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Demand Volatility and the Lag between the Growth of Temporary and Permanent Employment

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WP 2007-19

Demand Volatility and the Lag between the Growth of Temporary and Permanent Employment

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Abstract

The growth rate of temporary help service employment is often considered to be a leading business cycle indicator because the firing and hiring of temporary help workers typically lead that of permanent workers. However, few works in the literature focus on the mechanism that generates the lag between temporary and permanent growth. This paper investigates how firms extract signals of long-lived shocks from noisy transitory shocks and how this influences their hiring/firing decisions. Our simple model predicts that the average size of transitory demand shocks increases the lag while the average size of long-lived shocks shortens the lag. Our empirical findings based on cross-city analysis seem to support the above predictions, after controlling for city size, share of good-producing sectors and other city-specific demographic characteristics. In addition, we find that the effect of the size of transitory shocks depends on the degree to which transitory demand shocks of different industries is correlated.

Key words: temporary help workers, leading business cycle indicator, demand volatility,

JEL: J01 R1

1. Introduction

The temporary help services (THS) industry grew drastically over the last few decades. Between January 1990 and January 2006 in the U.S., THS employment more than doubled, growing from 1.2 million to 2.6 million workers, but total non farm employment grew only by 26%.[1] Moreover, a significant share of workers flow through the THS industries (Katz and et al., 1999). The use of temporary workers has spread across various industries and occupations, including temporary construction workers and temporary registered nurses. The rapid THS employment growth has attracted substantial attention from researchers (e.g., Segal and Sullivan, 1995, 1997; Golden, 1996; Polivka, 1996; Katz and et al., 1999; and Autor, 2003) who, along with industry analysts, have identified a number of reasons that the use of temporary workers may be attractive to firms.

One of the main reasons for firms' use of temporary workers is the need for flexibility in adjusting employment levels (see Ono and Sullivan (2006) for a description of other reasons). As compared to permanent work arrangements, temporary work arrangements allow firms to use labor for a short period of time without being responsible for workers' benefits as well as costs associated with hiring/firing workers. In contrast, permanent work arrangements may have an advantage in being able to motivate workers more easily but incur costs when adjusting employment level. Supporting the view that temporary workers facilitate flexibility in the labor market, Golden (1996) finds evidence that a rise in demand for output above the long-run trend produces a strong concurrent rise in THS employment.[2]

Consistently with such a role, THS employment growth is often considered to lead overall employment and is used as a leading business cycle indicator, as many firms use THS as a means to quickly adjust their operations to meet fluctuating demands for their products and services. Economists in various business areas as well as government institutions monitor trends in THS employment along with several other leading indicators to better forecast economic activity. At the U.S. level, Segal and Sullivan (1995) find that THS employment growth lead aggregate employment by at least a quarter or two over a course of a business cycle.[3] 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.

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[1] The data are obtained from BLS Current Employment Statistics Survey in June, 2007 and can be found at http://data.bls.gov/PDQ/outside.jsp?survey=ce .

[2] Note that there are many ways that "temporary employment," or "workers with alternative arrangements" are defined. It may include not only workers in a THS industry but also include independent contractors, on-call workers, and workers provided by contract firms. Our analysis focuses on THS workers.

[3] Findings in Segal and Sullivan (1995) are based on their calculations of five-quarter-centered moving averages of quarterly temporary and aggregate employment growth rates between 1973:Q2 and 1994:Q4.

Despite the increasing academic interest in the THS industry and the wide-spread role that THS employment series plays as a leading indicator, few empirical papers test the mechanism behind firms' decisions on timings to adjust temporary and permanent employment. In this paper, as a step toward understanding such a mechanism, we investigate determinants of the lag between the THS and permanent employment growth rates. In particular, we develop a model to shed light on the role that THS employment plays at a turning point of economic state (i.e. boom and downturn) when individual firms are not sure about the change in economic state. Our model shows that, on average over time, firms' lag between the adjustment of temporary employment and that of permanent employment is associated with the size of both transitory and long-lived demand shocks. For empirical analysis, we examine cross-city variations of the lag between temporary and permanent employment growth and test how these are related to the degree of demand fluctuations caused by different types of shocks. Several papers (Autor, 2003; Ono and Zelenev, 2003) consider that the use of THS workers differs across geographical areas. However, there is little documentation on cross-city variation of lags nor is there empirical testing on its determinants.

Our paper is related to the literature of irreversible investment cost and factor demand under uncertainty (Pindyck, 1991); more specifically it is related to the literature of adjustment costs and labor demand under uncertainty. Hamermesh (1989) investigates the effect of adjustment costs on firms' employment decision, which is motivated by the seemingly slowness in the adjustment of employment in response to shocks. Bentolia and Bertola (1990) study how the reduction in firing costs influences firms' firing and hiring decisions differently and how this affects the overall employment. Aguirregabiria and Alonso-Borrego (1999) and Campbell and Fisher (2004) introduce the use of temporary labor, i.e., labor with costless adjustment in their analyses of firms' hiring and firing decisions. In particular, Aguirregabiria and Alonso-Borrego (1999) use Spanish manufacturing data that record the number of temporary workers to investigate the effects of introducing temporary contracts on employment and firms' profits. Campbell and Fisher show that firms with higher idiosyncratic risks tend to have a higher portion of temporary labor in their total employment, which makes them more responsive to shocks since the firing and hiring of temporary workers incur no adjustment costs.

As compared to the previous papers, our paper focuses on the lag between the adjustment of permanent employment and that of temporary employment in response to demand shocks. By distinguishing long-lived shocks from transitory shocks, our paper shows that the sizes of different types of shocks have different impacts on the lag. Unlike the above mentioned papers that emphasize the role of adjustment costs in explaining the delay in the response of

permanent employment, our paper mainly addresses how firms identify signals of long-lived shocks from noisy transitory shocks, based on which the firms make their employment decisions.

Our model is a stylized model that focuses on firms' hiring/firing decision at the turning point of an economic state. In our model, when an economic state shifts, the firm cannot instantaneously tell whether the observed level of demand is due to transitory shock or the change in economic state. In order to avoid costs associated with hiring or firing permanent workers, firms adjust only THS workers until the firm becomes more confident that the change in demand is due to the shift of economic state and will persist in the long run. The firm infers the probability that a state has changed by comparing the current demand shock with the extent to which demand usually fluctuates around mean demand in each economic state. If the transitory volatility is higher, it is more difficult for the firm to tell whether the state has shifted, since the signal conveyed by the current demand level is too noisy. As a result, the firm is more hesitant to adjust permanent employment. Our first prediction is that the THS employment growth leads permanent employment growth more in a city with greater volatility of transitory shocks. In addition, our model also implies that the lead is shorter in a city with greater differences in mean demand levels between a downturn and boom, because it, on average, allows firms to distinguish a shock that is transitory from that is due to a shift of an economic state. This is the second prediction of our model.

Our cross-city examination tests the above two predictions of the model in the reduced form. Note that the temporary workers described in our theory can be not only temporary workers in the THS industry but also other workers under the flexible work arrangements such as individual contractors or on-call workers. However, the data for those occupations are not readily available at the appropriate level of time or geographical unit as we require for our examination. The relatively better availability of the data on THS employment is consistent with wide use of THS employment data for economic analysis in both business and academics. We examine how the variation in the average lag between THS and permanent employment growth rates across cities is associated with volatility that different cities face. Note that our theoretical model takes the relative wage of temporary workers as given. In the empirical estimation, we take into account the effect of relative wage.

Most of our data are from U.S. Bureau of Labor Statistics (BLS). Included in our study are 74 MSAs, for which we can learn monthly movement of THS employment.[4] Our measures of

[4] MSA definitions are based on the CBSA, which is used in the version of BLS employment data we used. For a few MSAs, the data are not available at an MSA level, but some of the subdivisions are available. We included MSA subdivisions in such cases.

city-level volatility are weighted averages of national level volatilities of each industry. We also control for other variables such as city size and demographic characteristics. While we outline our theoretical model focusing on one cause of THS employment growth leading permanent employment growth, there might be other factors. We provide more detailed discussion and interpretations in the empirical section.[5]

The rest of the paper is organized as follows. In Section 2, we present our model. Section 3 describes our empirical implementation. Section 4 discusses the empirical results. Section 5 concludes.

