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Incomplete Information and the Lag between Temporary and Permanent Employment Adjustment: A Cross-City Analysis

By

Yukako Ono[†]

Qinghua Zhang[‡]

Abstract

It is well-observed that the growth of temporary help service (THS) employment tends to lead that of total employment over business cycles. Such a tendency, however, varies vastly across geographic areas. This paper provides an explanation to such variations from the perspective of information environment. A firm can observe only overall demand shocks and cannot contemporaneously distinguish long-lived shocks (e.g., business cycle shocks) from transitory shocks. The information environment the firm faces can be characterized by the average volatility of transitory demand shocks and that of long-lived demand shocks, which determine the degree to which the firm can infer the nature of an observed shock.

Our empirical findings show that a city with the greater volatility of transitory shocks has a longer lag between the permanent and temporary employment growth, if the timing of transitory shocks differ sufficiently across industries in the city. This possibly reflects that the greater volatility of transitory shocks makes the information contained in a contemporaneous shock noisier and makes firms to postpone adjusting permanent employment level in responding to the shock. In contrast, the greater volatility of long-lived shocks shortens the lag, possibly because it allows firms more readily identify the nature of the contemporaneous shock.

Key Words

temporary help employment, THS employment, permanent employment, incomplete information, information extraction, business cycle shock, long-lived shock, transitory shock

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[†]Associate Professor, Faculty of Business and Commerce, Keio University
yono@fbc.keio.ac.jp

[‡]Associate Professor, Department of Applied Economics in Guanghua School of Management, Peking University
zhangq@gsm.pku.edu.cn

1. Introduction

The growth of temporary help service (THS) employment tends to lead that of total employment over business cycles (Segal and Sullivan, 1995).[1] It is often used as one of the leading business cycle indicators. In this paper, we investigate determinants for the geographic variations in the lag between temporary and permanent employment growth.[2] We find wide cross-city variation in the length of the lag. Our paper provides an explanation on such variations from the perspective of information environment. We perform empirical testing on the hypotheses based on our theoretical framework.

It is considered that, permanent work arrangements require adjustment costs for job creation and destruction, while temporary work arrangements impose less friction. However, firms often cannot distinguish long-lived shocks (i.e., business cycle shocks) from transitory shocks contemporaneously due to incomplete information. Thus, even when a firm faces a long-lived shock, without knowing the nature of the shock, the firm might adjust temporary employment first, in order to avoid costs associated with adjusting permanent employment. The firms might postpone the adjustment (or making only a partial adjustment) of permanent employment until more information is revealed.[3] The nature of shocks would vary across industries, and this leads to different information environments across cities due to the cross-city variation of industry mix. We argue that such difference would explain the cross-city variation of the lag between temporary and permanent employment adjustments.

To capture the information environment in a given city, we first measure the volatility of transitory shocks and that of long-lived shocks for each industry at the national level. We then take weighted average of each of these industry volatilities using the industry composition of the city as the weights. The relative volatility size of long-lived shocks to that of transitory shocks would determine the degree to which a firm can infer the nature of a contemporaneous shock. The volatility of transitory shocks would make the signal in the contemporaneous shock noisier and would make the firm hesitate to adjust its permanent employment level. On the other hand, if the volatility of long-lived shocks is larger in a city, it would accelerate the firm's adjustment of permanent employment level when a long-lived shock occurs, because 1) the firm can more readily identify whether or not the contemporaneous shock is long-lived and because 2) the expected loss from postponing the adjustment of permanent employment level would be greater. Consistent with theses views, our empirical findings show that the volatilities of these two types of shocks in a given city have contrasting association with the lag in employment adjustments in the city. Explanation for such relationships would not be obvious, if firms had perfect information.

Our paper makes two main contributions to the literature on employment adjustments. First, we shed light on the geographic variations in the lead-lag relationships between the growths of temporary and permanent employment. Second, we examine how information

[1] At the U.S. level, Segal and Sullivan (1995) find that THS employment growth leads aggregate employment by at least one quarter over a course of a business cycle. They also show that the lagged THS employment growth improves the forecast of aggregate employment growth even though THS employment is only a small fraction of the overall economy. The THS employment growth is also often used as a leading indicator for business cycle.

[2] Only a few papers (Autor, 2003; Ono and Zelenev, 2003) consider that the use of THS workers differs across geographical areas.

[3] Supporting the view that temporary workers facilitate flexibility in the labor market, Golden (1996) finds that a rise in demand for output above the long-run trend produces a strong concurrent rise in the THS employment.

environment influences the cross-city variation of labor market phenomenon.

In Section 2, we present a simple theoretical framework in which firms substitute one type of labor with the other - more efficient but less flexible labor (permanent labor) and less efficient but more flexible labor (temporary labor).[4] We assume that firms cannot contemporaneously differentiate long-lived demand shocks from transitory demand shocks and that firms identify the nature of the shocks later. This setup is different from most of the existing papers on costly employment adjustments in which firms have perfect information on the nature of demand shocks (Hamermesh, 1989; Bentolila and Bertola, 1990; Campbell and Fisher, 2004, etc.). Our theory leads to two hypotheses. The first is that temporary employment growth leads permanent employment growth more, when the volatility of transitory shocks is greater. The second hypothesis is that the lead is shorter, when the volatility of long-lived shocks is greater.

In Section 3, we present our empirical strategy to test the extent to which the above hypotheses explain the cross-city variation in the lead-lag relationship between permanent and THS employment growth rates. To do so, we first measure the lag for each city based on a distributed lag regression for each city, using the city-level permanent and THS employment growth rates based on the BLS (Bureau of Labor Statistics) monthly employment data at the level of metropolitan statistical areas (MSAs) in the U.S. We find significant cross-city variations in the employment adjustment lag; the standard deviation of the lag is 4.27 month, where the average lag is 5.28 month. We then measure the city-level volatility of transitory shocks and that of long-lived shocks, taking a weighted average of the national-level volatility measure of each industry for each type of shocks, using a city's industry mix as the weights.

To distinguish transitory from long-lived shocks for each industry at the national level, we adopt a filtering approach by Baxter and King (1999) and define long-lived shocks as persistent shocks of business cycle frequencies and transitory shocks as i.i.d. shocks of high frequencies.[5] Finally, we perform cross-city regressions of the employment adjustment lag on the volatility measures.

We also control for other variables such as the co-movement of transitory shocks among the industries of a given city, which we consider associated with the THS worker wage/mark-up. We also control for city size, industry structure, and demographic characteristics, which we discuss in the empirical section.

In Section 4, we discusses our empirical results. Our empirical analyses find that the lag between THS and permanent employment growth rates is shorter in a city with greater volatility of long-lived demand shocks. We also find that the lag is longer in a city with greater volatility of transitory demand shocks, as long as the degree to which the timing of transitory shocks coincide among the industries in the city is low enough. We discuss in more details in Section 4. We also perform several robustness analyses, which support our hypotheses. Section 5 concludes.

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[4] Similar definitions are also used in Campbell and Fisher (2004).

[5] Transitory shocks are mean reverting, while long-lived shocks are positively auto-correlated. In the empirical analyses, we treat shocks at business cycle frequency (18 to 96 months in cyclical length according to NBER definition) as long-lived shocks, because they present significant time persistency.

2. A theoretical framework

In this section, we lay out a framework that lead to the two hypotheses regarding the effects of demand volatilities on the lag between temporary and permanent employment adjustment. Let us consider two states (low and high) specified by mean demand level. We examine how firms adjust permanent employment level responding to a state-shift, which, in our framework, represents a long-lived shock. Due to incomplete information, the firm cannot tell contemporaneously whether the observed demand change is caused by a transitory shock or a state-shift. To avoid the costs of adjusting permanent employment, the firm either postpones or only partially adjusts its permanent employment. The decision is based on a probability of the state-shift that the firm infers based on the observed contemporaneous demand change and the typical volatility size of transitory fluctuations and that of long-lived shocks (i.e. the difference in the two states). that firms know from the historical data. In our framework, it is more difficult for the firm to identify a state-shift if the volatility of transitory fluctuation is greater, because it makes the signal conveyed in the observed contemporaneous demand noisier.

