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UNEMPLOYMENT RATE FLUCTUATIONS

Li Gan
Qinghua Zhang

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ABSTRACT

This paper studies how the thick market effect influences local unemployment rate fluctuations. The paper presents a model to demonstrate that the average matching quality improves as the number of workers and firms increases. Unemployed workers accumulate in a city until the local labor market reaches a critical minimum size, which leads to cyclical fluctuations in the local unemployment rates. Since larger cities attain the critical market size more frequently, they have shorter unemployment cycles, lower peak unemployment rates, and lower mean unemployment rates. Our empirical tests are consistent with the predictions of the model. In particular, we find that an increase of two standard deviations in city size shortens the unemployment cycles by about 0.72 months, lowers the peak unemployment rates by 0.33 percentage points, and lowers the mean unemployment rates by 0.16 percentage points.

Li Gan
Department of Economics
University of Texas
Austin, TX 78712
and NBER
gan@eco.utexas.edu

Qinghua Zhang
Guanghua School of Management
Beijing University
Beijing, China
zhangq@gsm.pku.edu.cn

1 Introduction

Unemployment rates vary widely across cities in the United States. Among the 295 Primary Metropolitan Statistical Areas (PMSAs), the average unemployment rate from 1981 to 1997 ranged from 2.4% in Columbia, Missouri (PMSA code 1740), to 19.6% in McAllen-Edinburg-Mission, Texas (PMSA code 4880). One main explanation to this phenomenon is the industry composition effect: since different cities have different industry compositions, nation-wide, industry-specific shocks have different composite effects on unemployment rates in different cities.¹

Although the industry composition effect is intuitive, people still find significant geographic differences in mean unemployment rates after controlling for the industry composition effect. Another hypothesis in the literature, risk diversification hypothesis, is based on the observation that in the local labor market, prosperous industries absorb the unemployment of those experiencing contractions. Therefore, a city with a more diversified industry structure has a lower variance in labor demand. As a result, the frictional unemployment rate in this city is also lower. For example, Mills and Hamilton (1984) argue that larger cities are usually more industrially diverse and thus have lower unemployment rates. Neumann and Topel (1991) provide a formal model on the effect of risk diversification.

A few empirical studies have confirmed the risk diversification hypothesis, e.g., Simon (1988) and Neumann and Topel (1991). Simon's study is based on U.S. data at the 2-digit SIC level that covers 91 large PMSAs over the years 1977–1981. He defines the frictional unemployment rate as a city's aggregate unemployment rate net of the effects of national shocks and industry composition. He finds that the frictional unemployment rate declines as local industrial diversity rises. Using U.S. data at the state level over the years 1950–1985, Neumann and Topel show that after controlling for the effect of industry composition, the unemployment rate is significantly and persistently lower in labor markets where the sectoral demand risk is more diversified.

¹In this paper, the term "city" has the same meaning as the term "PMSA."

However, little work in the literature studies variations in unemployment rate fluctuations across cities. Alperovich (1993)'s empirical work finds a significant and negative correlation between city size and the unemployment rate as well as the spell of individual unemployment in Israel. However, cyclical behaviors of the unemployment rate is not the focus of his study. Moreover, there is no theoretical model in his paper. Our paper contributes by exploring just that. We present a model that provides predictions on variations in both the frequency/duration and amplitude of unemployment cycles across cities, as well as an additional explanation to geographical differences in mean unemployment rates. We use data of 295 PMSAs in the U.S. over the years 1981- 1997 to test the predictions of the model empirically. We find that city size contributes significantly to the spatial heterogeneity of unemployment cycles.

Understanding variations in unemployment cycles has important policy implications, for the duration of unemployment cycles is closely related to the mean of the individual unemployment spell. It is also important to note the difference between national business cycles and local unemployment cycles studied in this paper. National Business cycles are typically caused by aggregate shocks to demand and/or productivities. However, local unemployment cycles in this paper are driven by market friction and idiosyncratic shocks across workers and firms. Therefore, our analysis on local unemployment rate fluctuations is conducted after controlling for the effects of industry composition and aggregate business cycles.

The intuition behind our model is as follows. Both workers and firms are heterogeneous in terms of their technological specificity. They are assumed to be located on a unit circle that represents the technology space. The matching quality is better and the wage rate is higher if the distance between a firm and a worker is shorter. A thicker market means that there are more workers and more firms on this unit circle. When a market is sufficiently thick, workers' expected return from job-searching is higher than the cost of the job search. Only in this situation, active job search begins and matches occur; otherwise, unemployed workers accumulate until the local labor market reaches a critical minimum size. Therefore, the local labor market becomes active at a certain frequency, which leads to cyclical fluctuations in

the unemployment rate. For example, job fairs in a city are usually held at intervals instead of continuously. In a simple version of the model, a cycle of unemployment starts with full employment. The pool of unemployed workers increase over time until it reaches a critical size when matches occur and unemployed workers get jobs. If the unemployment increases linearly, the length of the unemployment cycle is twice as long as the mean of individual unemployment durations. Because a larger city typically generates more unemployed workers during a given time period, it takes a shorter time for the city's labor market to attain the critical minimum size. Therefore, its labor market becomes active more frequently. Thus our model predicts a specific type of agglomeration economies, that is, larger cities on average have shorter unemployment cycles and lower unemployment rates.

That matching quality and wages depend on the distance between a firm and a worker is illustrated in the matching model of Helsley and Strange (1990) who use a unit circle to describe the technological space of firms and workers. Their model is used to study urban agglomeration economies². There is other work in the literature that studies how urban agglomeration facilitates the matching process in local labor markets, such as Ciccone and Hall (1996), Wheeler (2001) and Glaeser and Mare (2001). However, all the aforementioned work does not study the relationship between urban agglomeration and local unemployment cycles. Diamond (1982) presents a model of the thick market effect that hinges on search cost instead of on matching quality. His idea is that the more activity there is on one side of the market, the lower the contacting costs faced by those who are looking for trading partners on the other side. Shimer (2001) applies Diamond's trading externality and Mortensen and Pissarides (1994)'s matching model to explain his finding that state unemployment rates are negatively correlated with the share of youth in the working age population. He argues that if there are more "mis-matched" and ready-to-move young workers in a state, then the number of available workers is larger. A thicker labor market is more appealing for firms to create jobs. As a result, the state's unemployment rate is lower. However, his paper does not consider the

²For a general discussion on urban agglomeration economies, see Henderson (1986, 1988) and Duranton and Puga (2004). In addition, Wilson (1988) provides an empirical test for agglomeration economies.

effect of matching quality as well as the effect of the size of the economy on the unemployment rate. Our paper explicitly models how matching quality and matching probability are affected by city size in a dynamic setting. It establishes a systematic relationship between city size and local unemployment rate fluctuations.

Empirically, this paper tests three predictions in our model, after controlling for the effects of risk diversification and industry composition: (1) the length of an unemployment cycle is shorter in a larger city; (2) the peak unemployment rate decreases as city size increases; and (3) the average unemployment rate in a city is negatively correlated with city size.

One way to test the negative correlation between the length of the unemployment cycle and city size is to conduct a spectral analysis. If we think of the time series as compounded cycles with different frequencies, the spectral density of a certain frequency measures how much the cycle associated with this specific frequency contributes to fluctuations in the time series. We consider two types of frequencies: max-frequency and mean-frequency. Since a frequency is the inverse of a cycle length, our model predicts that the two types of frequencies are positively correlated with city size. Another way to investigate the relationship between the length of the unemployment cycle and city size is to carry out a duration analysis. The duration of an unemployment cycle is the time length of the unemployment cycle. We decompose an entire unemployment cycle into two stages: the peak-to-trough stage (the expansion in the economy) and the trough-to-peak stage (the contraction in the economy). Our model predicts that the length of the trough-to-peak stage is negatively correlated with city size.

Testing a negative relationship between peak unemployment and city size is relatively straightforward. After identifying peak points in unemployment cycles, we construct the average peak unemployment rate for each city and then find its relationship with the log of average city size.