2. Model

This section presents a theoretical model that provides two predictions regarding the effect of the demand volatility on the lag between the growth of temporary employment and that of permanent employment. Section 2-1 explains a basic setup for the model. In Section 2-2, we demonstrate a firm's employment decision in the stationary case where there is no persistent demand shock. Then in Section 2-3, we show how the firm adjusts its permanent and temporary employment level when facing a persistent demand shock, with a focus on the timing of its adjustment.

2-1. Setup

Consider a firm with production function

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

where l is efficient units of labor. When l is composed of labor by both permanent workers (l^P) and temporary workers (l^T), it is equal to $l = cl^T + l^P, \quad 0 < c < 1$. Temporary workers are less productive than permanent workers ($c < 1$). The firm's product is sold at price p. The wage rate

[5] Note that hiring and firing temporary workers is not the only way that firms accommodate demand fluctuations. Firms could adjust their inventory or overtime of permanent workers, which do not typically incur sunk fixed costs but increase variable costs. It is beyond the scope of this paper to analyze the interaction between these adjustments and the adjustment of temporary workers. Note also that firms could also perform temporary layoffs, which we consider as a way to lower the fixed costs of adjusting permanent employees (i.e. firms could save costs of training workers if the firms recall the workers they laid off). Firms' use of temporary workers, however, seems to suggest that a temporary layoff is not a sufficient measure to adjust labor. Note that since the early 1990s, the use of temporary layoffs over the recessions seems to have been diminished (McConnell and Tracy, 2005). If the diminished use of temporary layoffs is reflecting greater costs of adjusting permanent workers, it is possible that the lags between temporary and permanent worker growth is also increasing. While we focus on cross-city analysis using the period after 1990 in this paper, it would be interesting to examine the link between these declines and the increased use of temporary workers in future research.

of temporary labor is w, while that of permanent labor is normalized to be 1.[6] Note that $w/c > 1$ for firms to ever use permanent workers.

We assume that the firm can hire or let go temporary workers without any cost. We assume, however, that the firm has to bear certain costs to adjust its permanent employment level. Specifically, the adjustment cost is $\lambda |\Delta l^p|$, where $\lambda > 0$. In addition, we assume a one-time adjustment period; a permanent worker hired today has to be trained through the current period before becoming productive next period. A permanent worker laid-off today is also entitled to a grace period and remains on the payroll until the end of the period. This assumption simplifies our analysis as shown later. However, relaxation of this assumption will not change the key results of our model qualitatively.

At time *t*, the maximum units of efficient labor the firm can use is

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

We assume that the firm takes the prices for its product and inputs as given. We also assume that the firm's demand is exogenously given. Given the demand y_t and the level of permanent employment from last period l_{t-1}^P, the firm's employment of temporary labor at *t* is

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

We specify that $y_t = \mu_t + \varepsilon_t$, where ε_t is a random i.i.d. draw from a uniform distribution and represents the transitory demand shock. Thus, the demand y_t is uniformly distributed conditional on μ_t (i.e. $y_t \mid \mu_t \sim UNI(\mu_t - \sigma, \mu_t + \sigma)$. The standard deviation of y_t conditional on μ_t is $\sigma/\sqrt{3}$. From what follows, we use σ to measure the degree of volatility of the demand caused by the transitory shock ε. We assume that μ_t is independent of ε_t and serially auto-correlated over time. A change in μ_t represents a persistent shock to the demand. The firm can observe demand y_t at time t, while it cannot observe ε_t or μ_t.

2-2. Firms' decision on permanent labor when there is no persistent demand shock

[6] Here, *w* is the relative wage of temporary labor to permanent labor. In our model, *w* is exogenously given. In the empirical section, we discuss the possible endogeneity of *w* and how this would affect our estimation results.

Let us consider the stationary case where μ_t remains at μ. Note that because of the assumed one-time adjustment period, any change in permanent employment today does not affect the firm's contemporaneous gross profit. The firm determines the current permanent employment level to maximize the sum of expected future profits net of adjustment cost. The firm's value function at time *t* is

(3) $$J(l_{t-1}^P;\mu) = \max_{l_t^P} E\pi(l_{t-1}^P;\mu) - \lambda\,|\,l_t^P - l_{t-1}^P\,| + \beta J(l_t^P;\mu),$$

where $E\pi(.)$ is the expected gross profit of the firm and

(4) $$E\pi(l_{t-1}^P;\mu) = \int_{\mu-\sigma}^{\mu+\sigma} (py_t - wl_t^T(l_{t-1}^P) - l_{t-1}^P)\,dy_t,$$

where $l_t^T(.)$ is a function of the level of permanent employment from the previous period, which is defined by (2).

Solving the above Bellman equation (3), we have the optimal decision rule on the permanent employment level at time *t* as follows:

(5) $$l_t^{P*} = \begin{cases} l_t^{+P} > l_{t-1}^P : \beta J_1(l_t^{+P};\mu) = \lambda, & if\ \beta J_1(l_{t-1}^P;\mu) > \lambda \\ l_t^{-P} < l_{t-1}^P : \beta J_1(l_t^{-P};\mu) = -\lambda, & if\ \beta J_1(l_{t-1}^P;\mu) < -\lambda \\ l_{t-1}^P, & if\ \beta J_1(l_{t-1}^P;\mu) \in [-\lambda,\lambda] \end{cases}$$

where $J_1(.)$ is the first order derivative of the value function with respect to last period's permanent employment; l_t^{+P} is the targeted optimal level if the firm needs to increase its permanent employment from below; l_t^{-P} is the targeted optimal level if the firm needs to decrease its permanent employment from above. Using (5), and considering the stationary setup, we obtain $J(l_t^{+P};\mu) = \dfrac{E\pi(l_t^{+P};\mu)}{1-\beta}$ and $J(l_t^{-P};\mu) = \dfrac{E\pi(l_t^{-P};\mu)}{1-\beta}$. Let us denote $E\pi_1(.)$ as the first order derivative of the expected one-time gross profit with respect to last period's permanent employment. Note that because of the adjustment period, permanent employment from the previous period is the amount of permanent labor ready to be used this time.

Assumption 1. The parameter space of our model is such that $E\pi_1(.)$ is a strictly decreasing function of l_{t-1}^P.

Under Assumption 1, it is straightforward to show that both l_t^{+P} and l_t^{-P} are uniquely determined and $l_t^{+P} < l_t^{-P}$. Note that neither l_t^{+P} nor l_t^{-P} depends on l_{t-1}^P. Thus from now on, for notational simplicity, we omit the subscript "*t*".

It can also be shown that under Assumption 1, $J_1(.)$ is a strictly decreasing function of l_{t-1}^P.

Therefore, we can write $$\beta J_1(l_{t-1}^P;\mu)\begin{cases} > \lambda, & if\ l_{t-1}^P < l^{+P} \\ < -\lambda, & if\ l_{t-1}^P > l^{-P} \\ \in [-\lambda,\lambda], & o.w. \end{cases}$$

Thus, we have another decision rule which is equivalent to (5),

(5') $$l_t^{P*} = \begin{cases} l^{+P}, & if\ l_{t-1}^P < l^{+P} \\ l^{-P}, & if\ l_{t-1}^P > l^{-P} \\ l_{t-1}^P, & o.w. \end{cases}$$

This tells us that the firm increases its permanent employment level to l^{+P} if it starts from below l^{+P}, and the firm reduces its permanent employment level to l^{-P} if it starts from below l^{-P}. If the initial level lies within the interval $[l^{+P}, l^{-P}]$, then the firm will not make any adjustment of its permanent employment. This interval consists of all the sustainable permanent employment levels. The existence of such an interval is due to the adjustment cost.

In our stationary setting, demand fluctuates around μ over time due to the transitory shock ε. In any sustainable equilibrium, the firm's temporary employment fluctuates while permanent employment remains unchanged. Suppose the permanent employment is l^{+P}. The expected temporary employment at any given time is the same and from (2), it is calculated

(6) $$E(l_t^T) = \frac{\alpha\left((\mu+\sigma)^{\frac{1+\alpha}{\alpha}} - \tilde{y}^{\frac{1+\alpha}{\alpha}}\right)}{2c\sigma A^{\frac{1}{\alpha}}(1+\alpha)} - \frac{l^{+P}\ (\mu+\sigma-\tilde{y})}{2c\sigma},\ \text{where}\ \ \tilde{y} = A(l^{+P}\ )^{\alpha}.$$

2-3. Firms' adjustment of permanent labor when there is a persistent demand shock

Now, let us examine how firms respond (by adjusting permanent labor) to persistent demand shocks, which affect μ. One example of persistent shocks is the national business cycle shock that has a persistent effect on firms' demand. When such a shock occurs at time t, firms are

alerted about the possibility of a persistent shock. For example, at the turning points of national business cycles, there is a lot of speculation going on in the media. However, they may not be able to tell the exact type of the shock instantaneously. This is because a firm can only observe the overall level of demand y_t at time *t*. We assume that the change in μ is revealed in the next period.