2-1. Basics

Consider a firm with a production function specified as

$$f(l) = Al^{\alpha}, \quad 0 < \alpha < 1, \quad A > 0,$$

where l is effective units of labor. Let l^P represent the number of permanent workers and l^T the number of temporary workers. Assuming that they are a perfect substitute to each other, we write $l \equiv l^P + cl^T$, where $0 < c < 1$. The firm takes the price of product, p, and wages as given. The wage rate of temporary workers is w, and that of permanent workers is normalized to be 1. We assume $w/c > 1$, and that the firm can hire or fire temporary workers without any adjustment costs but bears certain costs when it adjusts its permanent employment level; otherwise firms would never use permanent workers. We specify such adjustment costs to be $\lambda \mid \Delta l_t^P \mid$, where $\lambda > 0$ and $\Delta l_t^P \equiv l_t^P - l_{t-1}^P$. To simplify our analysis, we also assume a one-time adjustment period; a permanent worker hired today has to be trained through the current period before turning productive, and a permanent worker fired today is entitled to a grace period and remains on the payroll through the current period. Relaxing this assumption does not qualitatively change the key results of our model. The maximum units of effective labor the firm can use at time t, is

$$l_t = l_{t-1}^P + cl_t^T, \quad 0 < c < 1. \tag{1}$$

The firm solves a cost minimization problem and decides how much temporary labor to use, given current demand, y_t, and the level of permanent employment from the last period, l_{t-1}^P. The firm's temporary employment level at time, t, is

$$l_t^T = \begin{cases} \dfrac{\left(\dfrac{y_t}{A}\right)^{\frac{1}{\alpha}} - l_{t-1}^P}{c}, & \text{if } \ y_t > A(l_{t-1}^P)^{\alpha}. \\ 0, \quad \text{otherwise} \end{cases} \tag{2}$$

From Equation (2), one can see that the firm adjusts its temporary employment level based on y_t as long as y_t is greater than the output level that can be produced solely by the permanent workers from the previous period.

We specify that $y_t = \mu_t + \varepsilon_t$, where μ_t represents mean demand, and ε_t represents a transitory demand shock and is a random i.i.d. draw from a normal distribution $N(0, \sigma^2)$. The standard deviation σ measures the volatility of transitory shocks. We assume that there are only two states of mean demand, μ_L and μ_H, where $\mu_H > \mu_L$, and thus $|\mu_H - \mu_L|$ represents the volatility of long-lived shocks.[6] A firm's information environment in period t is assumed such that the firm contemporaneously observes y_t and the history of μ and y up to period $t-1$; μ_t is revealed in the next period. The information set is denoted as $I_t^{IC} \equiv \{y_1, \{\mu, y\}_{-\infty}^{t-1}\}$. In such a setting, information on the state-shift arrives in a staggered fashion,[7] similar to other papers including Angeletos and La'O (2009).

We also assume that, when a state-shift occurs, the new state lasts for at least N periods, where $N > 2$. N is a public knowledge, and the firm uses this knowledge to infer whether or not the current period, t, has a potential for a state-shift. Specifically, if $\mu_{t-1} \neq \mu_{t-i}$, for some $i \in \{2, 3, 4, ..., N\}$, then, the firm knows that period t has no potential for a state-shift and that $\mu_t = \mu_{t-1}$. If $\mu_{t-1} = \mu_{t-i}$, $\forall i \in \{2, 3, 4, ..., N\}$, then the firm knows that period t has a potential for a state-shift. We specify the prior state-shift probabilities at a period with potential state-shift by the following transition matrix:

$$\begin{array}{cc} & t \\ & \begin{array}{cc} L & H \end{array} \\ t-1 \begin{array}{c} L \\ H \end{array} & \begin{bmatrix} p_{LL} & p_{LH} \\ p_{HL} & p_{HH} \end{bmatrix} \end{array}$$

We assume that there exists an equilibrium in which firms do not adjust permanent employment level in the period that has no potential for a state-shift. Such an assumption would be plausible, when the firm's prior probability of a state-shift defined above is not high enough to induce the firm to adjust permanent employment in advance. Given this assumption, we focus on employment adjustment only in the periods with a state-shift potential. The observed overall demand in such a period serves as a valuable signal for the firm to update the probability of a state-shift, and thus, influences its decisions on employment adjustment.

2-2. Firms' adjustment of permanent employment when a long-lived demand shock occurs

Let us consider the case in which a long-lived shock occurs and the mean demand ($\mu_1 \neq \mu_{t-1}$) shifts in period t. Period t is just one of the periods with a potential for state-shifts for a firm. The firm's value function at time t is

$$\begin{aligned}(3)\qquad & V(l_{t-1}^P, \mu_{t-1}, y_t, n_t = 1) = \max_{l_t^P} \pi(l_{t-1}^P, y_1) - \lambda| l_t^P - l_{t-1}^P| \\ & + \beta(p_{\mu_t \neq \mu_{t-1} | \mu_{t-1}, y_t} \cdot E[V(l_t^P, \mu_t, y_{t+1}, n_{t+1} = 0)]) + p_{\mu_t = \mu_{t-1} | \mu_{t-1}, y_t} \cdot E[V(l_t^P, \mu_t, y_{t+1}, n_{t+1} = 1)]),\end{aligned}$$

where n_t is a binary variable with 1 indicating that the current period has potential for a

[6] In this paper, we focus on how the amplitude of both transitory shocks and long-lived shocks influences the lag of the adjustment of permanent labor. However, we agree that the frequency of long-lived shocks might also affect the labor adjustment. Intuitively, if the long-lived shocks last forever, then the firm would make bigger changes in permanent labor since it is once-for-all. Also, the firm would wait longer before adjusting permanent employment; the firm does not need to hurry in order to capture the benefit of the positive shock

[7] Long-lived shocks are often caused by changes in the aggregate economic environment. Our assumption is based on the notion that it takes time for firms to perform the necessary data collection and analyses in order to fully understand such changes.

state-shift and 0 otherwise. The value function reflects two possibilities that the firm faces; i) the current state changed, and the next period would have no state-shift potential, and ii) the current state did not change, and the next period would continue to have a potential for a state-shift. The value function depends critically on the conditional probability of a state-shift, $p_{\mu_t \neq \mu_{t-1} \mid \mu_{t-1}, y_t}$, which is inferred based on the previous state of mean demand and the observed current demand level.

Adjusting permanent employment responding to the contemporaneous shock would benefit the firm if the state indeed has shifted, but if the state remained the same, postponing the adjustment of permanent labor until the information is revealed would allow the firm not only to avoid being stuck with a sub-optimal level of permanent employment but also to avoid the costs associated with adjusting permanent employment level. In our model, due to incomplete information, the firm contemporaneously either postpones the adjustment of permanent employment until the true state is revealed (next period) or makes only partial adjustments for permanent employment. This contrasts with the case under complete information (see Appendix A). The higher the inferred probability of a state-shift, the more likely the firm adjusts permanent employment level, and, if it adjusts, by the greater magnitude, given other things equal.

How is the probability of a state-shift inferred based on the firm's information environment; specifically, how is this probability related to volatility of transitional shocks and that of long-lived shocks? [8] Below, we examine the case in which the state-shifts from low to high from period $t-1$ to t ($\mu_{t-1} = \mu_L$ and $\mu_t = \mu_H$). The analysis is similar for the case where the state changes from high to low.