To find the relationship between the average unemployment rate and city size, we use a linear regression model. The model includes the log of average city size as one of the explanatory variables.

The empirical results in this paper are consistent with the three aforementioned predictions

of the model. In particular, we find that an increase of two standard deviations in city size shortens the unemployment cycle by about .72 months, lowers the peak unemployment rate by .33 percentage points and lowers the average unemployment rate by about .16 percentage points,

The rest of the paper is organized as follows: Section 2.1 presents the theoretical model that provides the three hypotheses for the empirical tests that follow. Section 2.2 discusses the data. Section 3 conducts a spectral analysis on the frequency of unemployment rate fluctuations. Section 4 carries out a duration analysis on the average length of unemployment cycles. It also studies the peak unemployment rate. Section 5 investigates the influence of city size on the mean unemployment rate. Section 6 summarizes the paper.

2 The Model and the Data

2.1 The Model

In this section, we present a simple model that illustrates the effect of the thick market and its associated agglomeration economy on local unemployment rate fluctuations. Zhang (2002) presents a dual version of the model with strategic behaviors that focuses on the local capital market. Workers and firms are heterogeneous in terms of their technological specificity. We assume idiosyncratic shocks to all the firms. This is reflected by the separation rate of a worker-job pair during any time period, denoted as ν .

Let N be the number of workers in a city who are immobile across cities, and let this be the measure of city size.³ Let the number of unemployed workers be U and let the number of job openings be V . We use a unit circle to represent the technology space. We can think of this unit circle as a clock. All the points on the circle are indexed from 0 to 1 clockwise. The locations of zero and one on the unit circle are at the same point and correspond with

³In reality, labor may be mobile. However, labor mobility is limited because of moving costs. The qualitative results from our theoretical model will hold given a limited labor mobility. Our empirical regressions control for the effect of migration across cities.

twelve-o'clock on a clock. All the V jobs are evenly spaced around the unit circle. Let b denote the location of the 1st job, $b \in [0, 1)$. The $j + 1$ -th job is then located at point $b + j/V$. However, if $b + j/V > 1$, the location of $j + 1$ -th job becomes $b + j/V - 1$. We assume b to be a random variable uniformly distributed over the unit circle $[0, 1)$. All the workers are independently and uniformly distributed over the unit circle $[0, 1)$.⁴ A worker knows his own location.

The matching mechanism is as follows. One worker can be matched with at most one job. One job can be matched with at most one worker. Job $j + 1$ located at point $b + j/V$ can only be matched with a worker who lies within the arc interval $[b + j/V - 1/2V, b + j/V + 1/2V)$.⁵ Suppose an unemployed worker is located at point $a \in [0, 1)$. If he falls into the $1/2V$ -interval of job $j + 1$, namely, if $a \in [b + j/V - 1/2V, b + j/V + 1/2V)$, then he is matched with job $j + 1$. The matching quality between job $j + 1$ and the worker is dependent on the shorter arc distance between them, denoted by $d_{a,j+1}$. The better the matching quality, the higher the productivity of the job-worker pair. Let $y \equiv y(d_{a,j+1})$ denote the value of the products and $y'(d_{a,j+1}) < 0$. Following Mortensen and Pissarides (1994), we assume that the worker gets paid from the job through bargaining and we assume a certain bargaining power $\theta > 0$. Thus, the worker's payoff from the job increases as their mutual distance decreases; that is, $w \equiv \theta y(d_{a,j+1})$ and $w'(\cdot) < 0$. When there is more than one worker located in the interval $[b + j/V - 1/2V, b + j/V + 1/2V)$, job $j + 1$ is then matched with the worker who is located closest to the job.

Ex ante, an unemployed worker chooses whether to look for a job or not. If he does, he incurs a positive search cost, denoted c ; otherwise, his search cost is zero.⁶ His decision is based

⁴Since the location of the first job b is random, the assumption that jobs are even-spaced preserves the uncertainty of match while simplifies the analytics of the model.

⁵Without this assumption, an assignment problem would arise when one worker is the favorite to two jobs. Any allocation rule would involve complicated computations of the model that make it impossible to get analytical results. Zhang (2002) addresses the assignment problem without making this assumption. The allocation rule there is the same as an efficient multiple-object auction with a capacity constraint. Her simulation results are similar to the analytical results of the simple model in this paper.

⁶All unemployed workers are seeking employment by definition. However, search has different intensities.

on the comparison between the expected payoff from search and the search cost. Suppose he is at point a . If the worker searches for a job in the job market, his payoff will be:⁷

$$W(a) = \begin{cases} w(d_{a,j+1}), & \text{if matched with job } j+1; \\ 0, & \text{if no match.} \end{cases} \quad (1)$$

Ex ante, a worker does not know the exact location of each job. To him, b is a random variable. Thus the ex ante expectation of a worker's payoff from searching is taken over $b \in [0, 1)$.

When the expected payoff from job-search at least compensates the search cost, i.e., $E[W(a)] \geq c$, an unemployed worker starts to actively search for jobs. Finding out the expected payoff requires the matching probability of a worker. Suppose there are U unemployed workers looking for jobs and there are V job openings. According to the matching mechanism described earlier, the expected number of matches is:⁸

$$M(U, V) = V \left[1 - \left(1 - \frac{1}{V} \right)^U \right].$$

The matching probability could be defined in terms of the number of unemployed workers (U) or in terms of the number of job openings (V). From now on, we assume $U = V$. This assumption is consistent with Davis and Haltiwanger (1992) where jobs are both created and destructed at roughly the same rate.

Our model is a simplification of reality where the search intensity can be either 0 or 1. If the intensity is 0, no search cost is incurred and seldom can a worker find a job. If the intensity is 1, there is a search cost c . The search cost may decrease as V or U increases, as in Diamond's model. For simplicity, we assume c to be a constant here. However, this assumption is not essential for the results of our model.

⁷If the worker is not matched with a job this time period, he waits until next time. Waiting has a value. Thus, the worker's payoff from a job should be net of this value. For simplicity, we assume that the value of waiting is a constant and normalize it to be zero. We admit that the value of waiting should in fact be a function of expected market size. In Zhang (2002), a fully dynamic model is developed and the value of waiting is endogenously determined.

⁸To understand the following equation better, let us think of V jobs as V empty boxes and U workers as U balls. The balls fall into the boxes randomly. For each box, the probability of at least one ball falling into it is $1 - (1 - 1/V)^U$. Because there are V boxes altogether, the expected number of filled boxes is thus $V \times (1 - (1 - 1/V)^U)$.

When $U = V$, the matching probability of an individual worker, denoted by P , is given by:

$$P(U) = 1 - \left(1 - \frac{1}{U}\right)^U \quad (2)$$

The matching probability in (2) has two properties. First, it decreases as U increases. This is because when U increases, it is more likely that more than one worker has arrived at the acceptable interval for the same job while the job only needs one worker.⁹ Second, $P(U)$ is not dependent on the location of a since the model treats all workers symmetrically.

Now consider the expected payoff of the worker at a , conditional on his being matched with a job, say job $j + 1$ located at $b + j/U$.¹⁰ Because the bargaining power is θ , the conditional expected payoff of the worker is equal to $\theta/(1 - \theta)$ times the conditional expected profits of the firm, denoted $E(\Pi|match)$. The worker's location a is the closest to the job among all the workers and moreover, it is within the interval $[b + j/U - 1/2U, b + j/U + 1/2U)$. The conditional expected payoff of the worker is thus given by:

$$\begin{aligned} E(W|match) &= \frac{\theta}{1 - \theta} E(\Pi|match) \\ &= \frac{\theta}{1 - \theta} \int_0^{\frac{1}{2U}} (1 - \theta)y(d_{a,j+1}) \frac{2U(1 - 2d_{a,j+1})^{U-1}}{\int_0^{\frac{1}{2U}} 2U(1 - 2d_{a,j+1})^{U-1} dd_{a,j+1}} dd_{a,j+1}, \\ &= \frac{2U\theta}{1 - (1 - \frac{1}{U})^U} \int_0^{\frac{1}{2U}} y(d_{a,j+1})(1 - 2d_{a,j+1})^{U-1} dd_{a,j+1}, \end{aligned} \quad (3)$$

where $0 \leq d_{a,j+1} = |a - b - j/U| \leq 1/2U$.¹¹

Consider a production function $y(d_{a,j}) = \bar{y} \exp(-\alpha d_{a,j})$ where $\bar{y} > 0$ and $\alpha \geq 10$. In this case, the expected payoff of this worker is:

$$E(W) = P(U)E(W|match)$$

⁹In a recent paper, Gan and Li (2002) show that if rankings are allowed to order individuals and jobs, and if unmatched workers are allowed to keep looking for jobs, the matching probability may be increasing with market size.

