities should have higher job-finding rates[7] –but this is not what we observe in the data. Also, the model implies that θ_i is decreasing in δ (preventing the positive correlation that we see between job finding and separation rates along city size).

2.4.8 Introducing cities

Let city c be endowed with a degree x_c of specialization (we can think of it as the probability that any given worker in city c is compatible with the firm she has been randomly matched to). Assume that specialization affects negatively matching efficiency (more unlikely to randomly find a suitable match), positively productivity and negatively separation rates (a compatible match is very productive, so it is more unlikely to be destroyed). That is,

$$\begin{aligned} m_{ic} &= \lambda_i \cdot f(x_c) \cdot m(v, u+e),\ i = \{0,1\},\ f'(x_c) < 0 \\ A_c &= A(x_c),\ A'(x_c) > 0 \\ \delta_c &= \delta(x_c),\ \delta'(x_c) < 0 \end{aligned}$$

Then, in equilibrium:

$$q(\theta_c) = \frac{1}{f(x_c)} \cdot \frac{\kappa}{\lambda_0} \cdot \frac{r + \delta(x_c)}{A(x_c)p - b}$$

Now the prediction of the model is

$$\theta_c'(x_c) < 0 \iff -\frac{f'(x_c)}{f(x_c)} > \frac{A'(x_c)p}{A(x_c)p - b} - \frac{\delta'(x_c)}{r + \delta(x_c)}$$

because $\uparrow x_c$ implies:

1. Lower matching efficiency, which implies $\downarrow \theta_c$.
2. Higher productivity and lower separation, which imply $\uparrow \theta_c$.

Reproducing the stylized facts documented in this thesis would require that (1) dominates over (2).

For instance, assume:

$$f(x_c) = x_c^{-\eta},\ A(x_c) = x_c^{\alpha},\ \delta(x_c) = x_c^{-\delta}$$

[7] Observe that Postel-Vinay & Robin (2002a) shares the same logic as the labor market model in the spirit of Pissarides (2000) presented in chapter 1 of this thesis.

Then,

$$\theta'_c(x_c) < 0 \Longleftrightarrow \eta > \eta^* \equiv \frac{\alpha x_c^\alpha p}{x_c^\alpha p - b} + \frac{\delta x_c^{-\delta}}{r + x_c^{-\delta}}$$

Note: η^* monotonically decreasing in x_c. In other words, given η the effect of x_c might be nonlinear.

2.4.9 Discussion on the meaning of 'specialization'

Let there be L_c types of firms and L_c types of workers in city c. We can interpret x_c as the inverse of the share of types that are compatible. Thus, 'specialization' is not about *technical* skills: it's about how *scarce* your type is! In particular, more scarcity implies lower likelihood of finding a compatible match, and hence: 1) Lower finding rates, and 2) Lower separation rates (where will you go?). Also, more scarcity can imply higher productivity in the style of 'increasing variety growth models'.

2.4.10 Micro-founding specialization

Consider a simplistic world with no on-the-job search where in every period there is an exogenous number v of open vacancies. Every period, the total number of matches is given by:

$$m_t = \lambda \cdot m(v_t, u_t)$$

where λ measures the efficiency of the matching technology $m(\cdot)$. The first role of specialization will be to micro-found λ. This is in the spirit of Kiyotaki & Wright (1993). Since $\bar{v}$ is fixed, I make the following simplifying assumption:

$$m(\bar{v}, u) = \min\{v, u\} = u$$

Assume there is a mass 1 of workers. Every period, a fraction u of them are unemployed and the remaining are employed. Flows out of unemployment correspond to new matches and flows into unemployment correspond to broken matches (which happens at rate δ). Thus,

$$u = \frac{\delta}{\delta + \lambda}$$

where the job finding rate comes from the fact that:

$$\frac{m_t}{u_t} = \lambda$$

Thus, if $\lambda = 1$ in this world every unemployed worker would be matched to a new firm every period. However, not all workers are alike. In fact, each worker is indexed by a type $x \in (0, 1)$ that represents the fraction of compatible potential employers. Each unemployed worker is allowed to choose x according to the following trade-off:

1. A high x makes a worker compatible with a large fraction of firms, which increases the likelihood of becoming employed; but...
2. A high x lowers the productivity of the worker, which is translated into a lower wage.

That is, I assume that specialization raises an employed's wage but depresses her chances of finding a job when unemployed:

$$\lambda = \lambda(x),\ \lambda' > 0$$
$$w = w(x),\ w' < 0$$

Hence, an unemployed worker chooses x to maximize the present discounted value of being unemployed:

$$rU(x) = b + \lambda(x) \cdot (W(x) - U(x))$$

where $W(x)$ is the value of being employed in "occupation" x:

$$rW(x) = w(x) + \delta\,(U(x) - W(x))$$

Combining both expressions, we can see that an unemployed worker chooses x in order to maximize:

$$rU(x) = b + \lambda(x) \cdot \frac{w(x) - b}{\rho + \delta + \lambda(x)}$$

That is,

$$\max_x \frac{\lambda(x) \cdot (w(x) - b)}{r + \delta + \lambda(x)}$$

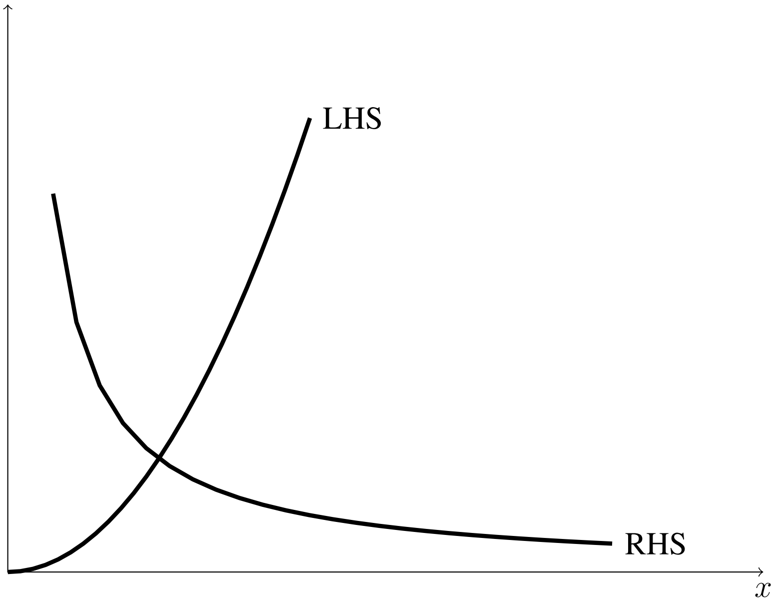
The first-order condition that pins down x is:

$$\frac{-\frac{w'(x)}{w(x)-b}}{r + \delta} = \frac{\frac{\lambda'(x)}{\lambda(x)}}{r + \delta + \lambda(x)} \tag{FOC}$$

which says that the discounted marginal loss in the employee's flow surplus must be exactly offset by the discounted marginal gain in the unemployed's probability of finding a job.

There is a natural functional form for $\lambda(\cdot)$: if x is the share of compatible potential employers, it is natural to assume $\lambda(x) = x$. So the next step is to

Figure 2.7: Equilibrium degree of specialization



understand what $w(\cdot)$ is. But before doing so note that if $\lambda(x) = x$, the right-hand side (RHS) of the FOC(x) is convex and decreasing in x. Thus, to ensure a unique solution we need to assume that $w''(x) < 0$ so that the left-hand side (LHS) is increasing in x:

$$\frac{\partial RHS}{\partial x} = \frac{\lambda''(x)\lambda(x)\left[r+\delta+\lambda(x)\right] - \lambda'(x)\left[\lambda'(x)(r+\delta+\lambda(x)) + \lambda(x)\lambda'(x)\right]}{\left[\lambda(x)\left(r+\delta+\lambda(x)\right)\right]^2}$$

$$\frac{\partial LHS}{\partial x} = -\frac{w''(x)\left[w(x)-b\right] - \left[w'(x)\right]^2}{(r+\delta)\left[w(x)-b\right]^2}$$

Graphically,

I model $w(x)$ as coming out of Nash Bargaining between firms and workers, but I keep the assumption that the number of open vacancies per period is exogenously given by $\bar{v}$. Thus, firms will be limited to collecting their share of the match surplus. Assume that there is an exogenous distribution of firms in which each firm is indexed by a type y. Firms can only produce with workers of their same type. Thus, a y-type firm's output is given by:

$$f(x,y,A) = \begin{cases} f(x,A) & \text{if } x = y \\ 0 & \text{if } x \neq y \end{cases}$$

where A is the exogenous productivity common to all firms. Note that all firms that operate with a compatible worker use the same technology. I assume that the marginal product of labor is increasing in its degree of specialization:[8]

$$\frac{\partial f(x,A)}{\partial x} \equiv f_x < 0$$

For the time being, I do not make any assumptions on $\partial^2 f(x,A)/\partial x \partial A$, although:

$$f_A > 0$$

Hence, the value of a filled job is given by:[9]

$$rJ(x) = f(x,A) - w(x) + \delta(V(x) - J(x))$$

where $V(x)$ is the value of an open vacancy, which is given by:

$$rV(x) = \lambda(x)(J(x) - V(x))$$

Note that there is no free entry condition, as the number of open vacancies is exogenously given.

Nash Bargaining sets a wage $w(x)$ such that:

$$W(x) - U = \beta(W(x) - U(x) + J(x) - V(x))$$

Substituting the Bellman equations for $W(x)$, $U(x)$, $J(x)$, and $V(x)$ yields:

$$w(x) = (1-\beta)b + \beta f(x,A)$$

Substituting this wage into the FOC for x:

$$\frac{-\frac{f_x(x,A)}{f(x,A)-b}}{r+\delta} = \frac{\frac{\lambda'(x)}{\lambda(x)}}{r+\delta+\lambda(x)} \tag{*}$$

which gives a solution for x given the parameters $\{A, b, r, \delta\}$ and the functional forms for λ and f. Note that if we assume $\lambda(x) = x$, uniqueness will be guaranteed when