Assuming that the firm adopts the Bayesian rule, the inferred probability of the state-shift from low to high, $p_{\mu_t = \mu_H \mid \mu_{t-1} = \mu_L, y_t}$, is written as

$$p_{\mu_t = \mu_H \mid \mu_{t-1} = \mu_L, y_t} = \frac{prob(\mu_t = \mu_H, y_t \mid \mu_{t-1} = \mu_L)}{prob(\mu_t = \mu_H, y_t \mid \mu_{t-1} = \mu_L) + prob(\mu_t = \mu_L, y_t \mid \mu_{t-1} = \mu_L)}. \tag{4}$$

Based on the prior transition probability matrix defined earlier, we can rewrite Equation (4) as

$$\begin{aligned} p_{\mu_t = \mu_H \mid \mu_{t-1} = \mu_L, y_t} &= \frac{p_{LH}\phi(y_t\,;\mu_H, \sigma)}{p_{LH}\phi(y_t\,;\mu_H, \sigma) + p_{LL}\phi(y_t\,;\mu_L, \sigma)} \\ &= \frac{1}{1 + \dfrac{p_{LL}}{p_{LH}} \exp\left(-\dfrac{(2y_t - \mu_H - \mu_L)(\mu_H - \mu_L)}{2\sigma}\right)}, \end{aligned} \tag{5}$$

where $\phi(y;\, \mu,\, \sigma)$ is the normal probability density function of y conditional on the mean demand level μ_L or μ_H. From Equation (5), we can see that; i) $p_{\mu_t = \mu_H \mid \mu_{t-1} = \mu_L, y_t}$ increases with the level of the observed demand, y_t, ii) $p_{\mu_t = \mu_H \mid \mu_{t-1} = \mu_L, y_t}$ decreases with the volatility of transitory shocks, σ, when y_t is large enough, i.e., $2y_t > \mu_H + \mu_L$, and iii) $p_{\mu_t = \mu_H \mid \mu_{t-1} = \mu_L, y_t}$ increases with the volatility of long-lived shocks measured by $\mu_H - \mu_L$, when y_t is large enough, i.e., $2y_t > \mu_H + \mu_L$.

In the above, ii) implies that the volatility of transitory shocks is negatively associated with the magnitude of the adjustment in permanent labor in response to a contemporaneous long-lived shock as long as the firm would not adjust its permanent labor when the observed

[8] Demand volatilities would change the expected value of state (see Equation (5)), which would also affect the adjustment of permanent employment. For simplicity, we assume that the parameter space is such that the effect of demand volatilities through the inferred probability dominates the effect through the expected value of state.

demand is too low; i.e. $2y_t \leq \mu_H + \mu_L$.[9] Also, under the same condition, iii) implies that the volatility of long-lived shocks is positively associated with the magnitude of the adjustment in permanent employment.

Note that, because our simple framework assumes only a one-period lag for the information revelation, it cannot explicitly explain the time lag greater than 1. Our model does, however, demonstrate that, due to the staggered arrival of information on the nature of a demand shock, the firm's full adjustment for permanent employment is delayed and that the extent of the partial adjustment depends on the firm's information environment.

Responding to the positive state-shift, the firm increases temporary employment instantaneously to meet the increase in the current demand. Thus, the extent of the delay in the full adjustment of permanent labor determines the time lag between temporary and permanent employment growth. This leads to two hypotheses. First, on average, permanent employment growth lags behind temporary employment growth more in responding to a state-shift, if the average transitory demand volatility is greater. Second, the employment adjustment lag is shorter if the difference in mean demand is larger (i.e. volatility of long-lived shocks is greater), because it allows firms to identify a state-shift more easily. We use these two hypotheses to test to what extent information environment explains the cross-city variation in the employment adjustment lag.

3. Empirical strategies and the construction of key variables

The outline of our empirical analyses is as follows. First, we use a distributed lag model to estimate the lag between permanent and temporary employment growth rates for each city. We then examine how the lag is associated with the city-level volatility of transitory demand shocks and that of long-lived demand shocks. We measure such volatilities by taking weighted averages of national-level industry volatilities (of transitory or long-lived shocks) with each city's industry mix as the weights. To distinguish transitory from long-lived demand shocks for each industry at the national level, we apply the Baxter and King's filtering approach (Baxter and King, 1999). Finally, we perform regressions of the employment adjustment lag on the volatility measures. The regression equation we focus on is specified as

$$L_k = \gamma_0 + \gamma_1 v_k^{Tr} + \gamma_2 v_k^{Lo} + \gamma_3 z_k + \varepsilon_k, \tag{6}$$

where L_k is the employment adjustment lag in city k, v_k^{Tr} is the volatility of transitory shocks for city k, v_k^{Lo} is the volatility of long-lived shocks , and z_k is a vector of other control variables. In Sections 3–1 and 3–2, we explain more details on how we construct our key variables, L_k, v_k^{Tr}, and v_k^{Lo}. In Section 3–3, we discuss other control variables that would also affect the timing of firms' employment adjustment. Such variables include the co-movement of transitory shocks, employment adjustment costs, as well as search friction for finding qualified permanent workers. In Section 4, we discuss our empirical results.

[9] The magnitude is zero if the firm makes no adjustment of permanent employment. This condition simply states that, when the observed demand is below the average of the two states, the firm would not bet on an increase in the state and thus would not adjust its permanent employment.

3–1. The lag between temporary and permanent employment growth rates for a city (L_k)

Data

To capture the cross-city variation in the lag between temporary and permanent employment adjustments, we use the BLS (Bureau of Labor Statistics) monthly employment data at the MSA-level between January 1990 and May 2005.[10] As for temporary employment at city level, we use the employment series of the Employment Service Industry (NAICS 5613), which includes the THS industry (NAICS 56132) (see Appendix C for industry definitions).[11] During our study period, monthly employment data for the Employment Services industry sector (NAICS 5613) are available for 74 MSAs, which our analysis covers. The list of MSAs is in Appendix B. As for permanent employment, we use total employment of all private sectors excluding the Employment Services industry. We look at the lead-lag relationship between such temporary and permanent employment series in terms of their growth rate. By taking growth rates, we remove linear trends, which would control for the increasing use of temporary workers in recent decades, and thus focus on the lead-lag relationship associated with stochastic shocks.

Figure 1 shows the 12-month growth rates for both THS and permanent employment for two cities. Figure 1-a is for Colorado Springs, CO, and Figure 1-b is for Portland-Vancouver-Beaverton, OR-WA. THS employment growth rates does seem to lead permanent employment growth rates in Portland on average, but such a relationship is weak in Colorado.

Construction of the lag

To measure the lag for each city, L_k, we estimate a finite distributed lag model. Let g_k^T and g_k^P represent the seasonally adjusted growth rates of temporary employment and that of permanent employment, respectively, in city k. Then we specify g_k^P as

$$g_{kt}^P = \alpha_{0k} + \beta_{0k} g_{kt}^T + \beta_{1k} g_{kt-1}^T + \beta_{2k} g_{kt-2}^T + \beta_{3k} g_{kt-3}^T + \dots + \beta_{\bar{L}k} g_{kt-\bar{L}}^T + \varepsilon_{kt}\,, \tag{7}$$

where we set the maximum lag, $\bar{L}$, as 12 initially. In our robustness analyses, we also apply the Akaike Information Criteria (AIC) method to determine $\bar{L}$, with which we obtain qualitatively the same results (see Section 4–2). In Equation (7), the sum of the β coefficients (the sum the contemporaneous effect and the effects of 1 to 12 months later) represents the total effects of the unit increment in THS employment growth on permanent employment growth. While such total effects are estimated positive for almost all the cities, the point estimates for β are not always greater than zero; the cumulative effects are not necessarily monotonic. Based on the estimates for Equation (7), various lag measures can be constructed, among which median lag is widely used especially in the literature on business cycle studies.[12] In this paper, we also use the median lag measure. If we add up the effects of temporary employment growth on permanent employment growth starting in the order of β_{0k}, ..., $\beta_{\bar{L}k}$, the median lag, L_k^m, is the first month that the cumulative effects exceeds the half of the total

[10] MSA definitions are based on the core-based statistical areas (CBSA). For a few MSAs, the data are not available at the whole MSA level but at subdivision level. We include MSA subdivisions in such cases.

[11] The BLS provides city-level monthly employment data for industries whose size in a given city is larger than a certain level; in most cases, the narrowest industry category available is the 4-digit North American Industry Classification System (NAICS) level. Among the available data series, a smallest category that includes THS industry is Employment Service industry. At the U.S. level, about 70% of workers in the Employment Services sector belong to the THS industry during our sample period, while the rest belong to Employment Placement Agencies and Professional Employment Organizations. The correlation coefficient between the growth rate of the THS industry and that of Employment Services is as high as 0.97.