For simplicity, we assume there are two states of μ specified by μ_l and μ_h (low and high states), where $\mu_l < \mu_h$ and $\mu_l + \sigma > \mu_h - \sigma$. The conditional distribution of demand is $y_t \mid \mu_l \sim UNI(\mu_l - \sigma, \mu_l + \sigma)$ for the low state and $y_t \mid \mu_h \sim UNI(\mu_h - \sigma, \mu_h + \sigma)$ for the high state. We consider the case of positive persistent demand shocks. The case of negative shocks can be analyzed in a similar way. For simplicity, we focus on three periods $\tau - 1$, τ, and $\tau + 1$. Up to $\tau - 1$, the state of mean demand remains unchanged at the low state. At τ, the mean demand switches to the high state and remains unchanged from time τ on. At $\tau + 1$, the true state of μ is revealed to the firm. Note that at τ, the firm cannot observe μ, and the firm can only draw inference on the probability of a state change according to the overall demand at τ and the average demand volatility it faced in the past.

Let $l_s^{+P} \equiv l^{+P}(\mu_s)$, and let $l_s^{-P} \equiv l^{-P}(\mu_s)$, where $s \in \{l, h\}$. We make the following assumption.

Assumption 2. The parameter space of our model is such that $l_l^{-P} < l_h^{+p}$.

According to Assumption 2, when there is a state change from s_1 to s_2, as long as the initial permanent employment level is within the sustainable range of state s_1, it is optimal for the firm to adjust its permanent employment to match the need of state s_2, if there is no uncertainty about the state change. However, with incomplete information, there would be a delay in the firm's response to a state change due to incomplete information.

Let $V(l_\tau^P; \theta)$ be the expected future profits when the firm sets the permanent employment to be l_τ^P at τ and when the firm believes that the probability that the state shifted from s_1 to s_2 is θ. Note that θ is subjective probability. We discuss how the firm forms such a

probability later in this section. The firm needs to choose l_τ^P in order to maximize the following objective function

(7) $$\max_{l_\tau^P} \beta V(l_\tau^P;\theta) - \lambda \,|\, l_\tau^P - l_{\tau-1}^P \,|,$$

where

$$V(l_\tau^P;\theta) = \theta J(l_\tau^P;\mu_{s_2}) + (1-\theta) J(l_\tau^P;\mu_{s_1}).$$

The optimal decision rule is

(8) $$l_\tau^{P*} = \begin{cases} l_\tau^{+P} > l_{\tau-1}^P : \beta V_1(l_\tau^{+P};\theta) = \lambda, & if\ \beta V_1(l_{\tau-1}^P;\theta) > \lambda \\ l_\tau^{+P} < l_{\tau-1}^P : \beta V_1(l_\tau^{+P};\theta) = -\lambda, & if\ \beta V_1(l_{\tau-1}^P;\theta) < -\lambda \\ l_{\tau-1}^P, & if\ \beta V_1(l_{\tau-1}^P;\theta) \in [-\lambda,\lambda] \end{cases}$$

where $V_1(.)$ is the first order derivative of $V(.)$ with respect to l_τ^P.

Next, let us examine the case when the state switches from low to high.[7] Suppose the initial level of permanent employment before the state change is within the sustainable range of the low state. We have the following proposition.

Proposition 1. Suppose $l_{\tau-1}^P \in [l_l^{+P}, l_l^{-P}]$. Under Assumption 1 and 2, we have:

i) $V_1 < 0$

ii) $l_\tau^{P*} \in [l_{\tau-1}^P, l_h^{+P})$ and l_τ^{P*} is uniquely determined by $\beta V_1(l_\tau^P;\theta) = \lambda$ when $l_\tau^{P*} > l_{\tau-1}^P$

iii) $V_1(l_\tau^P;\theta) > V_1(l_\tau^P;\theta'), \quad \forall l_\tau^P \in [l_{\tau-1}^P, l_h^{+P}), \forall \theta > \theta'$

iv) l_τ^{P*} increases with θ and strictly increases with θ when $l_\tau^{P*} > l_{\tau-1}^P$; v) $l_{\tau+1}^{P*} = l_h^{+P}$.

Proof. See Appendix B.

Proposition 1 tells us that due to uncertainty at the turning point, the firm either maintains its permanent employment level or makes a partial adjustment. The amount of adjustment (if there is any) at the turning point is bigger when the firm's subjective probability that the state switched is higher.

The intuition is clear. If the firm increases its permanent employment to the high state level at τ, the firm could rake in more profits next period if the revealed state is indeed high because the newly hired permanent workers today become productive in next period and

[7] The analysis of the case from high state to low state can be done in a similar way.

contribute to meeting the greater demand. On the other hand, if the economic state remains low, the firm would have to readjust its permanent employment back to the low state level and thus double pay the adjustment cost. The firm's decision hinges on the subjective probability that the state has shifted from low to high, which we denote by θ.

Define $d \equiv (l_h^{+P} - l_{\tau-1}^P)/2$, where d is equal to half of the full adjustment that the firm needs to make in permanent employment from the low state to the high state. We measure the lag between the state change and the adjustment of permanent employment in the following way. If the adjustment at the turning point τ is greater than or equal to d, which is half of the full adjustment, then the lag is zero; otherwise, the lag is 1. This is the median lag idea. According to iv) of Proposition 1, the firm's adjustment is greater than d at τ if and only if the firm's subjective probability of a state change exceeds a certain threshold, denoted by $\hat{\theta}$ s.t.

(9) $$l_\tau^{P*}(\hat{\theta}) = l_{\tau-1}^P + d\ .$$

In Appendix C, we show in detail how to solve for the permanent employment at the turning point., as well as for the threshold probability.

We assume that the firm derives the subjective probability θ in the following way.[8] Observing the current demand, y_τ, the firm asks itself what is the underlying probability with which the realized value y_τ is greater than a random drawn demand level if the current state of mean demand is still low. This probability gives the confidence level at which the firm could reject the hypothesis that μ_τ remains at its low level. Because we assume the demand follows a uniform distribution and the only difference between the high state and the low state distribution lies in the mean, we know that the firm faces uncertainty about the current mean only when the observed demand level falls within the intersection of the high state distribution interval and the low state distribution interval, namely $\mu_h - \sigma < y_\tau < \mu_l + \sigma$. Therefore, θ is calculated as

(10)

$$\theta = \begin{cases} 0, \quad if\ \ y_\tau < \mu_h - \sigma \\ prob(y < y_\tau \mid \mu_\tau = \mu_l, \mu_h - \sigma < y_\tau < \mu_l + \sigma) = \dfrac{y_\tau - \mu_h + \sigma}{2\sigma - \mu_h + \mu_l}, \text{if } \mu_h - \sigma < y_\tau < \mu_l + \sigma \\ 1, \quad \text{otherwise} \end{cases}$$

[8] There are other methods with which a firm derives the subjective probability. Although studying these methods is an interesting and important research topic, it is beyond the scope of this paper.

Based on (13), the threshold demand level, $\hat{y}$, at which the subjective probability exceeds the threshold value $\hat{\theta}$ can be derived from

(11) $$\hat{y} = (2\sigma - \mu_h + \mu_l)\hat{\theta} + \mu_h - \sigma,$$

Where $\hat{\theta}$ is defined in (12).

Now let us derive the probability that the firms increase permanent labor at τ, which is just equal to the probability that $y_\tau \geq \hat{y}$ given $\mu_\tau = \mu_h$:

(12) $$prob^R = \frac{\mu_h + \sigma - \hat{y}}{2\sigma} = (1-\hat{\theta}) + \frac{\mu_h - \mu_l}{2\sigma}\hat{\theta}.$$

Thus, under the above framework, the average time lag between the increase in the mean demand and the recruiting of permanent workers is

(13) $$L = 0 \times prob^R + 1 \times (1 - prob^R) = \hat{\theta} - \frac{\mu_h - \mu_l}{2\sigma}\hat{\theta}.$$

Next, let us look at the movement of temporary employment. Prior to the change of the state, the expected temporary employment is $El^T(l^P_{\tau-1}; \mu_l)$. At time τ, whether or not the firm increases its permanent labor responding to the shock, the productive permanent labor remains at the level that corresponds to the low state due to the adjustment period. Thus, the firm is likely to use more temporary workers as it is likely to face higher demand at time τ; that is, the expected temporary employment, denoted $El^T(l^P_{\tau-1}; \mu_h)$, should increase instantaneously when the state of mean demand switches from low to high.