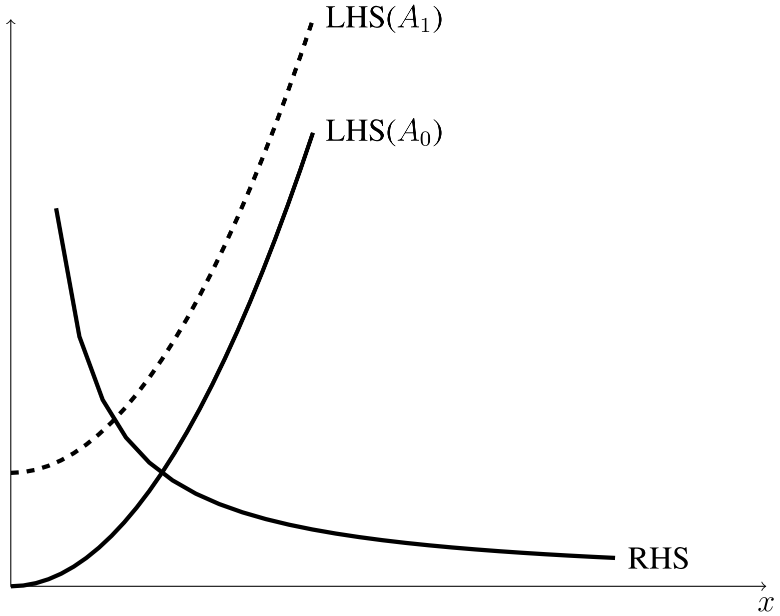
$$w''(x) < 0 \Longleftrightarrow f_{xx} < 0$$

Recall that we want x to decrease with city size. Since $corr(A, Size) > 0$, we need to compute $\partial x/\partial A$. To do so, rewrite (*) as follows:

$$-\frac{f_x(x,A)}{f(x,A)-b} = \frac{\lambda'(x)}{\lambda(x)\left(1+\frac{\lambda(x)}{r+\delta}\right)}$$

Note that the RHS does not depend on A. Hence, what we really need is that the LHS shifts inward when A grows:

Figure 2.8: Equilibrium degree of specialization: ΔA



The partial derivative of the LHS when holding x fixed is:

$$\left.\frac{\partial LHS}{\partial A}\right|_{x=\bar{x}} = -\frac{f_{xA}\left[f(x,A)-b\right]-f_x f_A}{\left[f(x,A)-b\right]^2}$$

Then, x will be decreasing in A when

$$f_{xA} < \frac{f_x f_A}{f(x,A)-b} < 0,$$

where recall that $f_x < 0$ and $f_A > 0$. That is, we need that the marginal product of specialization is strongly increasing in A. If this is the case, then workers in larger cities will choose lower x because of the stronger complementarity between A and specialization.

Lets assume a simple Cobb-Douglas production function:

$$f(x,A) = (1-x)^{\alpha} A^{\beta},$$

[8]Recall that the degree of specialization is decreasing in x.

[9]Note that we focus on a job with $x = y$. The value of a job with $x \neq y$ is never positive, so the meeting between the y-firm and the x-worker would never become an operational match.

which satisfies $\partial LHS/\partial x > 0$. Note that in this case:

$$\begin{aligned} f_x &= -\alpha(1-x)^{\alpha-1}A^{\beta} < 0 \\ f_A &= \beta(1-x)^{\alpha}A^{\beta-1} > 0 \\ f_{xA} &= -\alpha\beta(1-x)^{\alpha-1}A^{\beta-1} < 0 \end{aligned}$$

However, note that:

$$\frac{-f_x f_A}{-f_{xA}} = \frac{\alpha(1-x)^{\alpha-1}A^{\beta} \cdot \beta(1-x)^{\alpha}A^{\beta-1}}{\alpha\beta(1-x)^{\alpha-1}A^{\beta-1}} = (1-x)^{\alpha}A^{\beta} = f(x,A)$$

and therefore $\partial x/\partial A < 0$ would only be satisfied if $b < 0$, which is not plausible:

$$f_{xA} < \frac{f_x f_A}{f(x,A)-b} < 0 \iff \frac{\alpha(1-x)^{\alpha-1}A^{\beta} \cdot \beta(1-x)^{\alpha}A^{\beta-1}}{f(x,A)-b} < \alpha\beta(1-x)^{\alpha-1}A^{\beta-1}$$

$$\iff$$

$$\frac{f(x,A)}{f(x,A)-b} < 1$$

Lets now be more general and assume:

$$f(x,A) = [\alpha(1-x)^{\gamma} + \beta A^{\gamma}]^{\eta}$$

This implies that:

$$\begin{aligned} f_x &= -\eta\left[f(x,A)\right]^{\frac{\eta-1}{\eta}}\gamma\alpha(1-x)^{\gamma-1} < 0 \\ f_A &= \eta\left[f(x,A)\right]^{\frac{\eta-1}{\eta}}\gamma\beta A^{\gamma-1} > 0 \\ f_{xA} &= -(\eta-1)\left[f(x,A)\right]^{-\frac{1}{\eta}} f_A\gamma\alpha(1-x)^{\gamma-1} < 0 \iff \eta > 1 \end{aligned}$$

Then,

$$f_{xA} < \frac{f_x f_A}{f(x,A)-b} \iff \frac{\eta\left[f(x,A)\right]^{\frac{\eta-1}{\eta}}\gamma\alpha(1-x)^{\gamma-1} \cdot f_A}{f(x,A)-b} < (\eta-1)\left[f(x,A)\right]^{-\frac{1}{\eta}} f_A\gamma\alpha(1-x)^{\gamma-1}$$

$$\iff$$

$$\frac{f(x,A)}{f(x,A)-b} < \frac{\eta-1}{\eta} \iff \eta < \frac{b-f(x,A)}{f(x,A)} < 0$$

That is, the CES specification is not appropriate either.