[12] See Chapter 17 in Guiarati and Porter (2009).

Figure 1. Temporary and permanent employment growth rates

Figure 1-a. Colorado Springs, CO (MSA)

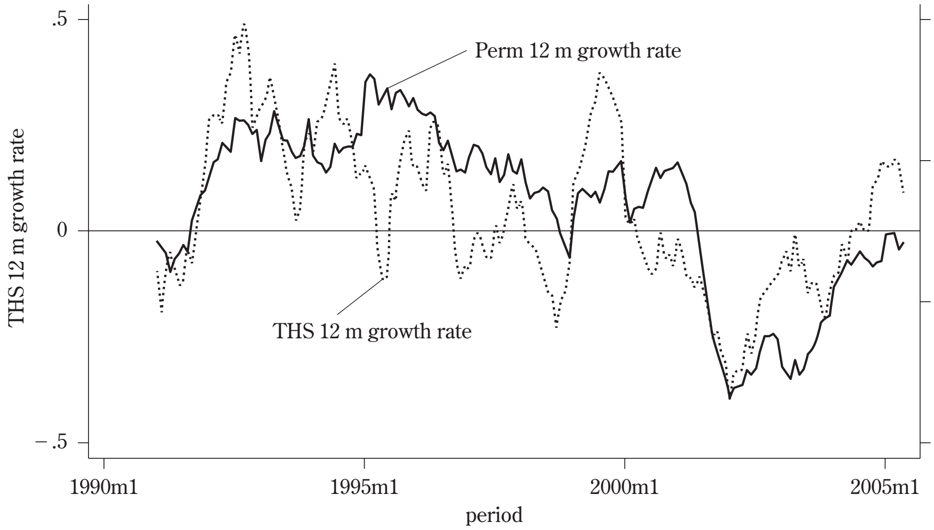
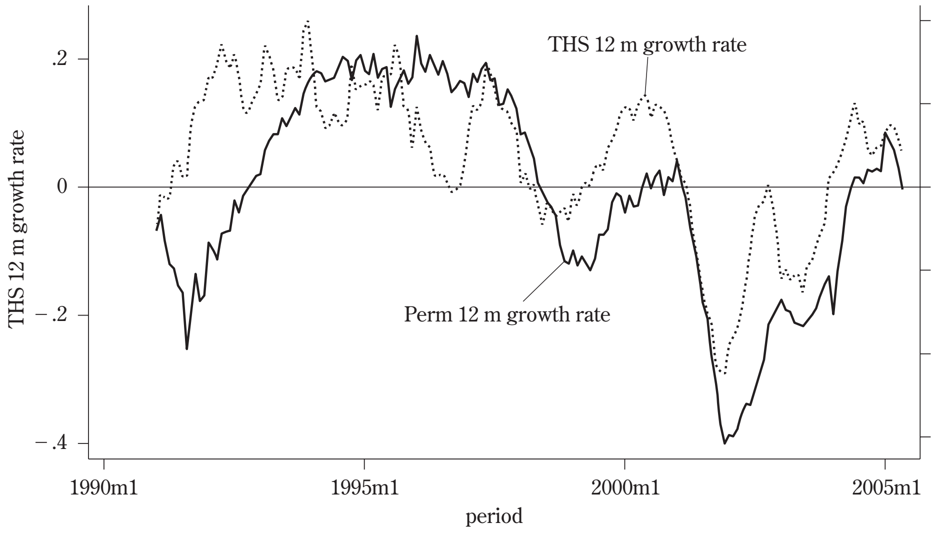


Figure 1-b. Portland-Vancouver-Beaverton, OR-WA (MSA)



effects, i.e. $\sum_{t=1}^{L_k^m} \beta_{tk} > 0.5 \sum_{t=1}^{\bar{L}} \beta_{tk}$, where $m = \min[\mathrm{m}, \bar{L}]$.

Note that, to estimate (7) for each city, we first seasonally adjust the employment growth series of both permanent and temporary employment. By doing so, we remove the employment fluctuations due to seasonal factors to better capture the lead-lag relationship between temporary and permanent employment adjustments in response to unpredicted stochastic shocks.

Table 1 shows the summary statistics of the median lag. The average of the median lag

Table 1. Lag measure, volatility measures and other controls: 74 cities

Variables	Mean	S.d.
Lag between permanent and temporary employment growth rates	5.284	4.267
Transitory shock volatility (cycle < 4 months)	1.080	0.041
Long-lived shock volatility (cycle between 18 to 96 months)	0.214	0.013
Ratio of transitory shock volatility to long-lived shock volatility	5.055	0.032
Co-movement of transitory shocks	0.646	0.032
City size: N. of permanent workers in log: avgerage over the sample period	6.096	0.984
Share of good producing industries	0.224	0.070
Share of manufacturing industries	0.154	0.075
Share of retailing and wholesale	0.192	0.017
Share of financial and banking services	0.245	0.055
Share of other business services	0.339	0.046
Unionization rate (in percentage)	13.29	7.121
Share of population (out of population aged between 18 and 66)		
Population aged between 18 and 24	0.090	0.014
Population aged between 25 and 44	0.285	0.034
Population with high school degree	0.210	0.036
Population with some college degree	0.221	0.023
Non-white population	0.249	0.109

is 5.28 months across cities, which is consistent with Segal and Sullivan's (1995) findings for the national level.

3-2. City-level volatilities of transitory and long-lived demand shocks

To capture the volatilities of transitory and long-lived demand shocks at city-level, as we mentioned, we first identify transitory and long-lived demand shocks for each industry at the national level. We then calculate the volatility size of each types of shocks at the national level. We then, for each city, take the weighted average of the industry volatilities, using the industry mix of a city as the weights.

Data

To capture industry-level volatility, we use the BLS monthly series of total weekly production labor hours including overtime for each NAICS-3digit industry at the national level (see Appendix D for the list of industries) for the period between January 1990 and October 2006.[13] Even for the U.S. as a whole, monthly output data are not available for many non-goods producing industries,[14] which use 65% of the temporary workers provided by

[13] The data are from the CES report performed by the BLS. Because the data on overtime are separately available only for manufacturing sectors, we do not use the separate series.

[14] The U.S. Census Bureau produces a monthly indicator for output based on their M3 (Manufacturers' shipments, inventories, and orders) survey for many manufacturing industries. However, such data are not available for non-manufacturing industries.

THS agencies.[15] We consider that the overtime portion of labor hours would fluctuate with transitory shocks as adjusting overtime of permanent workers would not generally incur fixed costs. To obtain city-level volatility measures, we use the industry mix based on the County Business Patterns (CBP) data as the weights and take weighted average of industry-level volatility for each city. We use the CBP from year 1998, which are almost the mid period of our hour data. Year 1998 is also the first year when the CBP uses NAICS for its industry classification, on which the BLS hours data are based. We checked to what extent industry mix in a given MSA changed over time using 1987 and 1997 CBP data. The correlation between industry shares in 1987 and those in 1997 for each MSA is on average 0.96.

Although we use the national-level industry data to capture volatilities due to the lack of city-level industry data, doing so would allow us to circumvent possible effects of unobserved city-specific factors. If there are any city-specific factors that influence both the lag and the demand fluctuations of all industries in the city, by using city-level hour data to capture demand fluctuation, we would capture a spurious relationship between these variables. The volatility captured for each industry at the national-level is not likely endogenous to a city-level lag between temporary and permanent employment growth rates. Note that, as robustness analyses, we also construct the volatility measures based on the level of hours; the results are qualitatively the same.