¹⁰Because ex ante all the jobs are symmetric, it does not matter which job is matched with the worker ex post when calculating the expected payoff.

¹¹Because $d_{a,j+1}$ is the shortest arc distance between job $j + 1$ and the U job seekers, using order statistic, we can derive the pdf of $d_{a,j+1}$, $f(d_{a,j+1}) = 2U(1 - 2d_{a,j+1})^{U-1}$.

$$\begin{aligned}
&= \left[1 - \left(1 - \frac{1}{U} \right)^U \right] E(W|match) \\
&= 2U\theta\bar{y} \int_0^{\frac{1}{2U}} \exp(-\alpha d_{a,j+1})(1 - 2d_{a,j+1})^{U-1} dd_{a,j+1}, \tag{4}
\end{aligned}$$

where P_U is given by (2) and $E(W|match)$ is given by (3). When $U \geq 3$, it can be shown numerically that $E(W)$ increases with U for any $\alpha \geq 10$. For example, given $\alpha = 100$, $\partial E(W)/\partial U = .018\theta\bar{y}, .006\theta\bar{y}, .001\theta\bar{y}$ when $U = 3, 30, 100$, respectively. This reflects the effect of a thick market on improving the average matching quality between jobs and workers. Since $E(W)$ increases as U increases, when U is large enough, $E(W)$ will surpass the search cost c . Let \bar{n} be the critical size of the market such that:

$$2\bar{n}\theta\bar{y} \int_0^{\frac{1}{2\bar{n}}} \exp(-\alpha d_{a,j+1})(1 - 2d_{a,j+1})^{\bar{n}-1} dd_{a,j+1} = c. \tag{5}$$

We consider the equilibrium where unemployed workers wait before searching for jobs until the total number of unemployed workers U in the city accumulates to \bar{n} , since over time more and more matched job-worker pairs are separated by idiosyncratic shocks. The \bar{n} in (5) is the critical size of the market. We claim that the existence of such a critical size of the market leads to cyclical unemployment fluctuations in a city. Before the number of unemployed workers reaches \bar{n} , unemployed workers do not search for jobs in the market. When the market size reaches \bar{n} , all the unemployed workers engage in job-searching and matches occur. Therefore, this model predicts that either all or none will search. We call such an occasion as a clearance of the market.

Formally, let us normalize the labor market's clearance time at time $t = 0$. Then at the beginning of time $t = 1$ the unemployment in the local market is U_0 , determined by:

$$U_0 = \bar{n} \left(1 - \frac{1}{\bar{n}} \right)^{\bar{n}}. \tag{6}$$

Let U_t be the number of accumulated unemployed workers by time t . Let T be the number of time intervals such that:

$$U_T \geq \bar{n} > U_{T-1}. \tag{7}$$

The inequalities in (7) state that T is the smallest number of time intervals such that the accumulated number of unemployed workers in the local market will be larger or equal to the minimum market size \bar{n} . Assuming that the separation rate of a worker-job pair during any time period is ν , we have:

$$U_t = U_{t-1} + \nu(N - U_{t-1}), \quad 1 \leq t \leq T.$$

Solving the above difference equation, we get:

$$U_t = N(1 - (1 - \nu)^t) + U_0(1 - \nu)^t, \quad 1 \leq t \leq T, \quad (8)$$

The unemployment rate at the end of time t , denoted as u_t , is thus:

$$\begin{aligned} u_t &= U_t/N = 1 - (1 - \nu)^t + \frac{U_0(1 - \nu)^t}{N}, \quad 1 \leq t \leq T, \\ &= 1 - \left(1 - \frac{U_0}{N}\right) (1 - \nu)^t \end{aligned} \quad (9)$$

Clearly, u_t increases with t , implying that over time, as the pool of unemployed workers increases, the unemployment rate goes up. The average unemployment rate over the time interval $[1, t]$ is:

$$\begin{aligned} \bar{u}_t &\equiv \frac{\sum_{i=1}^t u_i}{t}, \quad 1 \leq t \leq T, \\ &= 1 - \left(1 - \frac{U_0}{N}\right) \left[\frac{1 - \nu}{\nu} \left(\frac{1 - (1 - \nu)^t}{t} \right) \right]. \end{aligned} \quad (10)$$

From (10), $\partial \bar{u}_t / \partial t > 0$. since u_t increases as t increases, its average over t , \bar{u}_t , also increases with t .

At time T , the number of accumulated unemployed workers just reaches the critical minimum size for the labor market to clear. According to (7) and (8),

$$U_0(1 - \nu)^T + N(1 - (1 - \nu)^T) \geq \bar{n} > U_0(1 - \nu)^{T-1} + N(1 - (1 - \nu)^{T-1}).$$

Rearrange the above inequality as follows:

$$T \geq \frac{\ln((N - \bar{n})/(N - U_0))}{\ln(1 - \nu)} > T - 1. \quad (11)$$

From (11), we can see that T decreases as N increases. Intuitively, it takes less time for a larger city to accumulate enough unemployed workers in the local labor market, given ν . Because T measures the length of time from the trough to the peak of an unemployment cycle, our model predicts that the length of each unemployment cycle is therefore negatively correlated with city size.

At time T , the unemployment rate is at its highest. From (9), the peak point unemployment rate is given by:

$$u_T = 1 - (1 - \nu)^T \left(1 - \frac{U_0}{N}\right). \quad (12)$$

Equation (12) says that the peak unemployment rate u_T increases as T increases. Combined with Equation (9), this model predicts that the peak unemployment rate decreases as city size increases.

According to (10), the average unemployment rate over the time interval $[1, T]$ is:

$$\bar{u}_T = 1 - \left[\frac{1 - \nu}{\nu} \left(\frac{1 - (1 - \nu)^T}{T} \right) \right] \left(1 - \frac{U_0}{N}\right). \quad (13)$$

According to Equation (13), the average unemployment rate over a cycle increases as T increases. Because T decreases as city size increases, the average unemployment rate for the cycle is lower for larger cities.

To better illustrate our model, we draw the unemployment fluctuation rate in two hypothetical markets in Figure 1. We let the probability of separation be constant at $\nu = .01$. The critical size of the market $\bar{n} = 5,000$. In the top graph in Figure 1, city size is 60,000. In the bottom graph in Figure 1, city size is 30,000. From the two graphs, we see that it takes a longer time for the smaller city to reach the critical size. The length of the cycle in the larger city is 5.56 while the length of the cycle in the smaller city is 12. The average unemployment rate in the larger city is about 6%, while the average unemployment rate in the smaller city is about 12%. The peak unemployment rate in the larger city is 8.3%, while the smaller city's peak unemployment rate is 16.7%.

In summary, the model has three testable predictions: (1) the length of unemployment cycles is shorter in a larger city; (2) larger cities have lower peak unemployment rates; and (3)

the average unemployment rate should be negatively correlated with city size;

2.2 The Data

The empirical analysis is conducted on a sample of 295 PMSAs in the U.S. over the years 1981–1997. During this period, the U.S. economy experienced both recession and expansion.

The data on monthly unemployment rates is collected from the Employment and Earnings published by the Department of Labor’s Bureau of Labor Statistics (BLS). Denote city c ’s unemployment rate at time t by $unempr_{ct}$. The employment data by PMSA is compiled from County Business Patterns and by summing up the city’s employment over industries. Denote a city c ’s employment at time t by emp_{ct} .