However, the following technology will work:

$$f(x,A) = (\alpha+1-x)^{\beta A}, \alpha \geq 1, \beta > 0$$

In this case:

$$\begin{aligned}
f_x &= -\beta A(\alpha+1-x)^{\beta A-1} \\
f_A &= \beta(\alpha+1-x)^{\beta A}\ln(\alpha+1-x) \\
f_{xA} &= -\beta(\alpha+1-x)^{\beta A-1} - \beta^2 A(\alpha+1-x)^{\beta A-1}\ln(\alpha+1-x) = \\
&= -\beta(\alpha+1-x)^{\beta A-1}\cdot(1+\beta A\ln(\alpha+1-x))
\end{aligned}$$

Then,

$$f_{xA} < \frac{f_x f_A}{f(x,A)-b} \iff \frac{A\beta(\alpha+1-x)^{\beta A}\ln(\alpha+1-x)}{(\alpha+1-x)^{\beta A}-b} < 1+\beta A\ln(\alpha+1-x)$$

$$\iff$$

$$\frac{\beta A\ln(\alpha+1-x)}{1-\frac{b}{(\alpha+1-x)^{\beta A}}} < 1+\beta A\ln(\alpha+1-x)$$

which is easily satisfied if b is small enough or if β is large enough.

Summing up, at least in the way I modeled here, specialization will only work if there is an extremely strong complementarity between specialization and aggregate (city-wide) productivity.

2.5 The Law of Large Numbers

2.5.1 Intuition

A simple explanation of the decreasing-in-city-size labor market flows might be city size itself. To take an extreme case, a one-firm city (likely, a small city) will experience massive layoffs if the firm closes down and massive hiring when the firm settles down. To check the what kind of link between city size and labor market flows would imply this logic, I also present a simple mechanical model of labor market flows.

2.5.2 Setup

Gabaix (2009) shows that the city-size distribution of metropolitan areas in the US is well approximated by:

$$\ln(Rank) = 10.53 - 1.005\ln(Size)$$

where $Rank$ is a variable that sorts cities according to their population sizes (that is, New York would have rank 1, Los Angeles would have rank 2, etc.). I use this relationship to create 250 fictitious cities, each containing as many observations (workers) as implied by the log-rank-log-size relationship.

Assume every employed worker has a probability δ of transitioning to unemployment. Similarly, assume every unemployed worker has a probability λ of transitioning to employment. From the stylized facts in chapter 1 of this thesis, the average US worker in 2013 had:

$$\delta = 2.04\%, \ \lambda = 23.28\%$$

This implies that the probability that any given worker is unemployed is given by

$$ur = \frac{\delta}{\delta + \lambda}$$

I use ur to create an initial distribution of unemployed workers. Given this initial distribution, within a city I let each employed worker transition to unemployment with probability δ and each unemployed worker transition to employment with probability λ. In particular, every worker gets a random draw from a uniform distribution in the $[0, 1]$ interval. If the draw of an unemployed worker is smaller than λ, she transitions to employment within the city she is located in. Similarly, when the draw of an employed worker is smaller than δ she moves to unemployment within the city she is located in. The resulting distribution of unemployment rates, as well as employment-to-unemployment and unemployment-to-employment transition frequencies are plotted against (log) of city size in Figures 2.9 to 2.11.

As we can see, the dispersion of unemployment rates and labor market flows decreases with a city's size. However, taking the average city within a city-size bin, there is not statistical difference neither in unemployment rates nor in labor market flows across cities of different size.

2.6 Conclusion

There are four stylized facts on local labor markets that should discipline a spatial model of the labor market: 1) labor productivity is increasing in city size, 2) matches are governed by a constant-returns-to-scale function, 3) unemployment