Extraction of transitory and long-lived shocks

To extract transitory and long-lived demand shocks from total labor hour series, we adopt a frequency-domain filter as designed by Baxter and King (1999) instead of a time-domain filter such as the Kalman filter, because our purpose is to decompose labor hour fluctuations into cycles of different periodicities. Cycles of shorter periodicities correspond to volatility driven by higher frequency (transitory) shocks, while cycles of longer periodicities correspond to volatility driven by lower frequency shocks (long-lived). More specifically, we construct two filters. One is the high pass filter that passes high frequency and noisy components of the labor hours series with a periodicity less than or equal to 4 months, which are considered transitory (see Gan and Zhang, 2006); the filtered time series reflects transitory shocks. Second is the band-pass (BP) filter that passes cycles between 18 and 96 months in periodicity, which is consistent with business cycles defined by Burns and Mitchell (1946). We use the components that pass the BP filter to capture the long-lived shocks.[16]

Let us denote the filtered high-pass time series (transitory shocks) as $\{Tr_{jt}\}$ and the filtered business-cycle time series (long-lived shocks) as $\{Lo_{jt}\}$ for industry j. We calculate the standard deviations of $\{Tr_{jt}\}$ and $\{Lo_{jt}\}$ to measure the average volatility of transitory shocks and that of long-lived shocks for industry j at the national-level, and denote them as σ_j^{Tr} and σ_j^{Lo}, respectively. We specify the volatility of transitory shocks for city k, v_k^{Tr}, as $v_k^{Tr} \equiv \sum_{j \in I_k} \omega_{kj} \sigma_j^{Tr}$, and the volatility of long-lived shocks for city k, v_k^{Lo}, as $v_k^{Lo} \equiv \sum_{j \in I_k} \omega_{kj} \sigma_j^{Lo}$, where ω_{kj} is the share of industry j in city k, and I_k is the set of industries in city k.

[15] The figure is based on the February 1997 supplement to the Current Population Survey (CPS) (Cohany, 1998).

[16] There are various ways to construct filters. Here, we follow Baxter and King (1999). In approximating the ideal filter, a truncation point needs to be specified, and we set it at 30. We tested with a range of truncation points [24, 30, 54, 72] and found that shocks are not sensitive to the choice of a truncation point. We also experimented with other ways to construct filters such as that of Corbae, Ouliaris, and Phillips (2002). The results are similar.

Note that, in a city with the industries that experience higher volatility of transitory shocks, the demand for temporary labor would be greater in general, as suggested by the firm-level empirical analyses in Ono and Sullivan (2013). To the extent that the temporary labor is supplied locally, greater temporary labor demand in a city would raise the wage rate of temporary labor, which would influence the employment adjustment lags as we discuss below. In that sense, we estimate the effects of transitory shock volatility net of its effects through temporary labor wage.

3–3. Other control variables

Apart from our key volatility measures, we also control for other factors in our main regression analyses that would affect the employment adjustment lag but are not taken into account in our stylized theoretical framework. Below we discuss our motivation to include each of the control variable.

Co-movement of temporary shocks of industries in a city

If firms of different industries demand temporary labor at the same time, THS agencies cannot smooth their supply of temporary workers and would increase the wage mark-up to offset such a risk. Using the U.S. state-level data, Ono and Zelenev (2003) find that the THS share of employment is higher in states with more volatile industries. The share is, however, lower, in states with high degree of co-movement of industry output-fluctuations, which might be reflecting higher wage or mark-up for temporary workers in such states. It is possible that the higher temporary labor wage influences the lag between temporary and permanent employment adjustments.

Facing a positive demand shock, firms in a city with higher co-movement of transitory shocks would increase permanent labor more quickly, because temporary workers would be more costly in that city and be more likely to be short of supply due to the coincided increase in temporary worker demand by the industries in the city; this would shorten the lag. Responding to a negative shock, if firms have temporary workers from the previous period, the firms would fire them first and then consider cutting permanent employment level depending on how likely the negative shock is long-lived. In a city with high co-movement of transitory shocks, firms would more hesitate to cut permanent employment level, because, if the negative shocks turn out temporary, supplementing labor again by temporary employment would be relatively more costly in such cities. This would increase the lag.

While the direction of the overall effect of the co-movement of transitory shocks on the employment adjustment lag is ambiguous, to assess the effect of the volatility of transitory shocks, it would be important to account for the degree to which the timing of the transitory shocks of the industries in a city coincides to each other. That is, while our theoretical model does not incorporate such a factor, the effect of the volatility of transitory shocks might change depending on the co-movement of these shocks in the city. Thus, in addition to the volatility measures of long-lived shocks and transitory shocks, we include the interaction term between the volatility of transitory shocks and the co-movement measure. We also include the co-movement measure independently to keep the flexibility in the specification. The co-movement measure we use is defined as $\rho_k \equiv \sqrt{\sum_i \sum_{i \neq j} \omega_{ki} \omega_{kj} \sigma_{ij}^{Tr}}$, where σ_{ij}^{Tr} is the covariance of transitory shocks between industries i and j, and ω_{kj} is the share of industry i in city k .

City size: search efficiency

In a larger city, the thick market effect might shorten the search and screening process (Duranton and Puga (2004), Helsley and Strange (1990) and Gan and Zhang (2006)). If such effects are more relevant to permanent positions than to temporary positions, the larger city size would result in a shorter employment adjustment lag. Thus we control for city size. We also include its squared term to allow a possibility for its quadratic effects.

Industry composition and unionization rate: adjustment costs

We consider that costs for adjusting permanent employment level is a key factor that make firms to use temporary workers for timely labor adjustment and to postpone adjusting permanent employment. While it is difficult to measure adjustment costs directly, we include the shares of each industry in a city's total employment to control for a possible cross-city difference in adjustment costs due to different industry mix. We also include a city's unionization rate, which would also be associated with costs to adjust permanent employment.

Demographic characteristics

We also take account of demographic characteristics of a city, controlling for the share of the population by age, education, and race. As demonstrated in Polivka (1996), demographic characteristics of temporary workers are quite different from that of permanent workers. We include the shares of population with the characteristics more common among temporary workers than among permanent workers. On average, temporary workers tend to be younger, less educated, and non-white. The difference in demographic characteristics across cities would influence the supply of temporary workers and would affect the temporary labor wage. While the direction of the effect of the temporary labor wage might be ambiguous, controlling for such factors would still be helpful to assess the effects of our key variables.

We admit that there might still be remaining unobserved factors that influence the lag of employment adjustment after controlling for all the covariates discussed above. However, as long as they are not systematically correlated with the volatility measures, the estimated coefficients for our key variables would not be biased. The summary statistics of all of the aforementioned covariates are included in Table 1.

4. Empirical results

4-1. Main results

Table 2 shows the main results of the regressions of the city-level employment adjustment lags based on Equation (6). In Column (1) of Table 2, as covariates, in addition to our key volatility variables, we control for city size, city size square, the share of good-producing industry and unionization rate.[17] In Column (2), we control industry shares more finely including various service industries such as financial and banking industry, retailing and wholesale industry, and other business services industry. In Column (3), we add demographic characteristics such as the share of working population aged between 18 and

[17] Good-producing industry include agriculture, forestry, fishing, and hunting, mining, construction, and manufacturing

Tables 2. Cross-city regressions of the median lag between permanent employment and temporary growth rates, on volatility measures based on the growth rate of total labor hours and other controls

Dependent variable: Lag between permanent and temporary employment growth rates

	(1)	(2)	(3)
Long-lived shock volatility (s.d.)	− 132.95**	− 158.06**	− 189.75**
	(− 2.37)	(− 2.23)	(− 2.47)
Transitory shock volatility (s.d.): Cycle < 4 month	349.15**	428.25**	492.35**
	(2.21)	(2.13)	(2.44)
Transitory shock volatility (s.d.) × Co-movement measure	− 543.04**	− 660.24**	− 763.48**
	(− 2.25)	(− 2.13)	(− 2.44)
Co-movement measure	620.04**	742.70**	844.06**
	(2.28)	(2.16)	(2.44)
City size	− 2.11	− 1.47	− 1.23
	(− .29)	(− .19)	(− .15)
City size squared	.23	.16	.10
	(.40)	(.25)	(.14)
Share of good-producing sector	32.41***		
	(2.70)		
Share of manufacturing industry		− 19.07	− 27.60
		(− .51)	(− .75)
Share of retailing and wholesale		− 92.29	− 94.34
		(− 1.49)	(− 1.53)
Share of financial and banking services		− 47.21	− 62.06
		(− 1.30)	(− 1.62)
Share of other business services		− 60.07	− 65.51
		(− 1.46)	(− 1.53)
Unionization rate	.08	.12	.11
	(0.93)	(1.34)	(1.07)
Age: 18~24			− 62.31
			(− 1.28)
Age: 25~44			14.92
			(.50)
Share of high school			− 8.04
			(− .30)
Share of some college degree			− 16.77
			(− .51)
Non-white			5.55
			(.82)
Numbers of observation	69	69	69
R-squared	.14	.16	.22

*** indicates statistical significance at the 1% level.
** indicates statistical significance at the 5% level.
* indicates statistical significance at the 10% level.
( ): t-statistics based on robust standard errors
Constant term is included in the regression; 73 cities with positive total effects are included in the regressions.