The industry employment information is obtained from the data that covers 543 industries at the 3-digit SIC level. We use the yearly employment data in County Business Patterns to calculate industry shares for each PMSA. We also use increments in the national employment by industry to approximate the nationwide industry-specific shock. The data on national employment by industry is obtained from the Bureau of Labor Statistics. Let s_{ict} denote the employment share of industry i in city c at time t . Let Δ_{it} denote the nationwide employment growth rate of industry i during time t . The industry composition effect on city c at time t will then be:

$$\begin{aligned} INDCOM_{ct} &= \sum_i^{543} s_{ict} \times \Delta_{it}, \\ \text{where } c &= 1, 2, \dots, 295, \\ i &= 1, 2, \dots, 543, \\ \text{and, } t &= 1981 : 1, 1982 : 2, \dots, 1997 : 12. \end{aligned} \tag{14}$$

Note here s_{ict} ’s are the same for all the t ’s in the same year, because for each city, its industry shares do not change much over the course of a year.

A second variable is the risk diversification effect, denoted as $RISK_{ct}$. This variable measures uncertainty local labor demand that depends on the covariance of local labor demand across industries. Following Neumann and Topel (1991), we compile a variable $RISK$:

$$RISK_{ct} = s'_{ct} \Omega s_{ct}, \tag{15}$$

where s_{ct} is the vector of industry employment shares of city c at time t and Ω is the covariance of nationwide industry-specific (detrended) shocks. The higher $RISK_{ct}$, the higher the uncertainty in local labor demand. Because the market friction tends to be greater when the uncertainty of the employment is higher, $RISK_{ct}$ affects the unemployment rate in a positive way.

Unemployment benefits, denoted by *benefit*, are another important factor affecting unemployment rates. We use the ratio of average weekly benefit to average weekly total wage to represent unemployment benefits. The state-by-state ratio is obtained from the U.S. Department of Labor (<http://www.doleta.gov>). If a PMSA is across more than one state, we assign the mean ratio of these states to the PMSA.

Shimer (2001) suggests that the proportion of youth in a local market may affect the local unemployment rate. We use the ratio of population between age 15 and age 24 to the population between age 15 and age 64 as a measure of the proportion of youth, denoted as *youth share*. This state-by-state ratio is obtained from the U.S. census. If a PMSA is across more than one state, we assign the mean ratio of these states to the PMSA.

Another factor that may affect unemployment rates is the net migration.¹² To control for the effect of net migration, we use the mean net migration rate over the sample period at the PMSA level. Finally, it is possible that the area of the a city may affect the unemployment rate. We include the variable $\log(\text{square miles})$ and its square in the regressions.

Table 1 is a summary of statistics of the variables involved in the analysis of this paper. The sample period is January 1981 – December 1997. The unemployment rate, *unempr*, is measured in percentage points. City size in Table 1 is measured by a city’s average labor force over time. Since variable $\log(\text{size})$ will be used, we list the summary statistics of the log of city size.

Table 1 shows that both city size and unemployment rate vary significantly. The average labor force ranges from 247,289 in Enid, Oklahoma (PMSA code 2340), to 3,532,300 in Los Angeles-Long Beach, California (PMSA code 4480). The average unemployment rate ranges

¹²We thank two referees for pointing this out.

Table 1: Summary Statistics of PMSA Averages (1981–1997)

	mean	standard deviation	minimum	maximum	original data frequency
<u>PMSA average</u>					
unempr	6.60	2.30	2.43	19.58	monthly
emp	232,110	397,482	19,931	3,262,702	monthly
size	247,289	425,347	19,931	3,532,300	monthly
$\log(\textit{size})$	11.71	1.07	9.94	15.7	monthly
benefit	.362	.047	.264	.470	yearly
youth share	.231	.014	.191	.291	yearly
net migration rate	1.196	1.131	-.983	5.678	yearly
$\log(\textit{miles}^2)$	7.249	.861	3.843	10.58	fixed
INDCOM	.00208	.000506	.207	.393	monthly
RISK	.00266	.00134	.000979	.0130	yearly
INDCOM \times RISK	8.2894E-6	6.938E-6	1.575E-6	.0000683	monthly

from 2.4% in Columbia, Missouri (PMSA code 1740), to 19.6% in McAllen-Edinburg-Mission, Texas (PMSA code 4880).

In Figure 2, we draw mean unemployment rates and log of city size. The straightline in the figure is the fitted line. The slope of the fitted line is $-.366$ (.123). To ease the potential concern about “outliers,” we delete cities that have unemployment rates larger than 15%. The fitted slope (not shown in the figure) is still significantly negative at $-.250$ (.107). In Section 5, we investigate this relationship in more detail.

3 City Size and the Frequency of Unemployment Fluctuations — a Spectral Analysis

Our focus in this section is on the relationship between the frequency of fluctuations in a city’s unemployment rate and its size. In particular, we are interested in testing the first prediction

of our model in Section 2.1, namely, the length of the cycles T decreases as the city size N increases.

We conducted a spectral analysis on three samples. The first sample consists of 139 PMSAs in the U.S. during 1981–1997. The unemployment rate data is monthly. For each PMSA, the number of unemployment rate observations is at least 200, indicating at most 4 missing values in the monthly unemployment rate. The second sample contains 168 PMSAs in the U.S. during 1983–1997. For each PMSA, the number of unemployment rate observations is at least 176, again indicating at most 4 missing values. As for the third sample, the period covers 1986–1997; and there are 204 PMSAs. For each PMSA, the number of unemployment rate observations is at least 140. Because we allow for at most 4 missing values for each PMSAs in the monthly unemployment rate, as the sample period becomes longer, there are therefore fewer qualified PMSAs remaining in the sample. We can see that any one of the three sample periods experienced both recession and expansion in the U.S. economy. Each sample contains PMSAs of all sizes. Since the spectral analysis on the three samples all show similar results, for convenience, in this paper we only present regression results based on the first sample; that is, the one with the longest sample period (i.e., January 1981–December 1997). The sample size is 139.

Our model studies unemployment rate fluctuations that are driven by market friction and idiosyncratic shocks across workers and firms, it does not consider business cycles caused by aggregate shocks to demand and to productivities. Therefore, it is necessary to control for the effect of aggregate shocks to the local unemployment rates. Thus, before we investigate the spectrum of local unemployment cycles, we first detrend the unemployment rate time series. Specifically, we run regressions of the unemployment rate $unempr_{ct}$ on the stochastic trend $X_{ct} = \{INDCOM_{ct}, RISK_{ct}, RISK_{ct} \times INDCOM_{ct}\}$ to control for the effects of the industry composition and the risk diversification and their interaction¹³; and on the deterministic trend $Z(t) = \{1, t, t^2, t^3\}$ to control for the effects of time trends. Here the regression is conducted

¹³Because *benefit* and *youth share* are yearly variables and do not change much over time, we do not treat them as stochastic trend variables.

city by city. Our objective is to conduct a spectral analysis in the frequency domain of the residuals city by city.

3.1 The Band Spectrum Regression and Filtering

The regression to be carried out here is called a band spectrum regression. It is conducted in the frequency domain. Since we want to examine the frequency of unemployment rate fluctuations, it is natural to use a regression in the frequency domain to control for the effects of trend variables. Moreover, it is plausible to consider that the relationship between the unemployment rate and trend variables is frequency-dependent. For example, the high frequency irregular fluctuations in labor demand should have a different effect on a city's unemployment rate from that of business cycle fluctuations. When the relationship is frequency-dependent, a detrending regression in the time domain can generate biased estimates, see Corbae, Ouliaris and Phillips (2002). On the contrary, the band spectrum regression best captures the essence that the coefficients of trend variables are frequency-dependent and it leads to consistent estimates. The band spectrum regression method adopted here follows Corbae et al. (2002).