Figure 2.9: Law of large numbers: unemployment rates

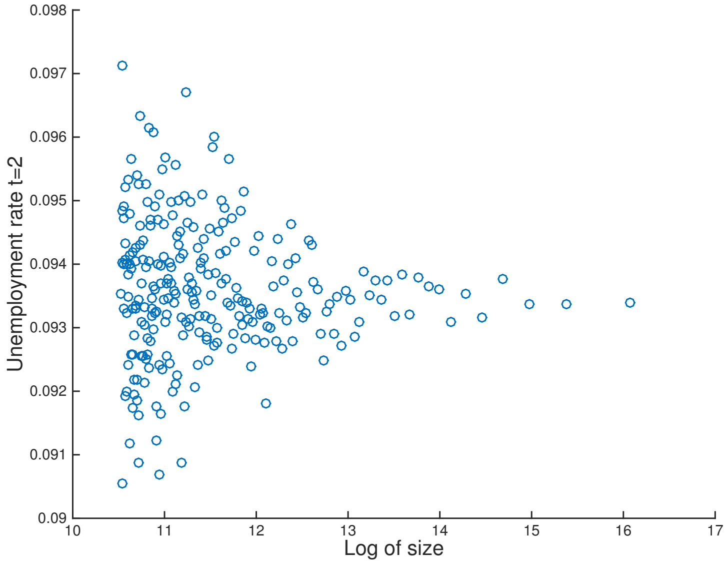


Figure 2.10: Law of large numbers: unemployment-to-employment rates

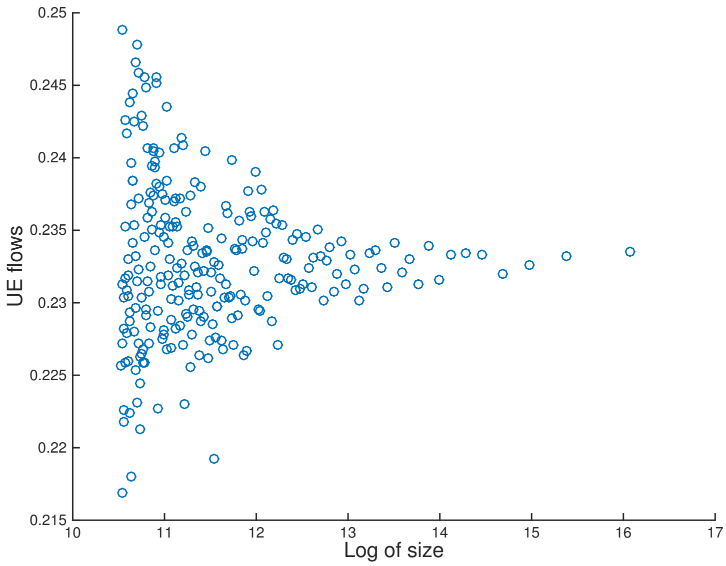
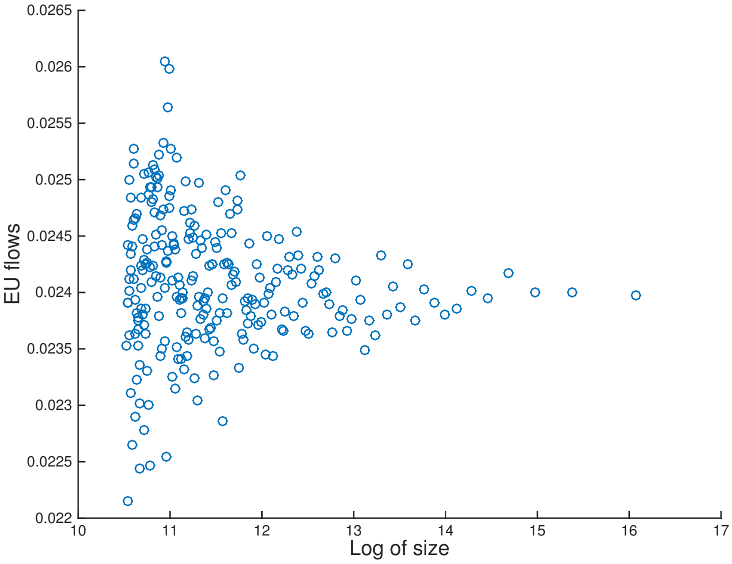


Figure 2.11: Law of large numbers: employment-to-unemployment rates



rates are constant across cities of different sizes, and 4) labor market flows are decreasing in city size. The basic logic of a model of frictional unemployment is at odds with the combination of these four facts: higher productivity induces higher vacancy posting and, thus, higher job finding rates. In this chapter I have proposed two departures from this logic: frictions in vacancy posting, and specialization of workers. Although these modifications have an appealing intuition, one needs to make strong assumptions for them to work (at least in the way I have formalized them in this thesis).

I have also considered an alternative mechanical explanation inspired by the Law of Large Numbers (LLN). The fact that the LLN produces higher dispersion of labor market flows and unemployment rates within smaller cities is qualitatively consistent with the data (albeit far from being so in a quantitative fashion). However, the LLN produces a symmetric dispersion, which is not what we observe in the data. Therefore, the stylized facts presented in chapter 1 do not seem to the output of a mechanical statistical process in the spirit of the LLN.