24, the share of working population aged between 25 and 44, the share of population with high school degree, the share of population with some college degree or above, and share of non-white population.

In all of the three specifications, the estimated coefficients for our key volatility measures are statistically significant, and as we add more control variables, the magnitude of the estimated effects becomes greater. The volatility of a long-lived shock obtains a negative and significant coefficient, which is consistent with our hypothesis that firms can more easily distinguish between transitory and long-lived shocks and adjust permanent employment level more quickly, when the average size of long-lived shock is larger. Based on the results in Column (3) of Table 2, if the volatility of long-lived shocks in a city is one s.d. (0.013; see Table 1) larger than its average of all cities, the employment adjustment lag would be 2.49 months shorter.

The volatility of transitory shocks obtains positive and significant coefficients, and its interaction term with the co-movement measure obtains negative and significant coefficients. The overall effect of the transitory shock volatilities is positive when the co-movement measure is low and turns negative when the co-movement measure is high.

In a city with industries whose transitory shock timings differ enough, the weighted average of the industry volatilities of transitory shocks does seem to have a positive relationship with the lag between temporary and permanent employment adjustment. This is consistent with our hypothesis that greater volatility of transitory shocks makes the information in contemporaneous demand shock noisier and make firms to postpone costly adjustments of permanent employment and increase the employment adjustment lag.

Based on Column (3) in Table 2, in a city with an average co-movement measure (.646), the overall effect of a one s.d. increase in the volatility of transitory shocks (.0411) is negative but close to zero (−.08 months). In a city with the co-movement as low as its 25th percentile point, the effect is positive at 1.43 months. In a city with the lowest co-movement measure (.574), the effect of a one s.d. increase in the volatility of transitory shocks is 2.17 months, which is remarkable, considering that the average employment adjustment lag across cities is 5.28 months.

The effect of the transitory shock volatility is negative in the city where the timing of transitory shocks of industry are synchronized and the co-movement measure of transitory shocks exceeds the above-mentioned threshold. We have discussed that higher temporary labor wage might shorten the lag at positive shock but legthen the lag at negative shock. When a negative shock occurs, firms without temporary employment to fire would only decide on permanent employment adjustment, while firms would increase temporary employment facing a positive shock regardless of the initial state of employment. It is possible that such asymmetry made the negative effects of co-movement dominant.

The estimated coefficients on city size and city size squared are both insignificant. While we try several specification including the case in which only city size is included, we do not observe any significant effects. Our results do not seem to suggest that the matching and screening are made more efficient (thick market effects) for permanent positions as the city size gets larger. A question regarding whether such thick market effects do not exist or exist to the same degree for both temporary and permanent positions is left for future works.

Regarding industry composition of a city, while the share of good-producing sector is positively and significantly associated with the lag (see Column (1) in Table 2), once we include finer industry controls (Columns (2) and (3) in Table 2), the coefficients for the shares of each industry turn insignificant. The coefficient for the unionization rate is not significant, either. Our results do not show evidence for the effect of costs to adjust permanent employment on the employment adjustment lag, to the degree that our control variables capture the cross-city variation of employment adjustment costs. None of the demographic control variables obtains statistically significant coefficients.

While our control variables do not obtain statistically significant coefficients, our results show that, as long as the co-movement of the timings of transitory shocks are low enough, the cross-city variations of our volatility measures have statistically significant association with the cross-city variation of the employment adjustment lag in the way consistent with our hypotheses in any specifications. The effects of our volatility measures are larger in the specification with more control variables.

4–2. Robustness analyses

Different band-pass ranges to identify long-lived shocks

In the estimation for Table 2, to identify long-lived shocks, we use the cycles that range from 18 months to 96 months. We perform robustness analyses with various definitions of long-lived shocks, expanding the frequency band so that it includes higher frequency shocks. Specifically, we perform the analyses, identifying long-lived shocks with a 15-to-96 month-band, a 12-to-96 month-band, and a 9-to-96 month-band. Table 3 shows the regression results. We found that, as we incorporate higher frequency shocks to the "long-lived shocks," its negative effect gets weaker and eventually becomes statistically insignificant. This seems to reflect that, when we mix higher frequency shocks with lower frequency business cycle shocks, the effects of the volatilities become ambiguous, which is consistent with our conjecture that the volatility of long-lived shocks and that of transitory shocks have opposite effects on the employment adjustment lag.

Lag based on Akaike's Information Criterion (AIC)

In the estimation shown in Table 2, as a dependent variable, we use the median lag for a given city identified by the finite distributed lag model shown in Equation (7) including 12 lags, assuming that a change in the growth rate of temporary employment is associated with that of permanent employment for as long as 12 months after the change. As robustness analyses, we use the lag identified based on more flexible method. In particular, we measure median lags based on a distributed lag model in which the cutoff number of lags in Equation (7) is determined by the AIC - a model selection criterion (Enders, 2004). The results with a median lag constructed using the AIC model are shown in Table 4. They are similar to the previous results shown in Table 2. The estimated coefficients are significant for all the key volatility measures (see Table 4, columns (2) and (3)).

Alternative volatility measure:
the ratio of transitory shock volatility to long-lived shock volatility

Next, as key explanatory variables, instead of including the volatilities of transitory shocks and long-lived shocks separately, we use the ratio of transitory shock volatility to long-lived shock volatility. The results are shown in Table 5. The effect of the ratio is positive and significant, as long as the co-movement of transitory shocks are low in a city. This is consistent with our conjecture, which is also supported in the previous regression results. If the volatility of transitory shocks is smaller relative to the volatility of long-lived shocks, it would be easier for firms to identify long-lived shocks, and this would in turn speed up the

Table 3. Robustness check: using different frequency bands to define long-lived shocks

Dependent variable: Lag between permanent and temporary employment growth rates

	Frequency band for long-lived shock		
	15 to 96 months	12 to 96 months	9 to 96 months
Long-lived shock volatility (s.d.)	−174.31**	−137.01*	−41.29
	(−2.38)	(−1.76)	(−.66)
Transitory shock volatility (s.d.): Cycle < 4 month	497.71**	417.60*	311.60
	(2.41)	(1.97)	(1.41)
Transitory shock volatility (s.d.) × Co-movement measure	−739.00**	−633.54*	−475.82
	(−2.40)	(−1.96)	(−1.41)
Co-movement measure	818.03**	691.84*	508.57
	(2.40)	(1.95)	(1.38)
City size	−.95	−2.08	−3.83
	(−.11)	(−.24)	(−.44)
City size squared	.08	.17	.31
	(.11)	(.23)	(.45)
Share of manufacturing industry	−24.15	−36.08	−42.66
	(−.66)	(−.99)	(−1.10)
Share of retailing and wholesale	−85.55	−85.52	−61.61
	(−1.41)	(−1.29)	(−.82)
Share of financial and banking services	−59.22	−67.16*	−57.56
	(−1.57)	(−1.71)	(−1.33)
Share of other business services	−60.22	−63.48	−53.11
	(−1.41)	(−1.45)	(−1.11)
Unionization rate	.12	.11	.10
	(1.10)	(1.06)	(.92)
Age: 18~24	−61.41	−58.80	−56.23
	(−1.26)	(−1.19)	(−1.14)
Age: 25~44	13.71	15.49	11.98
	(.46)	(.51)	(.38)
Share of high school	−8.62	−4.30	0.69
	(−.31)	(−.15)	(.02)
Share of some college degree	−20.22	−11.77	−10.78
	(−.62)	(−.36)	(−.33)
Non-white	5.06	5.64	3.93
	(.75)	(.74)	(.48)
Numbers of observation	69	69	69
R-squared	.21	.18	.14

*** indicates statistical significance at the 1% level.
** indicates statistical significance at the 5% level.
* indicates statistical significance at the 10% level.
( ): t-statistics based on robust standard errors
Constant term is included in the regression; 73 cities with positive total effects are included in the regressions.