From (6), we can show that $El^T(l^P_{\tau-1}; \mu_h) > El^T(l^P_{\tau-1}; \mu_l)$. This implies that on average, the increase in temporary employment leads that of permanent employment by *L*, while *L* stands for the average lag between the growth in temporary employment and that of permanent employment when there is a positive persistent demand shock. How does the volatility of demand influence the average lag between the growth in temporary employment and permanent employment? It is clear from (12) that $prob^R$ decreases with the size of transitory shocks, measured by σ.

From (13), the average lag *L* between the change in temporary employment and permanent employment increases with σ, given $\hat{\theta}$. Moreover, $prob^R$ increases with the difference in the mean demand between the high state and the low state, $\mu_h - \mu_l$, given $\hat{\theta}$. Note that $\mu_h - \mu_l$ reflects the size of persistent demand shocks. Thus the average lag between the

movement in temporary and permanent employment shortens with, the size of persistent shocks, given $\hat{\theta}$. Because $\hat{\theta}$ is endogenously determined and is a function of demand volatility, next, we solve for the threshold value $\hat{\theta}$ and the corresponding average lag numerically, through simulations under various demand volatility. In the simulations, we let the initial permanent employment level to be at the upper end of the sustainable interval, i.e., $l_{\tau-1}^{P} = l_{l}^{-P}$. The values of parameters used in the simulations are:

$$\alpha = 0.67, \quad \beta = 0.982, \quad A = 0.2, \quad p = 500, \quad \mu_l = 800,$$
$$\mu_h - \mu_l = 200\ (or\ 100), \quad \lambda = 0.5, \quad w = 0.8, \quad c = 0.5.$$

We let the one time interval here to have a length of 6 months. Therefore, the discount rate is approximately 0.982 if the monthly discount rate is 0.997. Three parameters are essential; they are marginal adjustment cost of permanent employment λ, the wage ratio of temporary labor to permanent labor *w*, and the productivity ratio of temporary labor to permanent labor *c*. It is hard to measure the marginal adjustment costs. Campbell and Fisher (2004) take the severance payment as between 0.5 to 1.5 times of the quarterly salary. We let the marginal adjustment costs to be equal to 0.5 times of the half-year salary. As for the wage ratio, we let *w=0.8*, since the wage ratio of temporary labor to permanent labor is about 0.8 on average in the U.S. over 1990-2006. We experiment with different values of *c*, and we obtain qualitatively similar results regarding the relationship between the average lag and the volatility of demand, as long as $c < w$.

Our simulations demonstrate that as σ increases, $prob^R$ decreases, and the average lag *L* between the growth of permanent and temporary employment increases (see Figure 1-a). The intuition behind this prediction is that when the firm faces less volatility caused by transitory shocks, it is easier for the firm to identify persistent shocks. Thus the firm responds more quickly to a positive persistent shock by increasing its permanent employment. Our simulations also show that as δ increases, $prob^R$ increases, and the average lag *L* decreases (see Figure 1-a). The firm responds more quickly by increasing the permanent employment when the size of a persistent shock is greater. This is because the greater the persistent shock, the easier the firm can identify it. It is also because the firm would suffer more loss if it were slow in increasing permanent employment level in response to greater increase in the mean demand level. From Figure 1-a, one can see that the average lag between temporary and permanent employment is shorter when the amplitude of a shift in the mean demand is 200 compared to the case of 100.

We have so far examined the case where the state shifts from low to high. Similar results can be obtained in the case of negative persistent shocks where the state of μ changes from μ_h to μ_l. In this case, the subjective probability of $\mu = \mu_l$ is calculated as

$$(14)\ \theta = \begin{cases} 0, & if\ \ y_\tau > \mu_l + \sigma \\ prob(y > y_\tau \mid \mu = \mu_h,\ \mu_{\mathrm{h}} - \sigma < y_\tau < \mu_l + \sigma) = \dfrac{\mu_l + \sigma - y_\tau}{2\sigma - \mu_h + \mu_L}, & \text{if } \mu_{\mathrm{h}} - \sigma < y_\tau < \mu_l + \sigma \\ 1, & \text{otherwise} \end{cases}$$

The expression of the average lag is the same as (13). Figure 1-b shows that the previous two predictions apply to the case of a negative persistent demand shock as well.

3. Data source and the construction of key variables

In our theoretical model, we consider the fluctuations of temporary and permanent employment that are caused by stochastic shocks and examine the lag between temporary and permanent employment series. However, in reality, both permanent and temporary employment grow with some time trend that is deterministic. Therefore, in the empirical section, we use growth rates of temporary and permanent employment, which removes the linear trend from both temporary and permanent employment series. This allows us to better capture the lag associated with stochastic shocks.

Based on the above theoretical prediction, we test to see how the lag between temporary and permanent employment growth rates for each city i, L_i, is associated with our measures for the average size of transitory shock , v_i^T and that of long-lived shock, v_i^P, using the observations available for 74 MSAs. Below, we explain details on data availability as well as how we construct our key variables.

3-1. Lag between temporary and permanent employment growth rates for a city

To calculate the lag between temporary and permanent employment growth rates for each city, we use BLS monthly employment data between January 1990 and May 2005. Starting with 1990, the BLS provides MSA level data for each city if the size of the industry in the city is larger than a certain level. In most cases, the narrowest industry category available is the 4-digit NAICS level. This limits us to the employment series of NAICS 5613 (Employment Services), which include NAICS 56132 (THS), to capture the growth rate of temporary employment. 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. When we compare the growth rates for these industries, the correlation coefficient between the growth rate of the THS industry and that of employment services is .97.

During our study period, employment data for the employment services sector (NAICS 5613) are available for 74 MSAs, which we use for our analysis. As for permanent employment, we use total employment of all private sectors excluding the employment services sector. Note that the time series data of temporary employment for each industry is not available at either the national level or MSA level.

In Figure 2, we plot the 12-month growth rates for both temporary and permanent employment for two cities. Figure 2-a is that for Colorado Springs, CO, and Figure 2-b is Portland-Vancouver-Beaverton, OR-WA. Temporary employment growth rates seem to lead in Portland, but such a relationship is weak in Colorado. An issue in this paper is to what extent can such a cross-city variation in lags be explained by variation in volatilities.

We use several methods to estimate the lag (denoted as L_k) between the temporary employment growth rate (denoted as g_k^T) and the permanent employment growth rate (denoted as g_k^P) for each city *k*. We seasonally adjust monthly growth rates and estimate the lag using not only the monthly growth rates themselves but also the smoothed series (i.e., moving averages) of temporary and permanent employment growth rates. As we demonstrated in our model, the mean value of temporary employment growth shifts in response to the shift of the mean demand, while its actual value fluctuates depending on realized value of outputs.

As one way to measure the lag, for each city *k*, we estimate a finite distributed lag model,[9]

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

where $\bar{L}$ is set as 12. The sum of the β coefficients represents the cumulative effects of a unit increment in temporary employment growth on permanent employment growth. We calculate both median and mean lags. Note that while the total effects (the sum of 13 point estimates including the contemporaneous effect and the effects 1 to 12 months later) are positive for almost all the cities, the point estimates for β are not always zero; the cumulative effects are not necessarily monotonic. We focus on using a median lag measure, which we define as the first

[9] An implicit assumption here is that temporary employment leads permanent employment. We will relax this assumption to do a robustness check.

month when the cumulative effect on permanent employment growth exceeds half of the total effects.[10]

Table 1 shows the summary statistics of lag measures and total effects. The median lags are around 4.5, which is consistent with Segal and Sullivan's (1995) findings for the national level. The total increment of the permanent employment growth rate 12 months after a unit increase in temporary employment growth is about one tenths, which corresponds to the difference between the s.d. of temporary and permanent growth rates. Among the cities included in our study, the s.d. of permanent employment growth is .00473 and that of temporary growth rate is .0407. For the three month moving average (MA) series, the s.d.s of permanent and temporary growth rates are .0028 and .0229, respectively. For other MA series, we also find similar tendencies.