Chapter 3

LITERATURE

3.1 Local labor markets

I started the first chapter with an interesting fact about local labor markets: cross-city variation in unemployment rates is large and it rivals variation over the business cycle. This is not the only interesting difference in labor market outcomes that has been documented in the literature. In particular, Moretti (2011) presents a few additional stylized facts about local labor markets. First, there are large differences in nominal labor costs across US metropolitan areas. As Moretti (2011) shows, in 2000 the average hourly nominal wage of a college graduate in the 10th percentile of the distribution across metropolitan areas is roughly 70% of what it would be if she lived in a city belonging to the 90th percentile. The differences remain large even after further controlling for race, experience, gender and Hispanic origin, and they are persistent over time. Note that if nominal wages are related to the marginal product of labor, these differences point towards large differences in labor productivity across metropolitan areas. Second, in fact, Moretti (2011) computes a county-level measure of total factor productivity (TFP) and also finds large and persistent differences across counties. And third, the differences in average real hourly wages across metropolitan areas are much smaller. As Moretti (2011) shows, this is because there are large differences in the cost of housing, and thus nominal wages seem to be adjusting in order to take account of differences in the cost of living.

Glaeser & Gottlieb (2009) also provide a nice summary of a few stylized facts. Their summary is particularly relevant to this thesis because it relates to city size. In particular, they structurally estimate a spatial equilibrium model and find that city size is positively associated with nominal wages (i.e. labor productivity) and with housing prices. Note that the positive correlation between city size and nominal wages could simply come from bigger cities attracting more talented workers.

However, Glaeser & Maré (2001) show that nominal wages are increasing in city size even after accounting for the ability of workers.

Overall, the literature documents significant variation in labor market outcomes across metropolitan areas. In particular, bigger cities seem to be places where workers are more productive but where the cost of living is also higher.

3.2 Unemployment rates and city size

The positive correlation between labor productivity and city size suggests that job finding might be larger in larger cities, as posting vacancies becomes more profitable. Thus, one could expect that larger cities would have lower unemployment rates. However, as we have seen in chapter 1, this does not seem to be present in the data for the US for 1996-2015. Still, there are a few published contributions on the subject, each of them claiming to find a significant coefficient for city size although there does not emerge a robust finding. The most cited ones are Vipond (1974), Sirmans (1977), Simon (1988), and Alperovich (1993). The most recent published contribution on the matter that I am aware of is Gan & Zhang (2006).

Vipond (1974) argues that there might be economies or diseconomies of scale in a citys labor market. Economies might arise from greater choice while diseconomies could arise from costlier communication. Using UK data for cities with population size greater than 50,000 for 1966, she finds that male unemployment rates are increasing in city size while female unemployment rates are decreasing in city size –controlling for the amount of commuting, the share of professional workers and managers, the age structure of the city, its labor market participation rate and the share of employment in manufacturing. However, as Sirmans (1977) notes, Vipond (1974) estimates separate equations for males and females. Because it is likely that men and womens unemployment rates are interrelated, Sirmans (1977) uses a Seemingly Unrelated Regressions model to take into account the possible correlation in the error terms. Although the coefficients in Sirmans (1977) are estimated with more precision, his results confirm the sign, the magnitude and the significance of Vipond (1974)s findings.

Alperovich (1993) argues that according to the law of large numbers bigger cities should have lower unemployment rates: if shocks are not correlated among firms, the larger the city the more diversified its economic structure will be, and hence we should observe both lower unemployment rates and shorter duration spells. He uses data from the 1983 and 1984 Israeli censuses for 53 cities of 10,000 and more inhabitants and controls for the median years of schooling of a citys residents, the mean number of persons per household, the median age of the citys inhabitants, population growth, distance to Tel-Aviv and the share of employment in manufacturing. With this specification, he finds that both unemployment rates and the frequency of long spells of unemployment are significantly decreasing in city size. Note that Alperovich (1993)s motivation comes from a diversification hypothesis, but he does not really control for it –besides controlling for employment in manufacturing. In fact, the coefficient on employment in manufacturing is not even significant. Simon (1988) takes the diversification argument more seriously and uses data on 91 MSAs in the US for 1977-1981 from the Employment and Earnings issues published by the Bureau of Labor Statistics to compute a city-specific Herfindahl index. He controls for median education, industry composition, unemployment benefits and city size. With these controls, he regresses unemployment rates on the Herfindahl index for the pooled sample with year dummies. As expected, the coefficient on the Herfindahl index is significantly positive, suggesting that more diversification implies lower unemployment rates. As for the effect of city size, he finds a significant positive coefficient, contradicting the findings of Alperovich (1993).

Finally, Gan & Zhang (2006) want to test whether the diversification hypothesis translates into differences in the cyclical behavior of unemployment across cities. Using monthly data on 295 Primary MSAs in the US for 1981-1997, they obtain a characterization of the cyclical behavior of each citys unemployment rate. Then, they regress this measure on city size, unemployment benefits, the share of young residents, the net migration rate and the physical extension of the city, and find that larger cities tend to have shorter unemployment cycles and lower unemployment rates at the peak of the cycle. They also add a control for industry composition and find that monthly unemployment rates are significantly decreasing in city size. Yet, the fact that they use monthly rates is troublesome as there might be seasonality effects and severe small sample size problems for the smaller cities.

Overall, the published evidence is old, the quality of the data they use is not satisfactory, and above all there does not emerge a consistent result for the relationship between city size and unemployment rates.