We divide the frequency domain into three bands. Band 1 consists of frequencies that correspond to cycles with a length from 2 to 4 months. This is a high frequency band. Band 2 includes frequencies associated with cycles longer than 4 months but shorter than 18 months. This is a medium frequency band. Since a typical waiting period in the job search process falls within this band, studying this band may reveal important information on the average waiting period in the job search process.¹⁴ Band 3 is a low frequency band, consisting of frequencies corresponding to cycles longer than 18 months. This band includes the national business cycle frequencies, since according to National Bureau of Economic Research definitions, a business cycle in the U.S. at the national level has a length of between 18 and 96 months.

Let W denote a discrete Fourier transformation such that for any time series y of length T ,

¹⁴The mean unemployment duration of individuals is 3.8 months during 1994–2000 (Abraham and Shimer, 2001). According to our discussion in Section 1, the length of an unemployment cycle is roughly twice as long as the mean unemployment duration.

W is a $T \times T$ matrix and Wy is the discrete Fourier transformation of y . The T fundamental frequencies in Wy are $0, 2\pi/T, 4\pi/T, \dots$, and $2\pi(T-1)/T$. Let A^j be a $T \times T$ diagonal matrix with value 1 at the k -th row if $2\pi(k-1)/T$ lies within Band j as previously defined, and which otherwise has a value of 0. In other words, by taking the product of A^j and Wy , we can zero out all the fundamental frequencies in Wy that lie outside of Band j .

The regression model specifies:

$$\begin{aligned} Wunempr_{ct} = & A^1WZ(t)\alpha_c^1 + A^2WZ(t)\alpha_c^2 + A^3WZ(t)\alpha_c^3 \\ & A^1WX_{ct}\beta_c^1 + A^2WX_{ct}\beta_c^2 + A^3WX_{ct}\beta_c^3 + Wu_{ct} \end{aligned} \quad (16)$$

where α_c^i, β_c^i , and $i = 1, 2, 3$ are parameters to be estimated and which vary by city. Note that Equation (16) allows parameters to be different in different bands, capturing the possibility that the relationship between unemployment rates and control variables is frequency-dependent. After the regression, we take the residuals for each city c and conduct the inverse Fourier transformation. The resulting time series is an estimate of the detrended unemployment rate, denoted $\{u_{ct}\}$.

Before we conduct a spectral analysis, there is one more step to go: filtering. We need to smooth the irregular high frequency fluctuations in u_{ct} in order to obtain more robust results. That's why we filter out the high frequencies in u_{ct} that lie within Band 1. Also, because our primary interest is local unemployment cycles, we need to control for the effect of the time trend and the effect of national business cycles that might still remain after the band spectrum regression. Thus we filter out the low frequencies in u_{ct} that lie within Band 3. We then focus on the frequencies within Band 2. As stated above, this band consists of frequencies associated with cycles longer than 4 months but shorter than 18 months. Studying this band reveals important information on the average waiting period in the job search process. It sheds light on local unemployment cycles that are caused by friction in the local labor market. We use Corbae and Ouliaris (2002)'s filter to remove any frequency in u_{ct} that lies within either Band 1 or Band 3. Corbae and Ouliaris's filter works in the frequency domain and it is natural for us to use this filter after the band spectrum regression¹⁵. Moreover, Corbae and Ouliaris's

¹⁵We also tried the method of Baxter and King (1999). We used the extracted time series obtained through

filter has the following merits: 1) it generates a statistically consistent estimator of the ideal band pass filter; 2) it controls for stochastic trends and deterministic trends easily; and 3) it involves no set up of parameter values and no loss of observations at either end of the time series.

After filtering $\{u_{ct}\}$, we obtain a new time series for each city c , denoted u_{ct}^* . Our spectral analysis is conducted on the frequency domain of $\{u_{ct}^*\}$.

3.2 Spectral Analysis

Our spectral analysis reveals how cycles with different frequencies account for fluctuations in a city's unemployment rate. A frequency of ω is associated with a cycle of length of $2\pi/\omega$. Let $s_y(\omega)$ be the power spectral density at ω of a time series y ; and $\int_0^\pi s_y(\omega)d\omega$ is the total energy contained in fluctuations in y , denoted G_y . Thus, $\int_{\omega-\delta}^{\omega+\delta} s_y(f)df$ represents the portion of the energy that is attributed to frequencies that lie within the δ -interval of frequency ω . This reflects how much frequencies within that interval contribute to fluctuations in y .

We estimate the power spectrum density for each city. For city c and a given δ_c , we find a frequency ω whose δ_c -interval contributes the most to the energy of $\{u_{ct}^*\}$. This frequency contributes more to fluctuations in the city's unemployment rate than any of the other frequencies.

Formally, we define city c 's max-frequency as:

$$\omega_c^{max} = arg \max_{\delta_c \leq \omega \leq \pi - \delta_c} \int_{\omega - \delta_c}^{\omega + \delta_c} \theta(|\omega - f|) s_{u_c^*}(f) df,$$

where $\theta(\cdot)$ is a weight function. We let:

$$\theta(f) = \begin{cases} 0, & \text{if } |f - \omega| > \delta_c; \\ \frac{.8^{2|f - \omega|/\delta_c}}{\int_{\omega - \delta_c}^{\omega + \delta_c} .8^{2|f - \omega|/\delta_c} df}, & \text{if } |f - \omega| \leq \delta_c. \end{cases}$$

This weight function has the property that the closer the frequency f is to ω , the larger the weight assigned to this frequency will be.

Baxter and King's filter to run the same regression as in Section 4.3. The results (not shown here but available upon request) are consistent with the ones reported in Table 3 of this paper.

Table 2: Summary Statistics of Frequency Variables

	mean	std dev	minimum	maximum
max-frequency	.631	.235	.368	1.520
mean-frequency	.793	.0985	.616	1.030

Selecting an appropriate δ_c depends on how smooth the power spectral density curve of time series $\{u_{ct}^*\}$ is and what method is used to estimate the power spectral density.¹⁶ A smaller δ_c implies less robustness but more accuracy in calculating the max-frequency. After some experiments, we choose $\delta_c = .049$, which is 3% of the length of the spectral domain $[0, \pi]$ we investigate. Another frequency we are interested in is given by:

$$\omega_c^{mean} = \int_0^\pi \frac{s_{u_c^*}(f)}{G_{u_c^*}} f df.$$

The variable ω_c^{mean} is called the “mean-frequency” since it is a weighted average of frequencies over the frequency domain where the weight of each frequency is its (normalized) power spectral density. The higher the mean-frequency, the more contributions from high frequency cycles to unemployment fluctuations there are.

Table 2 is a summary of statistics of the frequency variables. The max-frequency and mean-frequency are .631 and .793, corresponding to 10.0 months and 7.9 months, respectively.

In order to understand the spectral analysis conducted in this section, we present an example comparing the $\{unempr_t\}$, $\{u_t^*\}$, and the power spectrum of $\{u_t^*\}$ of two cities. The first city, Monroe, Louisiana (PMSA code 5200), is relatively small and has an average labor force of 52,589. The other city is Los Angeles (PMSA code 4480), with an average labor force of 3,532,300.

The example is illustrated in Figure 3. The first row in Figure 3 depicts the unemployment rate $unempr_{ct}$ for Monroe and Los Angeles. The average unemployment rate in Monroe is 8.30%; while in Los Angeles, the average unemployment rate is 7.69%. This is consistent with the our models’ first prediction.

¹⁶We use a MATLAB function “pmtm”. It is a function using the multi taper method (MTM) to estimate the power spectral density.

The detrended and filtered unemployment rates u_{ct}^* are illustrated in the figures in the second row. We will come back to these figures in Section 5. In the third row, we draw the power spectrum of u_{ct}^* for both cities. The max-frequency in Monroe is .44, corresponding to a cycle of $2\pi/.44 = 14.3$ months. For Los Angeles, its max-frequency occurs at 1.08, which corresponds to a cycle of around 6 months.¹⁷ We may also turn to a more robust measurement, the mean-frequency. Monroe has a lower mean-frequency (.6) than that of Los Angeles (.73), which means that the larger city has shorter cycles than the smaller city on average, consistent with the first prediction of our model.