Table 4. Robustness check: lag measure constructed using AIC method

Dependent variable: Lag between permanent and temporary employment growth rates

	(1)	(2)	(3)
Long-lived shock volatility (s.d.)	−117.99*	−192.18**	−244.33***
	(−1.93)	(−2.64)	(−3.03)
Transitory shock volatility (s.d.): Cycle < 4 month	266.03	418.24*	505.60**
	(1.52)	(1.72)	(2.11)
Transitory shock volatility (s.d.) × Co-movement measure	−417.04	−638.05*	−778.86**
	(−1.58)	(−1.73)	(−2.14)
Co-movement measure	462.97	707.60*	828.75**
	(1.55)	(1.74)	(2.10)
City size	−8.89	−6.35	−7.47
	(−1.02)	(−.72)	(−.82)
City size squared	.79	.55	.64
	(1.14)	(.77)	(.85)
Share of good producing sector	33.05**		
	(2.34)		
Share of manufacturing industry		10.61	6.43
		(.33)	(.19)
Share of retailing and wholesale		−99.19	−99.25
		(−1.45)	(−1.38)
Share of financial and banking services		−21.66	−41.57
		(−.64)	(−1.10)
Share of other business services		−39.61	−27.28
		(−.97)	(−.61)
Unionization rate	.05	.07	.001
	(0.49)	(.69)	(−.01)
Age: 18~24			−134.28**
			(−2.66)
Age: 25~44			14.60
			(.45)
Share of high school			−40.39
			(−1.18)
Share of some college degree			8.57
			(.25)
Non-white			4.41
			(.59)
Numbers of observation	64	64	64
R-squared	.19	.24	.35

*** indicates statistical significance at the 1% level.
** indicates statistical significance at the 5% level.
* indicates statistical significance at the 10% level.
( ): t-statistics based on robust standard errors
Constant term is included in the regression; 69 cities with positive total effects are included in the regressions.

Table 5. Robustness check: using the ratio of transitory shock volatility to long-lived shock volatility

Dependent variable: Lag between permanent and temporary employment growth rates

	(1)	(2)	(3)
Ratio of transitory shock volatility to long-lived shock volatility	75.61**	80.05**	93.37**
	(2.29)	(2.05)	(2.35)
Ratio × Co-movement measure	−112.42**	−117.93*	−138.11**
	(−2.20)	(−1.95)	(−2.26)
Co-movement measure	579.00**	601.35*	693.21**
	(2.18)	(1.98)	(2.21)
City size	−2.90	−2.55	−2.14
	(−.40)	(−.34)	(−.26)
City size squared	.27	.22	.15
	(.48)	(.37)	(.23)
Share of good producing sector	16.32		
	(1.55)		
Share of manufacturing industry		−25.81	−36.10
		(−.70)	(−1.00)
Share of retailing and wholesale		−65.58	−68.12
		(−1.10)	(−1.17)
Share of financial and banking services		−34.87	−46.56
		(−0.97)	(−1.26)
Share of other business services		−53.40	−61.24
		(−1.25)	(−1.42)
Unionization rate	.10	.15	.14
	(1.15)	(1.64)	(1.35)
Age: 18~24			−45.52
			(−.94)
Age: 25~44			2.40
			(0.08)
Share of high school			−2.10
			(−.07)
Share of some college degree			−15.28
			(−.49)
Non-white			6.45
			(.88)
Numbers of observation	69	69	69
R-squared	.13	.15	.20

*** indicates statistical significance at the 1% level.
** indicates statistical significance at the 5% level.
* indicates statistical significance at the 10% level.
( ): t-statistics based on robust standard errors
Constant term is included in the regression; 73 cities with positive total effects are included in the regressions.

adjustment of permanent labor and shorten the lag. In addition, the overall effect of the ratio on the lag depends on the co-movement measure as expected.

Volatility measures based on total labor hours

As a final robustness check, we perform our analyses using the volatility measures calculated based on the level of total hours instead of the growth rates. Note that a volatility measure based on the level of total hours would be subject to the size of the industry. Using the growth rates, we circumvented this issue. Here, we standardize each industry's total hours series by dividing it by its average level over the sample period and multiplying the resulting series by 100 afterwards. We then calculate volatility measures using the standardized series. We also calculate the co-movement measure based on such series. As shown in Table 6, using these measures based on the level of hours, we obtain qualitatively similar results.

5. Conclusion

The growth rate of THS employment has been used as one of the leading business cycle indicators. This paper studies the geographic variations in the lead-lag relationship between permanent and temporary employment growth. We find that information environment has important implications in explaining the cross-city variation in employment adjustment lag. Specifically, our analyses show that a city with greater volatilities of transitory shocks on average has a longer lag, if the timing of transitory shocks differ sufficiently across industries in the city. In contrast, the volatility of long-lived shocks shortens the lag. Our results suggest that the relative size of volatilities of these two type of shocks play important roles when firms infer the nature of the shock and that the variation in such information environment across cities explain a sizable part of the cross-city variation of the lag between temporary and permanent employment adjustments.

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Table 6. Robustness check: volatility and co-movement measures constructed using the level of total labor hours

Dependent variable: Lag between permanent and temporary employment growth rates

	(1)	(2)	(3)
Transitory shock volatility (s.d.): Cycle < 4 month	397.78	503.51*	727.88**
	(1.51)	(1.79)	(2.39)
Transitory shock volatility (s.d) × Co-movement measure	−1030	−1270*	−1850**
	(−1.56)	(−1.80)	(−2.43)
Long-lived shock volatility (s.d.)	−11.60**	−17.34**	−22.74***
	(−2.11)	(−2.23)	(−2.71)
Co-movement measure	733.14	877.20*	1239.13**
	(1.64)	(1.88)	(2.49)
City size	−3.44	−1.99	−2.55
	(−.49)	(−.27)	(−.32)
City size squared	.34	.19	.19
	(.63)	(.32)	(.30)
Share of good producing sector	37.77**		
	(2.26)		
Share of manufacturing industry		−26.18	−34.87
		(−.78)	(−1.04)
Share of retailing and wholesale		−93.88	−105.31*
		(−1.61)	(−1.72)
Share of financial and banking services		−41.69	−47.74
		(−1.32)	(−1.41)
Share of other business services		−69.74*	−70.63
		(−1.71)	(−1.64)
Unionization rate	.07	.13	.14
	(0.86)	(1.56)	(1.45)
Age: 18~24			−67.72
			(−1.36)
Age: 25~44			26.20
			(0.92)
Share of high school			−6.85
			(−.27)
Share of some college degree			−3.70
			(−.12)
Non-white			7.13
			(1.13)
Numbers of observation	69	69	69
R-squared	.12	.16	.22

*** indicates statistical significance at the 1% level.
** indicates statistical significance at the 5% level.
* indicates statistical significance at the 10% level.
( ): t-statistics based on robust standard errors
Constant term is included in the regression; 73 cities with positive total effects are included in the regressions.

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Appendix

A. Firms' adjustment of permanent labor when there is a long-lived demand shock, under complete information

Let us analyze how firms adjust permanent labor when there is a long-lived shock, which shifts the state of mean demand at time t ($\mu_t \neq \mu_{t-1}$). Under complete information, when the state shifts, the firm instantaneously learns the state-shift; in addition to the history of μ and y up to period $t - 1$, under complete information, the firm contemporaneously knows both μ_t and y_t. The information set is $I_t^C \equiv \{\mu_t, y_t, \{\mu, y\}_{-\infty}^{t-1}\}$.