3.3 Matching functions and scale effects

The matching function is a simple device that summarizes the complicated exchange process between workers and firms (Petrongolo & Pissarides (2001)). In the context of this thesis, it is important to address the question of whether the size of the labor market is an argument of the matching function. Given that the matching function depends on the stock of vacancies and unemployed workers, a first test is to check whether the function exhibits increasing, constant or decreasing returns to scale. Table 3 in Petrongolo & Pissarides (2001) provides a summary of the works that have addressed this question. This has been done in different ways (estimating the aggregate Beveridge curve, directly estimating the country-aggregate matching function, industry-specific matching functions, or using a cross-section of local labor markets), but a consistent finding emerging from the literature is that after controlling for the ratio of vacancies to unemployed workers, job finding rates do not vary with the total number of unemployed workers or vacancies.

The job-search literature has interpreted this finding as evidence that labor market size is unimportant for job search outcomes. However, this interpretation might be too bold. For instance, as Petrongolo & Pissarides (2001) note, most studies treat the aggregate economy as a single labor market, ignoring the possibility that the aggregate economy might simply be the collection of spatially distinct isolated local labor markets . Related to this observation, Coles & Smith (1996) find constant returns to scale on average but with more dense local labor markets delivering higher matching rates –given the size of the vacancy and unemployment pools. Also, Petrongolo & Pissarides (2006) note that constant returns to scale are found in reduced-form estimates. This observation opens up the possibility that if we look at the different stages of the matching process we find scale effects in some of them. In particular, by separating the matching probability into 1) the meeting probability and 2) the probability that a meeting becomes a match, they show that constant returns at the aggregate level can be compatible with increasing returns at one of the structural levels of the search process. There is also another possibility. Namely, that there are no scale effects in the matching function but that there is some mechanism by which city size induces differences in the labor markets tightness.

In the remaining of this section I briefly review two hypotheses about the role of city size on labor market outcomes.

3.3.1 Agglomeration Economies

I have already mentioned that there is evidence supporting a positive correlation between city size and productivity. One possibility is that this correlation is explained by agglomeration economies. Intuitively, agglomeration economies are advantages that come from reducing transportation costs for goods, people and/or ideas (Glaeser & Gottlieb (2009)). Estimating agglomeration economies is not easy, as city size is an endogenous variable, but there is a robust consensus that they exist. For instance, in table 4 in Glaeser & Gottlieb (2009) they present several standard ways of estimating them. Typically, to address the endogeneity of city size, lagged population and geography are used as instruments. Their results are robust evidence of significant agglomeration economies. Although there is no consensus on the relative importance of the different sources of agglomeration economies (Glaeser & Gottlieb (2009) and Moretti (2011)), three main channels stand out: reduced costs of moving goods across space, labor market pooling, and the diffusion of ideas.

3.3.2 Matching quality and city size

Another hypothesis explored in the literature is that rather than directly affecting unemployment rates and job finding and destruction, the size of the market affects the quality of the matches. Intuitively, larger markets offer more choice to both firms and workers, and this might result in better pairs. This hypothesis might be particularly relevant for labor markets with significant heterogeneity in firms and workers. What do we mean exactly by better matches? One possible definition of the quality of the match is the degree of assortative matching. In this sense, Andersson, Burgess & Lane (2007) use data from the Longitudinal Employer-Household Dynamics Program and provide evidence that denser urban labor markets are associated with more assortative matching. This evidence is constructed in two steps: 1) they find significant complementarities between firms and workers (better-quality firms and workers are more productive when paired together), and 2) this complementarity is increasing in the density of the county where the pair is located. Because there is a positive correlation between city size and density, this could suggest that matching quality is increasing in city size.

This hypothesis is relevant for this thesis because the quality of the match can influence the probability that it gets destroyed. In this sense, if the quality of matches is increasing in city size it is plausible that the job destruction rate is decreasing in city size as documented above. However, why job-finding rates might also decrease with city size remains to be explained.

3.4 Models

The standard spatial equilibrium model dates back to Roback (1982). In this model, workers choose where to work and live based on the location-specific quality of life which depends on wages, housing prices, and local amenities. However, most versions of this model assume competitive market-clearing labor markets. In this subsection I will discuss the spatial equilibrium model with frictional unemployment. Unemployment is introduced by assuming that each local labor market works as in the simple Pissarides (2000) model. My first formulation in chapter 2 is most closely related to the model presented in Beaudry et al. (2014).

In particular, Beaudry et al. (2014) build a model by combining a spatial equilibrium model with a search and matching model of the labor market, where cities differ in productivity, amenities and available land. All local labor markets are ex-ante identical (same separation rate, matching function, unemployment benefits) but for the cost of posting a vacancy which is partly exogenous and partly increasing in the number of firms per capita. Workers are not always free to move to other cities, although mobility shocks are assumed to be sufficiently frequent so that in equilibrium utilities are equalized. Their estimation of the model yields several relevant results for this thesis: larger cities are associated with 1) higher wages, 2) higher employment rates, and 3) higher housing prices, although the statistical significance is not very strong.

Bibliography

Albouy, D., (2008). *Are Big Cities Bad Places to Live? Estimating Quality of Life Across Metropolitan Areas*, NBER Working Paper 14472.