3.3 Results from Summary Regressions

We use simple regressions of the variables of max-frequency and mean-frequency on the log of city size and Y_{ct} to summarize the relationships, where Y_c is a vector of other variables that may influence unemployment rates, discussed in Section 2.2. Specifically,

$$\begin{aligned} \text{max-frequency}_c &= \alpha^f + Y_c \zeta^f + \eta^f \log(\text{size}_c) + \epsilon_c^f, \\ (\text{or mean-frequency}_c) \end{aligned} \tag{17}$$

where

$$Y_c = \{\text{mean benefit}_c, \text{mean youth share}_c, \text{mean net migration rate}_c, \log(\text{miles}_c^2)\},$$

According to our model in Section 2.1, the sign of η^f should be positive. The regression results are shown in Table 3. As predicted by the model, both max-frequency and mean-frequency are significant and positively correlated with city size. To assess the magnitude of the effect of city size, consider an increase of two standard deviations in the log of city size. The max-frequency increases by .135. If the initial max-frequency is .631, which equals the mean of max frequency across cities, the corresponding unemployment cycle will be shortened by 1.75 months. As to the mean-frequency, it increases by .066. If the initial mean frequency is .793,

¹⁷The first peak in Los Angeles' power spectrum occurs at frequency .52, corresponding to a cycle of 12 months. This is the seasonal effect. It is slightly dominated by the city's max-frequency, because its spectral density is smaller than that of the max-frequency.

Table 3: Frequency Regression Results

dependent variable	max-frequency	mean-frequency
constant	.084 (.086)	.605 (.358)
log(size)	.063 (.022)	.031 (.0092)
benefit	-.600 (.423)	.014 (.177)
youth share	.590 (1.67)	-.639 (.699)
net migration rate	-.0035 (.021)	-.0015 (.0086)
log(<i>miles</i> ²)	.0044 (.188)	.0031 (.078)
[log(<i>miles</i> ²)] ²	-.0031 (.013)	-.0011 (.0053)
R^2	.078	.099
No. of obs.	139	139

Standard errors are in parentheses.

which equals the mean of mean-frequency across cities, the corresponding unemployment cycle will be shortened by .61 months. To summarize, the results in this section support our model's the first prediction: larger cities have shorter unemployment cycles. According to Table 3, the average benefit, the average youth share, and the average net migration rate are statistically insignificant, which indicates that these three variables cannot explain cyclical fluctuations of unemployment rates.

4 The Duration Analysis

In this section we carry out a different experiment: we investigate the duration of cyclical fluctuations in the unemployment rate city by city. Following Diebold and Rudebusch (1990), “duration” here refers to the length of each cycle, while a “cycle” is the time length between two consecutive turning points of an unemployment rate. We will define the turning points later in this section.

A duration analysis differs from the spectral analysis in two aspects. First, in a duration analysis, identifying turning points of a cycle depends on the subjective rule we use. In a spectral analysis, a cycle is defined in the strict sense of periodicity. Thus, the results of a spectral analysis do not depend on the rule used to identify the turning points of a cycle. Second, the results from a spectral analysis are concerned with a whole cycle. Thus, it is impossible to discern different behaviors at different stages of a cycle. In contrast, a duration analysis reveals the relationship between city size and the length of both trough-to-peak cycles and peak-to-trough cycles. Moreover, through identifying turning points, a duration analysis sheds light on the amplitude of cyclical fluctuations. Thus, it can provide an empirical test on the second prediction of our model in Section 2.1; namely, larger cities have lower peak unemployment rates.

4.1 Duration of Unemployment Cycles

We examine the duration of cyclical fluctuations of $\{u_{ct}^*\}$, for each city c , where $\{u_{ct}^*\}$ is the detrended and filtered unemployment rate defined in the previous section. A cycle of $\{u_{ct}^*\}$ is the time length between two consecutive turning points of $\{u_{ct}^*\}$. The following are some useful definitions.

- A *trough point* is the point where an upturn is about to start. Because we are considering the unemployment rate, an upturn in $\{u_{ct}^*\}$ signals a downturn in the economy.
- A *peak point* is the point with the highest value of $\{u_{ct}^*\}$ between two consecutive trough points.

- A *trough-to-trough duration* is the length between two consecutive trough points.
- A *trough-to-peak duration* is the length between a trough point and the first peak point right after it.
- A *peak-to-trough duration* is the length between a peak point and the first trough point right after it.

The key then is to figure out how to identify an upturn in $\{u_{ct}^*\}$. The classic criterion for identifying a downturn in a business cycle is the “two consecutive declines” rule associated with GDP. Here, we apply a similar criterion (with a slight modification) to determine unemployment cycles. Specifically, an upturn is signaled either by two consecutive periods of growth in the unemployment rate or by three consecutive time periods where each has a higher unemployment rate than the preceding; moreover, there should be at least two periods of growth in the unemployment rate in these three time periods. The modification made here is to control for small noises in the time series.

According to the above criterion, time t is a trough point of $\{u_{ct}^*\}$ if and only if:

$$\left\{ \begin{array}{l} \left(u_{ct-2}^* > u_{ct}^*, u_{ct-1}^* > u_{ct}^* \right) \text{ and} \\ u_{ct+1}^* > u_{ct}^* \text{ and} \\ u_{ct+2}^* > u_{ct+1}^* \text{ or } \left(u_{ct+2}^* > u_{ct}^*, u_{ct+3}^* > u_{ct+2}^* \right). \end{array} \right. \quad (18)$$

4.2 City Size and Durations of Unemployment Cycles

We first identify each city’s peak and trough points of unemployment cycles according to (18). Next we calculate each city’s average trough-to-trough duration, trough-to-peak duration, peak-to-trough duration and peak unemployment rate. Table 4 provides a summary of statistics of these variables. The average length of cycles, measured by the average trough-to-trough duration, is 7.0 months. Note, in Table 2, that the mean-frequency is .793, corresponding to a cycle of 7.9 months. The difference between the two measures arises from the fact that cycles are measured according to different methods.

Table 4: Summary Statistics of Duration Variables

	mean	std dev	min	max
trough-to-trough	7.01	1.01	5.27	10.9
trough-to-peak	3.4	.43	2.56	4.95
peak-to-trough	3.6	.71	2.57	6.89
peak rate	.61	.375	.188	2.76

Standard errors are in parentheses.

Table 5: Regression Results of Duration Analysis

	trough-to-trough	trough-to-peak	peak-to-trough	peak rate
constant	7.94 (3.61)	4.14 (1.54)	3.81 (2.51)	4.47 (1.31)
log(size)	-.337 (.093)	-.117 (.039)	-.220 (.064)	-.154 (.034)
benefit	-.310 (1.79)	-.681 (.760)	.360 (1.24)	-.748 (.647)
youth share	-.619 (7.07)	3.86 (3.01)	-4.55 (4.91)	-5.22 (2.56)
net migration rate	.091 (.087)	-.024 (.034)	.123 (.060)	-.027 (.031)
log(<i>miles</i> ²)	.851 (.792)	-.024 (.337)	.876 (.550)	-.181 (.287)
[log(<i>miles</i> ²)] ²	-.054 (.053)	.0039 (.023)	-.058 (.037)	-.016 (.019)
R^2	.122	.103	.137	.161
No. of obs.	139	139	139	139

Standard errors are in parentheses.

Table 5 lists results from some simple regressions that summarize the relationship between the log of city size and unemployment cycles. In the first column, the trough-to-trough duration, i.e., the length of an entire cycle, is significantly and negatively correlated with city size. In particular, an increase in two standard deviations of the log of city size will result in a decrease in the duration of unemployment cycles by .72 months. If we decompose the entire cycle into two parts, Table 5 shows that the trough-to-peak duration is significantly and negatively correlated with city size, while the peak-to-trough duration is also significantly and negatively correlated with city size.