3-2. Average size of transitory and permanent demand shocks faced by industries in a city

To capture the transitory and persistent demand shocks faced by industries in a city, we first capture the volatilities of each industry at the national level. To obtain city-level volatility, we then calculate the weighted average of industry volatilities using the industry mix of the city. Even for the U.S. as a whole, monthly industry output data are not available for many industries especially among non-manufacturing industries.[11] While monthly employment data are readily available for many industries, such data record the number of permanent employees (workers on payroll). The fluctuation of permanent employees would not be ideal to capture the transitory shock based on our framework. Moreover, the volatility of permanent employment would be endogenous to an industry's tendency to use temporary workers. We use the BLS monthly data for total weekly production labor hours including overtime,[12] which is likely to fluctuate with transitory demand shock. In particular, we consider that the overtime portion of labor hours would fluctuate with transitory shocks as adjusting overtime would not generally incur fixed costs.[13]

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[10] The correlation coefficients between the median and mean lags range between .70 and .75. Some lags are measured as below zero or greater than 12 by applying the definition of mean lag.

[11] 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.

[12] The data are from the Current Employment Statistics report performed by the BLS. The production workers (in both goods producing and non-goods producing sectors) are generally defined as non-supervisory employees. The data on overtime are separately available only for manufacturing sectors.

[13] To capture the fluctuation of labor and corresponding outputs, it would be ideal to look at the total labor hours that also include hours worked by temporary workers. However, since temporary workers are on the payroll of THS firms, their hours are not included in the industry to which they actually contribute.

Note also that while it is not feasible to use MSA-level hour data because of the limited availability of such series, the use of national-level data is preferable because it removes possible effects of unobserved city-specific factors. If there are any city-specific factors that influence both the lag and the output fluctuations of all industries in the city, by using city-level data to capture fluctuation, we would capture a spurious relationship between these variables. The volatility of national-level industry labor hours data is unlikely to be endogenous to a city-level lag between temporary and permanent employment growth.

To distinguish between transitory and persistent demand shocks, we apply the filtering to the data for total production labor hours including overtime. We decompose the fluctuations of labor hours 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.

Specifically, we construct two filters. One is the High Pass (HP) filter that passes components of the demand series with periodicity less than or equal to 4 months. The HP filter passes high frequency and noisy components that are considered transitory (see Gan and Zhang, 2006). Therefore, the filtered time series reflects transitory shocks. We also construct the Band Pass (BP) filter that passes cycles between 18 and 96 months in periodicity. This BP filter is well known as the business cycle, which is defined by Burns and Mitchell as cyclical components of no less than 6 quarters (18 months) in duration and no more than 32 quarters (96 months). We consider the resulting time series through the BP filter to capture the long-lived shocks.[14]

For each industry at a national level, we use the standard deviation of a filtered business cycle series (denoted as σ_j^P for industry j) as a measure of the size of the long-lived shock, and use the standard deviation of a filtered high pass series to measure the size of the transitory shock (denoted as σ_j^T). We then calculate the volatility measures for each city taking weighted averages of industry-level volatility using a city's industry mix. In particular, the volatility of long-lived shocks for city *i* is $v_k^P = \sum_{j \in I_j} w_{kj} \sigma_j^P$, where I_i is the set of industries in city *k*, and w_{ij} is the share of industry *j* in city *c*. The transitory volatility for city *i* is $v_k^T = \sum_{j \in I_j} w_{kj} \sigma_j^T$. We calculate the industry mix based on the 1998 County Business Patterns (CBP) data. The year 1998 is

[14] 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. The truncation point we chose, denoted as K, is 36. We tested a range of values for *K*=[24, 32, 54, 72] and find shocks are not sensitive to the choice of *K*. We also experimented with other ways to construct filters, such as that of Corbae, Ouliaris, and Phillips (2002). The results are similar.

almost the middle of the period for which we use BLS hours data, as well as the first year when the CBP uses NAICS as industry classification that is used for the BLS hour data.[15]

Analogous to the way we calculate the lag, we use the growth rates of total labor hours (including overtime) rather than the level to capture the volatility. Note that we also could have used the level of labor hours for capturing the volatility of demand in each industry. However, the volatility measure based on level is subject to the size of industry. By using the growth rates instead of the level of total labor hours, we naturally solve this problem. We thus can use the share of each industry in a city as a weight and obtain the city-level volatility as a weighted average volatility across industries.

3-3. Other control

Note that while our model takes the relative wage of temporary workers as given, it is possible that greater transitory volatility causes higher wages for temporary workers because it increases the demand for temporary workers in general. The higher relative wage for temporary workers may weaken the positive effect of the transitory volatility on the lag because it diminishes the benefit from using temporary workers. Such an effect may be more pronounced in a city where transitory shocks of different industries in the city co-move more closely. If many industries require temporary workers at the same time, the companies providing temporary labor services cannot smooth their supply of temporary workers and may increase the mark-up to offset such a risk (Ono and Zelenev, 2003). Thus, we expect that the positive effect of the transitory volatility on the lag is smaller when the co-movement is greater. Therefore, we incorporate the interaction between the transitory volatility and a co-movement measure.

The co-movement measure we use is defined as $\rho_k \equiv \sqrt{\sum_i \sum_{i \neq j} w_{ki} w_{kj} \sigma_{ij}^T}$, where σ_{ij}^T is a covariance of transitory shocks between industry i and industry j , and w_{ki} is the share of industry i in city k . We obtain transitory shocks for each industry at the national level through filtering as specified in section 3-2.

In addition, we control for city size as represented by the average of the log of city permanent employment during our study period because the thick market effect may influence the efficiency of matching in the labor market. We also control for some demographic characteristics of MSA population, such as the share of the population by age, education, and race in order to

[15] We checked to what extent industry mix in a given MSA change 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 .96.

control for the supply of temporary workers. As demonstrated in Polivka (1996), demographic characteristics of temporary workers are quite different from that of permanent workers. Thus, the differences in demographic characteristics across cities may influence the supply of temporary workers. Moreover, we control for the city's share of good producing sector. The intensity of their use of temporary employment is higher as compared to the service sector (Cohany, 1998). We discuss more details as we show results. Table 2 shows the summary statistics of all variables.

4. Empirical Results

Table 3 shows our estimation results. The results with the lag measure based on monthly growth rates are in Table 3-a, those with the lag based on 5-month MA series, 9-month MA series, 11-month MA series and 15-month MA series are in Tables 3-b, c, d, and e, respectively. All the results we present here are based on median lags.

Among the regressions with various moving average series, we found the results using the lag measures based on 9- and 11-month MAs reveal statistically significant evidence that supports our hypothesis. To compare different results, we show the results with lag measures based on simple growth rates, 5-month MA, 9-month MA, 11-month MA, and 15-month MA.

First, the regressions based on a simple specification without co-movement measures show only a few statistically significant coefficients (see column (1) in Table 3). Among them, the results based on 11-month and 15-month MAs show the expected sign for the average size of long-lived shocks.

With the interaction term between the average size of transitory shocks and the co-movement measure, the effects of all the variables are more tightly estimated, as you can see in the results in column (2) in the series of tables. In particular, the coefficient for the size of transitory shocks is significant and positive; its interaction with the co-movement measure is significant and negative in the results based on 9-month and 11-month MA. The results remain qualitatively the same even after we control for demographic variables (see column (3) of Table 3-c and 3-d). The effect of the average size of transitory shock is positive when the co-movement measure is small, and the effect is negative when the co-movement measure is large. Using the results with specification (3) in both 9- and 11-month MAs (Tables 3-c and 3-d), with a simple calculation, we can see that the effect of the average size of transitory shocks turn from positive to negative as the co-movement measure exceeds a threshold that is slightly above its mean. When the transitory shocks are diversified enough across industries in a city, greater average size of such shocks increases the lag between temporary and permanent employment of the city, which is consistent with our model's prediction. However, when transitory shocks are more

correlated among industries, as we discussed previously, it is possible that the negative effect of higher relative wage for temporary workers dominates the positive effects that our theory predicts. While our model does not incorporate the wage effect, it may be instructive to do so in the future.

We calculate the magnitude of the effect of a s.d. change in the size of transitory shock (.000411), which depends on the degree of co-movement. Using the specification (3) with a 9-month MA, in a city with an average co-movement measure (.00646), the effect is positive but small at around .4 months. However, in a city with the lowest co-movement measure (.00574), it is 2 months. We also calculate the magnitude of the effect of the size of a long-lived shock using the same result. A s.d. increase in the size of a long-lived shock decreases the lag by 1.08 months. Note that the coefficients for the size of long-lived shocks are quite different between the 9- and 11-month MA results, although they both have the predicted sign. The estimated effect based on the 11-month MA series is greater than that based on the 9-month MA. According to column (3) in Table 3-d, a s.d. increase in the size of the long-lived shock decreases the lag by 2.46 months.