With the assumption of a one-time adjustment period for permanent workers, any change in the permanent employment today does not affect the firm's contemporaneous profit except for adjustment costs. Thus, the firm chooses the current permanent employment level to maximize the sum of expected future profits net of adjustment costs. The firm's value function at time t is

$$J(l_{t-1}^P, \mu_t, y_t, n_t = 1) = \max_{l_{t-1}^P} \pi(l_{t-1}^P, y_t) - \lambda|l_t^P - l_{t-1}^P| + \beta E[J(l_t^P, \mu_{t+1}, y_{t+1}, n_{t+1} = 0)|I_t^C]$$

where, $\pi(\,.\,)$ is the one-period profit of the firm and is calculated as

$$\pi(l_{t-1}^P, y_1) = py_t - wl_t^T(l_{t-1}^P, y_1) - l_{t-1}^P,$$

where $l_t^T(\,.\,)$ is a function of permanent employment as defined in Equation (2). n_t is a binary variable with 1 indicating that the current period is a potential state-shift point and 0 otherwise. Because a long-lived shock will last for more than two periods (N > 2), we thus have $n_{t+1} = 0$, when a long-lived shock is observed to occur at time t. The firm will instantaneously make full adjustment of its permanent employment at time t, as long as the difference between two states is large enough.

B. List of MSA included in this study

MSA (CBSA) code	MSA name	MSA (CBSA) code	MSA name
1	Albuquerque, NM	2923	New Orleans-Metairie-Kenner, LA
75	Ann Arbor, MI	2997	New York-White Plains-Wayne, NY-NJ
147	Appleton, WI	3071	Newark-Union, NJ-PA
218	Atlanta-Sandy Springs-Marietta, GA	3145	Oklahoma City, OK
292	Austin-Round Rock, TX	3219	Omaha-Council Bluffs, NE-IA
366	Bakersfield, CA	3293	Orlando-Kissimmee, FL
438	Baltimore-Towson, MD	3367	Oxnard-Thousand Oaks-Ventura, CA
512	Boise City-Nampa, ID	3441	Pensacola-Ferry Pass-Brent, FL
584	Charlotte-Gastonia-Concord, NC-SC	3513	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD
658	Chicago-Naperville-Joliet, IL	3587	Phoenix-Mesa-Scottsdale, AZ
732	Cincinnati-Middletown, OH-KY-IN	3661	Pittsburgh, PA
806	Cleveland-Elyria-Mentor, OH	3735	Portland-Vancouver-Beaverton, OR-WA
880	Colorado Springs, CO	3808	Raleigh-Cary, NC
954	Columbia, SC	3882	Richmond, VA
1027	Columbus, OH	3956	Riverside-San Bernardino-Ontario, CA
1101	Dallas-Fort Worth-Arlington, TX	4030	Sacramento-Arden Arcade-Roseville, CA
1175	Denver-Aurora, CO	4104	Saginaw-Saginaw Township North, MI
1249	Des Moines, IA	4173	Salt Lake City, UT
1321	Detroit-Warren-Livonia, MI	4247	San Antonio, TX
1395	Durham, NC	4321	San Diego-Carlsbad-San Marcos, CA
1466	Edison, NJ	4395	San Francisco-Oakland-Fremont, CA
1539	El Paso, TX	4469	San Jose-Sunnyvale-Santa Clara, CA
1612	Fayetteville-Springdale-Rogers, AR-MO	4543	Santa Rosa-Petaluma, CA
1683	Flint, MI	4615	Sarasota-Bradenton-Venice, FL
1753	Fort Smith, AR-OK	4687	Seattle-Bellevue-Everett, WA
1827	Fresno, CA	4761	Spartanburg, SC
1901	Gary, IN	4832	St. Louis, MO-IL
1974	Grand Rapids-Wyoming, MI	4906	Tampa-St. Petersburg-Clearwater, FL
2046	Greenville, SC	4980	Tucson, AZ
2118	Harrisburg-Carlisle, PA	5054	Tulsa, OK
2191	Hickory-Lenoir-Morganton, NC	5127	Virginia Beach-Norfolk-Newport News, VA-NC
2262	Honolulu, HI	5201	Washington-Arlington-Alexandria, DC-VA-MD-WV
2332	Houston-Sugar Land-Baytown, TX	5275	West Palm Beach-Boca Raton-Boynton Beach, FL
2406	Indianapolis, IN	5349	Wichita, KS
2480	Kalamazoo-Portage, MI		
2553	Las Vegas-Paradise, NV		
2627	Little Rock-North Little Rock, AR		
2701	Los Angeles-Long Beach-Santa Ana, CA		
2775	Milwaukee-Waukesha-West Allis, WI		
2849	Minneapolis-St. Paul-Bloomington, MN-WI		

C. Definition of the industries categorized in NAICS 5613

(Source: http://www.census.gov/eos/www/naics)

NAICS 5613 Employment Services

This industry group includes establishments classified in the following industries: 56131, Employment Placement Agencies, 56132, Temporary Help Services, and 56133, Professional Employer Organizations.

NAICS 56131 Employment Placement Agencies

This industry comprises establishments primarily engaged in listing employment vacancies and in referring or placing applicants for employment. The individuals referred or placed are not employees of the employment agencies.

NAICS 56132 Temporary Help Services

This industry comprises establishments primarily engaged in supplying workers to clients' businesses for limited periods of time to supplement the working force of the client. The individuals provided are employees of the temporary help service establishment. However, these establishments do not provide direct supervision of their employees at the clients' work sites.

NAICS 56133 Professional Employer Organizations

This industry comprises establishments primarily engaged in providing human resources and human resource management services to staff client businesses. Establishments in this industry operate in a co-employment relationship with client businesses or organizations and are specialized in performing a wide range of human resource and personnel management duties, such as payroll accounting, payroll tax return preparation, benefits administration, recruiting, and managing labor relations. Employee leasing establishments typically acquire and lease back some or all of the employees of their clients and serve as the employer of the leased employees for payroll, benefits, and related purposes. Employee leasing establishments exercise varying degrees of decision making relating to their human resource or personnel management role, but do not have management accountability for the work of their clients' operations with regard to strategic planning, output, or profitability. Professional employer organizations (PEO) and establishments providing labor or staff leasing services are included in this industry.

D. List of industries (NAICS 3-digit) included to calculate our volatility indices

Oil and gas extraction	General merchandise stores
Mining, except oil and gas	Miscellaneous store retailers
Support activities for mining	Non-store retailers
Utilities	Truck transportation
Construction of buildings	Transit and ground passenger transportation
Heavy and civil engineering construction	Pipeline transportation
Specialty trade contractors	Scenic and sightseeing transportation
Food manufacturing	Support activities for transportation
Beverage and tobacco products	Couriers and messengers
Textile mills	Warehousing and storage
Textile product mills	Motion picture and sound recording industries
Apparel	Broadcasting, except Internet /Telecommunications
Leather and allied products	ISPs, search portals, and data processing /Others
Wood products	Credit intermediation and related activities
Paper and paper products	Securities, commodity contracts, investments
Printing and related support activities	Insurance carriers and related activities
Petroleum and coal products	Funds, trusts, and other financial vehicles
Chemicals	Real estate
Plastics and rubber products	Rental and leasing services
Nonmetallic mineral products	Professional and technical services
Primary metals	Management of companies and enterprises
Fabricated metal products	Administrative and support services
Machinery	Waste management and remediation services
Computer and electronic products	Ambulatory health care services
Electrical equipment and appliances	Hospitals
Transportation equipment	Nursing and residential care facilities
Furniture and related products	Social assistance
Miscellaneous manufacturing	Performing arts and spectator sports
Merchant wholesaler, durable goods	Museums, historical sites, zoos, and parks
Merchant wholesaler, non-durable goods	Amusements, gambling, and recreation
Motor vehicle and parts dealers	Accommodations
Furniture and home furnishings stores	Food services and drinking places
Electronics and appliance stores	Repair and maintenance
Building material and garden supply stores	Personal and laundry services
Food and beverage stores	Membership associations and organizations
Health and personal care stores	Food services and drinking places
Gasoline stations	Repair and maintenance
Clothing and clothing accessories stores	Personal and laundry services
Sporting goods, hobby, book and music stores	Membership associations and organizations