The test results are consistent with the thick market model presented in Section 2. According to the first prediction of our model, larger cities in general have shorter trough-to-peak durations. Due to the thick market effect, a city's unemployed workers accumulate before the local labor market reaches a large enough size to have workers actively search for jobs. Larger cities typically need less time to reach that market size, which implies shorter trough-to-peak durations.

It is worth pointing out that the average length of peak-to-trough is 3.4 months (Table 5). Our model has not yet considered how the matching between firms and workers proceeds after the minimum critical size \bar{n} is reached. It assumes that matching occurs instantly. However, it may take time after firms and workers meet. Table 6 shows a significant negative correlation between the peak-to-trough duration and city size. The explanation to this fact is an interesting topic for future research. It might be that urban agglomeration speeds up the matching process.

As to the relationship between city size and peak unemployment rates, it is clear from the last column in Table 5 that the peak unemployment rate is significantly and negatively correlated with city size. This result supports the second prediction of the model in Section 2. A lower peak unemployment rate in a larger city indicates a shallower recession in that city. In particular, an increase in two standard deviations in the log of city size lowers the peak unemployment rates by .33 percentage points.

Table 5 also shows that the average benefit and the average youth share cannot explain any duration variables. However, the youth share is marginally significant in explaining the

peak unemployment rate.

The figures in the second row of Figure 3 illustrate how the durations and peak unemployment rates of unemployment cycles are different for two different cities. Monroe, Louisiana, which is a small city, has a much larger average peak unemployment rate than that of Los Angeles. The average peak rate in Monroe is .801%, while the average peak rate in Los Angeles is .451%. Moreover, the average length of cycles is also longer in Monroe (7.6 months) than that of Los Angeles (6.8 months).

5 City Size and Mean Unemployment Rate

In this section, we examine the relationship between the average unemployment rate and city size. The basic model we are interested in is as follows:

$$unempr_{ct} = \alpha_c + \gamma_t + X_{ct}\beta + Y_{ct}\zeta + \eta \log(size_c) + \epsilon_{ct}, \quad (19)$$

where the X_{ct} and Y_{ct} are vectors of control variables. In particular, we consider:

$$\begin{aligned} X_{ct} &= \{RISK_{ct}, INDCOM_{ct}, RISK_{ct} \times INDCOM_{ct}\} \\ Y_{ct} &= \{\text{benefit}_{ct}, \text{youth share}_{ct}, \text{mean net migration rate}_c, \log(miles_c^2)\}, \end{aligned}$$

where the variable $RISK_{ct}$ in X_{ct} is constructed in (15), and the variable $INDCOM_{ct}$ in X_{ct} is constructed in (14). The expected sign for $RISK_{ct}$ is positive and for $INDCOM_{ct}$ is negative. The coefficient for the interaction term is unclear. The vector X_{ct} represents the two previous hypotheses about difference in local unemployment rates: the industry composition and the risk diversification. The vector Y_{ct} includes other variables that may affect local unemployment rates, such that unemployment benefit and youth share. Both variables are discussed in Section 2.2.

To investigate the relationship between the unemployment rate and city size, we include an additional term $\log(size_c)$ in the model. City size is defined by the city's average total labor force in our sample period. The coefficient on the log of average city size, η , is expected to be negative: the larger the city size, the lower the unemployment rate.

Our model only studies unemployment rate fluctuations that are driven by market friction and idiosyncratic shocks across workers and firms, it does not consider business cycles caused by aggregate shocks to demand and to productivities. Therefore, it is necessary to control for the effect of aggregate shocks to the local unemployment rates. In Equation (19), the term γ_t is the fixed time effect. It is used to control for the effect of the time trend.

Another term α_c in (19) represents the unobserved city heterogeneity. Since the variable $\log(\text{size}_c)$ does not change over time, we cannot use a fixed city effect model. Instead, we let α_c be a random variable, such that $E(\alpha_c|X_{it}, \log(\text{size}_c)) = 0$. This specification represents a random city effect model. For the purpose of comparison, we also estimate models that do not include the term $\log(\text{size}_c)$.

We use the random effect model rather than the fixed effect model for two reasons. First, using time invariant city size is consistent with our theoretical model that only considers the effect of size variation across cities (not across time). Second, using the random effect model avoids a potential problem that the unemployment rate at time t at a city may affect net migration of the city at time $t+1$. Therefore, that effect may lead to correlation between the error term ϵ_{ct} and the city size at time $t+1$. Since the correlation mainly occur in the time domain, using the average city size minimizes (if not eliminates) that correlation. To further control the effect of migration or the growth of the city, we include the average net migration rates in the regressions.¹⁸

The reduced-form specification outlined in equations (19) is chosen for two reasons. First, since the reduced-form specification is consistent with previous study about local unemployment rates of Simon (1988) and Neumann and Topel (1991), we can compare our results to their work. Second, the theoretical model in Section 2 only offers predictions in *signs* on how a local unemployment rate varies with the city size.¹⁹ It is, therefore, appropriate to work with

¹⁸We also include the total population growth rates in the regressions. Results (not shown here) are virtually the same.

¹⁹For example, Equation (13) describes the the average unemployment rate \bar{u}_T would decrease if the city size N increases, i.e., $\partial \bar{u}_T / \partial N > 0$. Other parameters in Equation (13), such as the unemployment in the local market at beginning of time U_0 , and the separation rate of a worker-job pair during a time period ν , are the

the reduced-form specification.

Table 6 lists the regression results. Column (1) does not have city size while Column (2) includes city size. In these specifications, the coefficients for the variable *INDCOM* are significantly negative, supporting the industry composition hypothesis. The coefficients for the variable *RISK* are positive but significant. In addition, our estimates are consistent with the results in Shimer (2001) who shows that a larger youth share leads to a lower unemployment rate.²⁰

More importantly, in the regression results reported in Column (2) the log of city size has a significantly negative effect on a city's unemployment rate: The coefficient for $\log(\textit{size})$ is $-.0752$ ($.0129$). The third prediction of our model is supported: larger cities have lower unemployment rates.

To compare the magnitude of the effects of all three hypotheses, we calculate changes in the unemployment rate given an increase of two standard deviations for each of the five variables *INDCOM*, *RISK*, youth share, unemployment benefits, and $\log(\textit{size})$. If we apply the estimates from Column (2), the unemployment rate would decrease by $.018$ percentage points if *INDCOM* increases, increase by $.006$ percentage points if *RISK* increases, decrease by $.06$ percentage points if youth share increases, increase by $.096$ percentage points, and decrease by $.16$ percentage points if city size increases. The effect of city size is thus much more important than effect of industry composition and risk diversification. It is about 60% larger than the effect of unemployment benefits, and more than twice as much as the effect of youth proportion.

same across cities with the different sizes. The values of these variables do not affect the negative relationships between the city size N and the unemployment rate \bar{u}_T .

²⁰Our results remain essentially the same when the birth rate is used as the instrumental variable for youth share.

Table 6: Unemployment Rate Mean Regression Results

Variables	(1)	(2)
time fixed effect	yes	yes
city random effect	yes	yes
constant	.485 (.520)	1.423 (.539)
lagged unemployment rate	.874 (.0020)	.873 (.0021)
INDCOM	-18.64 (1.033)	-18.66 (1.033)
RISK	10.61 (5.69)	1.467 (5.88)
INDCOM \times RISK	360.8 (163.8)	424.9 (163.4)
unemployment benefit	1.058 (.128)	1.019 (.127)
youth share	-1.765 (.528)	-2.147 (.531)
mean net migration rate	-.0051 (.011)	.0080 (.011)
log(miles ²)	-.141 (.140)	-.203 (.139)
$[\log(\text{miles}^2)]^2$.0105 (.0095)	.0179 (.0095)
log(size)		-.0752 (.0129)
R^2	.915	.916
No. of Obs.	50439	50439

Standard errors are in parentheses.