As a robustness check, using 11-month MA series, we additionally control for the ratio of the city's temporary to permanent employment. Such a ratio would help control for city-level relative temporary wage. It is also suggested by other papers that the size of adjustment costs would influence such a ratio. The qualitative results for all the variables remain the same, and we obtain even slightly stronger effects of both volatility measures

The significance of coefficients for city size vary across specifications. The city size effect is marginally significant according to the results based on the 9-month MA (see column (3), Table 3-c). The lag declines with city size when the city size is small; however, the lag increases with city size once the city size exceeds a certain level. There are various reasons why city size may be associated with the lag. An explanation lies in another role of temporary workers on which our model does not focus. Due to the imperfect information problem in the labor market, firms often use temporary workers before they find a qualified permanent worker, or they use temporary arrangements to screen for permanent workers. The longer it takes for firms to find a qualified permanent worker, the longer the lag between temporary and permanent employment growths would be. In a larger city, because of the thick market effect, firms are able to find better matched workers on average. This may shorten the search and screening process. On the other hand, in a larger city, firms may form a higher expectation of matching and become more selective in hiring permanent workers. This may cause a longer search and screening process. The results seem to indicate that, among smaller cities, the thick market effect dominates; once the city size reaches a certain level, the selective effect begins to take over.

The demographic controls included in the regressions are the share of population with characteristics more common among temporary workers as compared to that of permanent workers. On average, temporary workers tend to be younger, low-educated, and non-white. In our results, the share of non-whites has a significant and positive impact on the lag based on the 11-month MA results (see column (3), Table 3-d). This may be because of the supply effect. The share of young population in a city tends to be negatively associated with the lag. Significant coefficients were not obtained for the low-educated population share.

Finally we note that several specifications suggest that the share of the good-producing sector is positively associated with the lag (see column (3), Table 3-c and 3-d). One story behind this result is that the cost per efficient temporary labor may be lower for the good-producing sector as compared to the service sector, given the same wage. It is possible that manufacturers require more standardized and well-defined tasks than service sectors, which causes productivity difference between permanent and temporary workers in the good-producing sector to be smaller than that in the service sector.

5. Conclusion

By combining uncertainty and adjustment costs, this paper shows that incomplete information may have important implications for firms' responses to demand shocks. Specifically, our findings seem to suggest that firms draw inference on the mean demand based on the volatility that they experience. The average sizes of both transitory and long-lived shocks seem to affect the inference and in turn affect firms' timing of adjusting permanent and temporary workers. Our cross-city analysis finds that the demand volatility caused by transitory shocks increases the lag between the temporary and permanent employment growth in cities where the degree to which transitory shocks are correlated across industries is low enough. The volatility of permanent shocks seems to have the opposite effect on the lag. These findings shed light on the dynamics of permanent and temporary employment over business cycles.

Tables and Figures

Table 1

Lag measures based on monthly growth rates:

	N. of MSAs with positive total effects	Median lag[1]	Total effects
Non-smoothed series	70	4.84 (2.61)	.0956 (.0559)
Moving average series			
5 month moving average	73	4.63 (3.18)	.102 (.0606)
9 month moving average	73	4.70 (3.72)	.110 (.0639)
11 month moving average	74	5.05 (4.10)	.116 (.0659)
15 month moving average	73	5.86 (4.40)	.119 (.0661)

[1] The first month that the cumulative effects exceed half of the total effects.
( ): standard deviation

Correlation between lags based on different MAs

	Non-smoothed	5-month MA	9-month MA	11-month MA
5 month MA	0.691			
9 month MA	0.655	0.857		
11 month MA	0.526	0.670	0.804	
15 month MA	0.412	0.627	0.755	0.792

Table 2 Volatility measures and other controls: 74 cities

Variables	Mean	S.d.
Transitory shock s.d.: Cycle < 4 months	.0108	.000411
Long-lived shock s.d.	.00214	.000131
Co-movement measure	.00646	.000318
City size: Log permanent workers: average over the sample period	6.01	.97
Share of good producing industries	.224	.0705
Share of population		
Population of the age between 18 and 24 (out of age between 18 and 66)	.142	.016
Population without four year college degree	.801	.0526
Non-white population	.249	.109

Table 3 Results of regressions of the median lag between temporary and permanent employment growth rates on volatility measures and other controls

Table 3-a Lag based on monthly growth rates

	(1)	(2)	(3)
Transitory shock s.d.:	-76.309	11955	13664
Cycle < 4 month	(-0.30)	(0.92)	(1.10)
Transitory shock s.d:		-2019188	-2306807
×Comovement measure		(-1.04)	(-1.25)
Long-lived shock s.d.	1113	-5080	-4137
	(0.29)	(-1.19)	(-1.12)
Comovement measure		26232	28945
		(1.22)	(1.42)
City size	-5.78	-7.41*	-7.39*
	(-1.25)	(-1.70)	(-1.75)
City size squared	.426	.535	.527
	(1.21)	(1.58)	(1.59)
Share of good producing	-1.08	12.4	8.102
	(0.15)	(1.42)	(1.00)
Age: 18~24			-35.5*
			(-1.68)
Low education			7.41
			(1.00)
Non-white			.161
			(.05)

*** 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; 70 cities with positive total effects are included in the regressions.

Table 3-b Lag based on 5-month MA series

	(1)	(2)	(3)
Transitory shock s.d.:	-26.2	13095	14432
Cycle < 4 month	(-0.30)	(0.92)	(0.95)
Transitory shock s.d:		-2084150	-2251267
× Comovement measure		(-0.97)	(-0.98)
Long-lived shock s.d.	3090	261	-2095
	(0.80)	(0.07)	(-0.48)
Comovement measure		24378	25809
		(1.02)	(1.02)
City size	-8.82	-9.49*	-9.56*
	(-1.75)	(-1.81)	(-1.83)
City size squared	.716	.761	.745*
	(1.82)	(1.87)	(1.84)
Share of good producing	6.50	13.0	16.43
	(0.71)	(1.35)	(1.55)
Age: 18~24			-38.3
			(-1.49)
Low education			-6.22
			(-0.69)
Non-white			2.75
			(.98)

*** 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 3-c Lag based on 9-month MA series

	(1)	(2)	(3)
Transitory shock s.d.:	853	36907***	37696***
Cycle < 4 month	(-0.74)	(3.08)	(2.88)
Transitory shock s.d:		-5623776***	-5690817***
× Comovement measure		(-3.05)	(-2.82)
Long-lived shock s.d.	-1821	-5817	-8280*
	(-.48)	(-1.36)	(-1.67)
Comovement measure		63014***	63446***
		(3.06)	(2.83)
City size	-9.19	-10.1	-10.7*
	(-1.47)	(-1.6)	(-1.68)
City size squared	.776	.837*	.863*
	(1.60)	(1.71)	(1.84)
Share of good producing	14.2	22.5*	26.33**
	(1.43)	(1.99)	(2.10)
Age: 18~24			-31.96
			(-1.11)
Low education			-9.46
			(-.92)
Non-white			1.06
			(.33)

*** 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; 72 cities with positive total effects are included in the regressions.