Alperovich, G., (1993). *City Size and the Rate Duration of Unemployment: Evidence from Israeli Data*, Journal of Urban Economics, Vol. 34, 347-357.

Andersson, F., Burgess, S., & Lane, J., (2007). *Cities, matching and the productivity gains of agglomeration*, Journal of Urban Economics 61, 112-128.

Beaudry, P., Green, D. A., & Sand, B., (2014). *Spatial Equilibrium with Unemployment and Wage Bargaining: Theory and Estimation*, Journal of Urban Economics, vol. 79, 2 - 19.

Brueckner, J. K., (1987). *The Structure of Urban Equilibria: A Unified Treatment of the Muth-Mills Model*, Handbook of Regional and Urban Economics, Chapter 20.

Coles, M. G., & Smith, E., (1996). *Cross-Section estimation of the matching function: evidence from England and Wales*, Economica, 63:252, 589-598.

Crampton, G. R., (1999). *Urban Labour Markets*, Handbook of Regional and Urban Economics, Chapter 39.

Duranton, G., & Puga, D., (2003). *Micro-foundations of Urban Agglomeration Economies*, NBER Working Paper 9931.

Eeckhout, J., Pinheiro, R., & Schmidheiny, K., (2014). *Spatial Sorting*, Journal of Political Economy, University of Chicago Press, vol. 122(3), 554 - 620.

Gabaix, X., (2009). *Power Laws in Economics and Finance*, The Annual Review of Economics, 255 - 293.

Eeckhout, J., Pinheiro, R., & Schmidheiny, K., (2014). *Spatial Sorting*, Journal of Political Economy, vol. 122(3), 554 - 620.

GABAIX, X., (2009). *Power Laws in Economics and Finance*, The Annual Review of Economics, 255 - 293.

GAN, L., & ZHANG, Q., (2006). *The thick market effect on local unemployment rate fluctuations*, Journal of Econometrics, Vol. 133, 127-152.

GLAESER, E. L., (1998). *Are cities dying?*, Journal of Economic Perspectives, 47:4, 983-1028.

GLAESER, E. L., (2007). *The Economics Approach to Cities*, NBER Working Paper 13696.

GLAESER, E. L., & GOTTLIEB, J. D., (2009). *The wealth of cities: agglomeration economies and spatial equilibrium in the United States*, Journal of Economic Literature, vol. 47(4), 983 - 1028.

GLAESER, E. L., & MARÉ, D. C., (2001). *Cities and Skills*, Journal of Labor Economics, vol. 19(2), 316 - 342.

KIYOTAKI, N., & WRIGHT, R., (1993). *A Search-Theoretic Approach to Monetary Economics*, The American Economic Review, vol. 83(1), 63 - 77.

KLINE, P., & MORETTI, E., (2013). *Place Based Policies with Unemployment*, NBER working paper 18758.

KROMER, B. K., & HOWARD, D. J., (2011). *Comparison of ACS and CPS Data on Employment Status*, SEHSD Working Paper Series, 2011-31.

MOEN, E. R., (1997). *Competitive Search Equilibrium*, Journal of Political Economy, vol. 105(2), 385 - 411.

MORETTI, E., (2011). *Local Labor Markets*, Handbook of Labor Economics, vol. 4b, edited by Card, D., and Ashenfelter, O., 1237-1313.

PETRONGOLO, B., & PISSARIDES, C., (2001). *Looking into the black box: a survey of the matching function*, Journal of Economic Literature, Vol. 39(2), 390-431.

PETRONGOLO, B., & PISSARIDES, C., (2006). *Scale effects in markets with search*, The Economic Journal, Vol. 116(508), 21-44.

PISSARIDES, C., (2000). *Equilibrium unemployment theory*, MIT Press Books, 2nd edition, The MIT Press.

POSTEL-VINAY, F., & ROBIN, J. M., (2002a). *The Distribution of Earnings in an Equilibrium Search Model with State-Dependent Offers and Counteroffers*, International Economic Review, Vol. 43(4), 989 - 1016.

POSTEL-VINAY, F., & ROBIN, J. M., (2002b). *Equilibrium Wage Dispersion with Worker and Employer Heterogeneity*, Econometrica, Vol. 70(6), 2295 - 2350.

PISSARIDES, C., (2000). *Equilibrium unemployment theory*, MIT Press Books, 2nd edition, The MIT Press.

ROBACK, J., (1982). *Wages, Rents, and the Quality of Life*, Journal of Political Economy, Vol. 90(6), 1257 - 1278.

SHIMER, R., (2005). *The Cyclical Behavior of Equilibrium Unemployment and Vacancies*, American Economic Review, Vol. 95(1), 25 - 49.

SIMON, C. J., (1988). *Frictional Unemployment and the Role of Industrial Diversity*, The Quarterly Journal of Economics, Vol. 103(4), 715-728.

SIRMANS, C. F., (1977). *City Size and Unemployment: Some New Estimates*, Urban Studies, Vol. 14, 99-101.

US CENSUS BUREAU, (2006). *Current Population Survey: Design and Methodology*, Technical Paper 66.

VIPOND, J., (1974). *City Size and Unemployment*, Urban Studies, Vol. 11, 39-46.