6 Conclusion

This paper explores the relationship between city size and pattern of unemployment rate fluctuations. We present a model of the local labor market in which when more workers are looking for jobs and more job openings are available, the matching quality between jobs and workers increases. A higher matching quality leads to a higher wage. Workers incur search costs if they actively search for jobs. Unemployed workers accumulate in a local market until the market reaches a critical size such that the expected payoff is higher than the cost of job-searching. Since a given shock produces more unemployed workers in larger cities during a given time period, it takes a shorter time for larger cities to reach the critical size described above. Consequently, the model predicts: (1) the length of unemployment cycles decreases as city size increases; (2) the peak unemployment rate is negatively correlated with city size; and (3) the average unemployment rate is lower in larger cities.

Our empirical analysis utilizes data that covers 295 PMSAs in the U.S. over the years 1981–1997. After controlling for the effects of industry composition and risk diversification, we find that larger cities have shorter unemployment cycles. Specifically, the unemployment cycle will be shortened by roughly .72 months if city size increases by two standard deviations. We also find milder trough-to-peak unemployment cycles for larger cities. The peak unemployment rate will be lowered by .33 percentage points if city size increases by two standard deviations. Finally, city size has a significantly negative effect on the mean unemployment rate. In particular, the unemployment rate will be lowered by roughly .16 percentage points. All these empirical results are consistent with our model’s predictions.

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Figure 1: Illustration of the Thick Market Effect on Unemployment Fluctuations

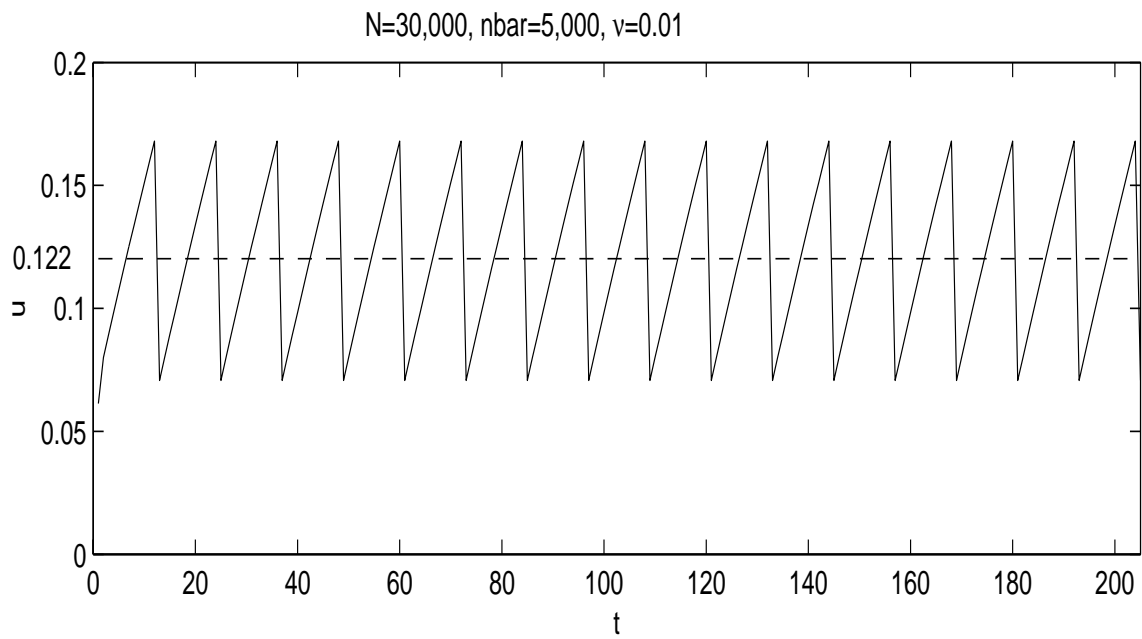
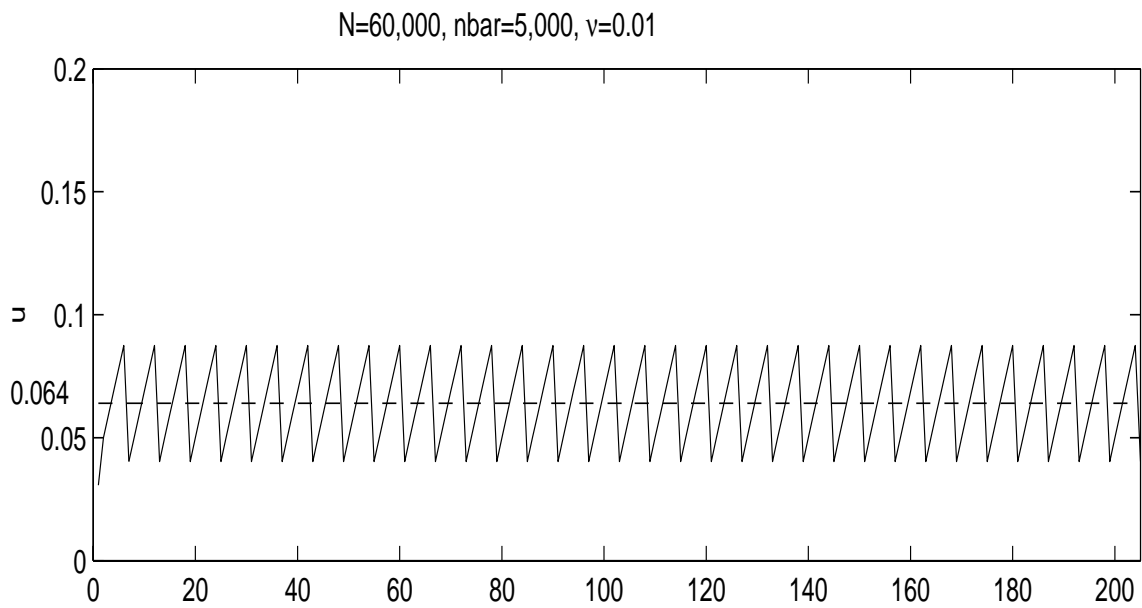


Figure 2: Logarithm of City Size and Mean Unemployment Rates

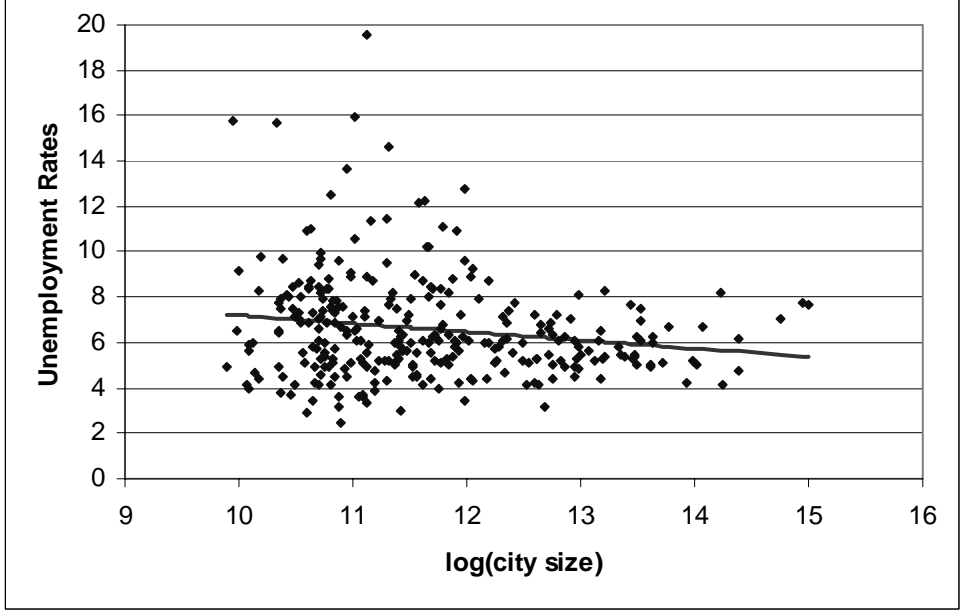


Figure 3: Patterns of Unemployment Rates in Monroe, LA, and Los Angeles, CA