Table 3-d Lag based on 11-month MA series

	(1)	(2)	(3)
Transitory shock s.d.:	188	29636**	31249*
Cycle < 4 month	(.17)	(2.06)	(1.97)
Transitory shock s.d:		-4692915**	-4916061**
× Comovement measure		(-2.15)	(-2.04)
Long-lived shock s.d.	-7137*	-14377***	-18782***
	(-1.68)	(-2.78)	(-2.98)
Comovement measure		55113**	56965**
		(2.83)	(2.13)
City size	-1.82	-3.25	-2.18
	(-.27)	(-.47)	(-.30)
City size squared	.238	.333	.206
	(.45)	(.60)	(.35)
Share of good producing	16.72	32.6***	40.5***
	(1.47)	(2.88)	(3.00)
Age: 18~24			-53.0*
			(-1.68)
Low education			-6.52
			(-.64)
Non-white			9.87**
			(2.06)

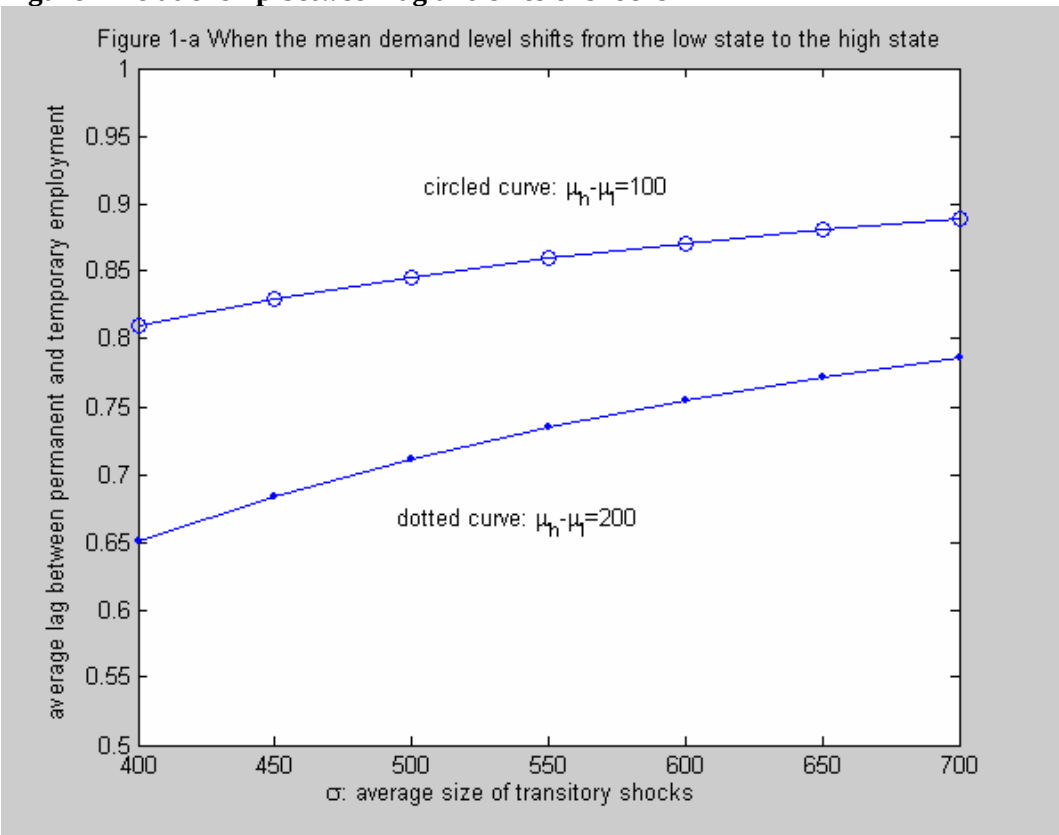
*** indicates statistical significance at the 1% level.
** indicates statistical significance at the 5% level.
* indicates statistical significance at the 10% level.
( ): t-statistics based on robust standard errors
Constant term is included in the regression; 73 cities with positive total effects are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

Table 3-e Lag based on 15-month MA series

	(1)	(2)	(3)
Transitory shock s.d.:	-29.5	15177	15883
Cycle < 4 month	(.03)	(2.06)	(1.21)
Transitory shock s.d:		-2438084**	-2470415
× Comovement measure		(-1.29)	(-1.23)
Long-lived shock s.d.	-9131**	-13179**	-18531***
	(-2.21)	(-2.45)	(-3.20)
Comovement measure		29191	28898
		(1.35)	(1.27)
City size	-2.94	-3.86	-3.87
	(-.47)	(-.61)	(-.59)
City size squared	.365	.425	.391
	(.75)	(.86)	(.74)
Share of good producing	35.66***	45.1***	53.8***
	(3.42)	(4.13)	(4.87)
Age: 18~24			-70.5*
			(-1.94)
Low education			-14.0
			(-1.25)
Non-white			4.53
			(.68)

*** 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.

Figure 1 Relationship between lag and sizes of shocks



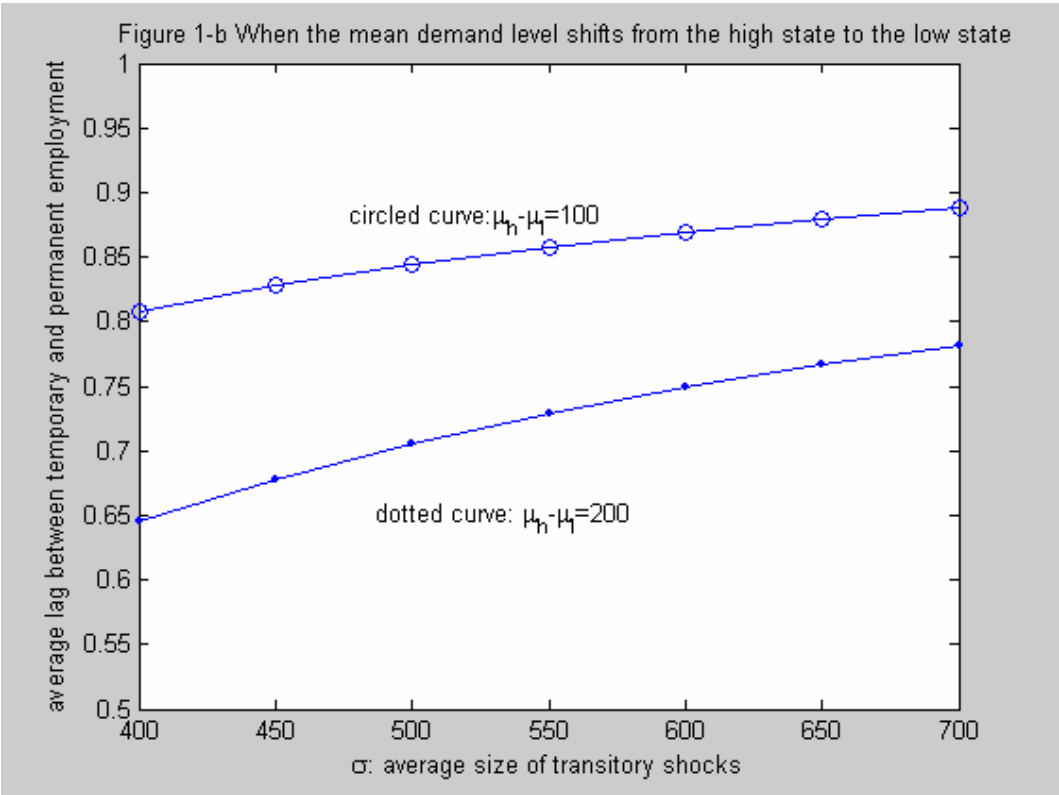


Figure 2. Temporary and permanent employment growth rates

Fig. 2-a Colorado Springs, CO

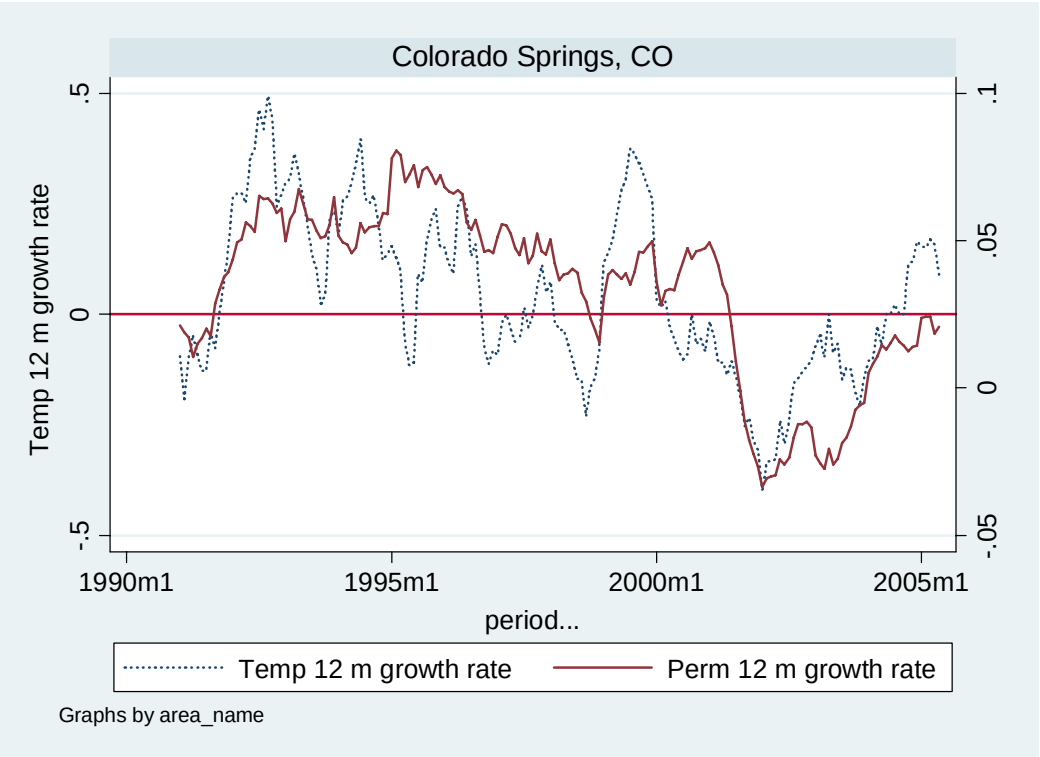
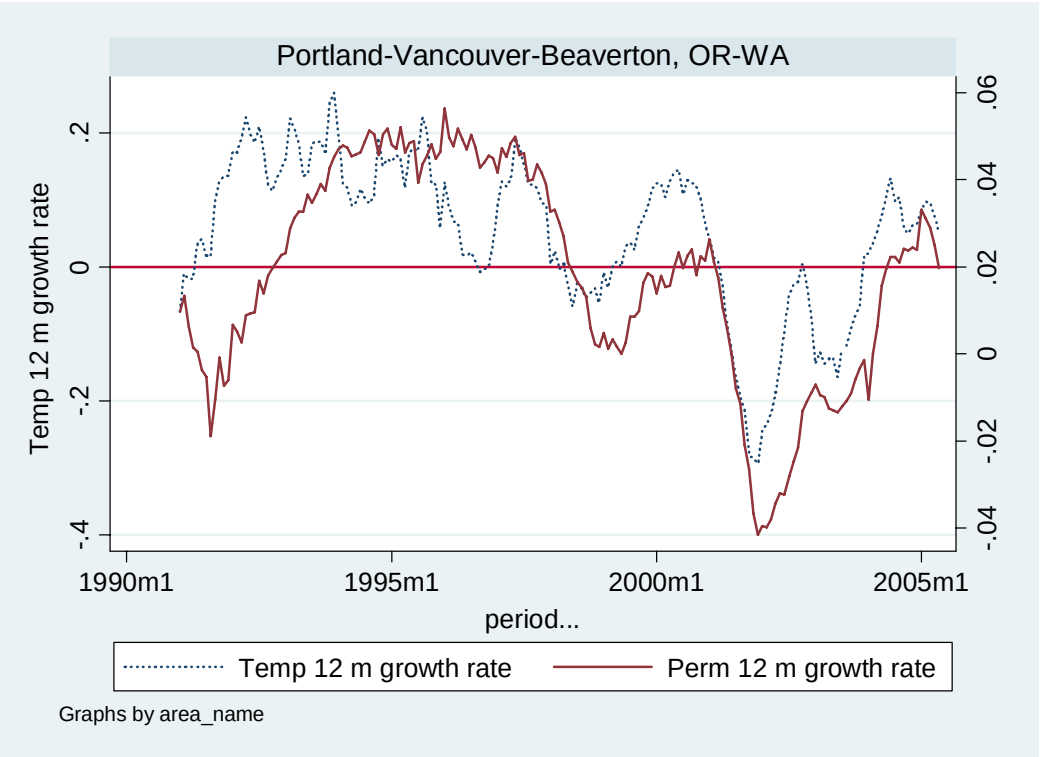


Fig. 2-b Portland-Vancouver-Beaverton, OR-WA



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Appendix

A. Definition of the industries

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.

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.

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.

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.

B. Proof of Proposition 1

i) Because $V(l_\tau^P;\theta)=\theta J(l_\tau^P;\mu_h)+(1-\theta)J(l_\tau^P;\mu_l)$, and because $J_1(.)<0$ under Assumption 1, we have $V_1(.)<0$.

ii) Because $l_{\tau-1}^P \in [l_l^{+P}, l_l^{-P}]$, and because $\beta J_1(l_{\tau-1}^P;\mu_h)>\lambda$ under Assumption 2 and $\beta J_1(l_{\tau-1}^P;\mu_l)>-\lambda$ according to the optimal decision rule (5), we have $\beta V_1(l_{\tau-1}^P;\theta)>-\lambda$. Also, because $\beta J_1(l_h^{+P};\mu_h)=\lambda$ and $\beta J_1(l_h^{+P};\mu_l)<-\lambda$ under Assumption 2, we have $\beta V_1(l_h^{+P};\theta)<\lambda$. Therefore, according to the optimal decision rule (10), $l_\tau^{P*}\in[l_{\tau-1}^P, l_h^{+P})$. Lastly, because $V_1(.)<0$, we know l_τ^{P*} is uniquely determined by $\beta V_1(l_\tau^P;\theta)=\lambda$ when $l_\tau^{P*}>l_{\tau-1}^P$.

iii) This is because $J_1(l_\tau^P;\mu_h)>J_1(l_\tau^P;\mu_l), \quad \forall l_\tau^P \in [l_l^{+P}, l_h^{+P})$ under Assumption 2.

iv) Because of ii) and iii), we have l_τ^{P*} increases with θ and strictly increases with θ when $l_\tau^{P*}>l_{\tau-1}^P$.

v) Because of ii), and according to the optimal decision rule (5'), we have $l_{\tau+1}^{P*}=l_h^{+P}$.

C. Solution for the optimal permanent employment

First, we illustrate how to solve for l^{+P}. The case of l^{-P} is similar. Firstly,

(C.1)
$$\pi(l^{+P})=\begin{cases} py-w\dfrac{\left(\dfrac{y}{A}\right)^{\frac{1}{\alpha}}-l^{+P}}{c}-l^{+P}, & \text{if } y>A(l^{+P})^{\alpha} \\ py-l^{+P}, & o.w. \end{cases}$$

Let us denote $A(l^{+P})^{\alpha}$ by $\tilde{y}$. Then we can obtain

(C.2)
$$E\pi_1(l^{+P})=\frac{w}{c}\left(\frac{\mu+\sigma-\tilde{y}}{2\sigma}\right)+\frac{w\alpha\tilde{y}}{2c\sigma}\left(\left(\frac{A}{w}\right)^{\frac{1}{\alpha}}-1\right)-1.$$

Plugging (C.2) into $\beta J_1(l^{+P};\mu)=\beta E\pi_1(l^{+P};\mu)+\beta\lambda=\lambda$ and replacing $\tilde{y}$ with $A(l^{+P})^{\alpha}$, we obtain

(C.3) $$l^{+p} = \left(\frac{\mu + \sigma - \left(\frac{\lambda(1-\beta)+\beta}{\beta} \right) \frac{2c\sigma}{w}}{A\left(1-\alpha\left(\left(\frac{A}{w}\right)^{\frac{1}{\alpha}}-1\right)\right)} \right)^{\frac{1}{\alpha}}.$$

From (C.3), one can see that permanent employment is a function of the mean level of demand μ and the degree of demand volatility caused by transitory shocks measured by σ.

Similarly, we can get

(C.4) $$l^{-p} = \left(\frac{\mu + \sigma - \left(\frac{-\lambda(1-\beta)+\beta}{\beta} \right) \frac{2c\sigma}{w}}{A\left(1-\alpha\left(\left(\frac{A}{w}\right)^{\frac{1}{\alpha}}-1\right)\right)} \right)^{\frac{1}{\alpha}}$$

Suppose the mean demand shifts from the low state to the high state. And suppose before the shift, the permanent employment level is at the upper end of the sustainable range corresponding to the low state. Then, according to the optimal decision rule (11), the optimal permanent employment at the turning point τ is

(C.5) $$l_{\tau}^{p*} = \left(\frac{\theta(\mu_h+\sigma)+(1-\theta)(\mu_l+\sigma) - \left(\frac{(1-\beta(2\theta-1))\lambda+\beta}{\beta} \right) \frac{2c\sigma}{w}}{A\left(1-\alpha\left(\left(\frac{A}{w}\right)^{\frac{1}{\alpha}}-1\right)\right)} \right)^{\frac{1}{\alpha}}$$

From (C.5), we can see that l_{τ}^{p*} is a function of θ, the subjective probability of a state shift. Combining (C.3-5), and using (9), we can calculate the threshold probability $\hat{\theta}$ such that the adjustment of permanent employment at the turning point is more than half of the full adjustment.

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