LABOR MARKET BEHAVIOR IN WASHINGTON: A COINTEGRATION APPROACH

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Generally, it is well understood that new business investment brings changes in population, increase in labor force participation rate, and migration of new residents. However, Powers (1996) argued that natural capital in the many places in the West is driving population growth and that drives job growth. Powers believes that the causality operates in a reverse way in regions having good environment and amenities, such that population is attracted by environmental amenities and the population changes brings about changes in employment. Washington is a good test of the Powers hypothesis, because of its beautiful environment and amenities.

It is important to both local policymakers and social scientists to understand who benefits from local job growth. There is mixed research results regarding the extent that new migrants tend to account for new employment. Bartik (1993) found that about one-quarter of the new jobs go to local workers because of the increase in the labor force participation rates of local residents in the long run. He considered the long run effects by estimating the effects of 1% job growth in a certain period on the labor force participation rate seventeen years after that period. In contrast Blanchard and Katz's (1992) research reached a different conclusion - in five to seven years the employment response consists entirely of the migration of new migrants. Their finding is that long-run effect of the job growth on the labor force participation rate is negligible. Yeo and Holland (2000) found a composite result. Their finding is that most of the new jobs are captured by in-migrants instead of the county residents in the long run. Also, the long-run effect of the job growth on the labor force participation remains to some degree, although its effect is small.

In many studies, the population, employment, and labor force participation rate are considered as important variables to explain the local labor market. In this study, we first examine causality arguments above. Second, we investigate interactions among these variables in Washington using cointegration analysis. Third, we decompose each of these series into a stationary component and a non-stationary component, and identify these components. Forth, by investigating the effects of one standard deviation shock to the employment on the population and the labor force participation rate by impulse response analysis, we provide the results of this study – the long run effect of employment on the local labor force participation rate and the party who benefits from local job growth – for comparison with the results of previous studies.

Cointegration Analysis and Error Correction Representation

Cointegration analysis allows us to examine the long run equilibrium relationship among nonstationary variables. In our case, cointegration analysis allows us to investigate the long run effects of the employment and participation rate on the population. The concept of cointegration was developed by Engle and Granger (1987). A time series Z_t that is stationary after being differenced d times is said to be integrated of order d, $I(d)$. For an m-dimensional nonstationary process Z_t which is $I(d)$, if there are r linearly independent vectors β_i such that $\beta_i' Z_t$ is $I(b)$, $b < d$, then Z_t is said to be cointegrated of order *(d, d-b)* denoted by $Z_t \sim CI(d, d-b)$ with cointegrating rank $r <$

m. The r vectors, β_i, are called cointegrating vectors, and the stationary linear combination $\beta_i' Z_t$ is called the long-rum equilibrium error. Engle and Granger (1987) defined cointegration as "If each element of a vector of time series Z_t is stationary only after differencing, but a linear combination $\beta_i' Z_t$ needs not be differenced, the time series Z_t have been defined to be co-integrated of order (1, 1) with cointegrating vector β_i". For this study we focus on the case where Z_t is $I(1)$, and thus $\beta_i' Z_t$ is $I(0)$, stationary because the variables considered in this study are $I(1)$.

We consider an m-dimensional vector autoregressive process of order p, VAR(p),

$$(1) \qquad Z_t = \delta + \sum_{i=1}^{p} \Phi_i Z_{t-i} + \varepsilon_t ,$$

where δ is an $m \times 1$ vector of constant term, Φ_i is an $m \times m$ matrix of parameters, and ε_t is a white noise with positive definite covariance matrix Ω.

As in Engle and Granger (1987), the model in (1) can be re-expressed in the following error correction model (ECM) representation,

$$(2) \qquad W_t = \delta + C Z_{t-1} + \sum_{i=1}^{p-1} \Phi_i^* W_{t-i} + \varepsilon_t ,$$

where $W_t = Z_t - Z_{t-1}$ is stationary, $\Phi_i^* = -\sum_{k=i+1}^{p} \Phi_k$, $C = -I_m + \sum_{i=1}^{p} \Phi_i$. The term CZ_{t-1} is called the error correction term, and the coefficient matrix C contains information about the long-run equilibrium relationship among the components of Z_t. If there is no stationary long-run equilibrium relationship among the variables in Z_t, the rank of C is zero, and we use the standard VAR model of order *p-1* for the first differenced series W_t. If the vector process Z_t is stationary, then C is a full rank matrix. The rank of C is greater than zero and less than m, i.e., $0 < r = rank(C) < m$, if Z_t is cointegrated of order (1, 1) with cointegrating rank r, which means that there exists a long-run equilibrium relationship among the components of Z_t.

To estimate ECM in (2) with the rank restriction, we reparameterize the C matrix as $C = \alpha\beta'$, where α and β are full rank $m \times r$ parameter matrices or rank r. Then we can rewrite (2) as

$$(3) \qquad W_t = \delta + \alpha\beta' Z_{t-1} + \sum_{i=1}^{p-1} \Phi_i^* W_{t-i} + \varepsilon_t .$$

It is shown, for example in Ahn and Reinsel (1990), that $\beta_i' Z_t$ is a stationary cointegrating combination, where β_i is the i^{th} column of β. Johansen and Juselius (1990) interpreted the matrix α as the average speed of adjustment towards the estimated equilibrium state such that a low coefficient indicates slow adjustment and a high coefficient indicates rapid adjustment.

Decomposition of Time Series

Cointegrated time series can be decomposed into non-stationary components and stationary components. We decompose Z_t as in Kasa (1992) by rewriting

$$Z_t = \beta(\beta'\beta)^{-1}\beta' Z_t + (I - \beta(\beta'\beta)^{-1}\beta')Z_t$$
$$= \beta(\beta'\beta)^{-1}\beta' Z_t + \beta_\perp(\beta_\perp'\beta_\perp)^{-1}\beta_\perp' Z_t \quad (4)$$

where $m \times (m-r)$ $\beta_\perp$ is such that $\beta_\perp'\beta = 0$, $\beta' Z_t$ is a cointegrating combination, that is, a stationary factor and $\beta(\beta'\beta)^{-1}$ is the factor loading matrix of the stationary factor, and $\beta_\perp' Z_t$ is a common trend, or non-stationary factor and $\beta_\perp(\beta_\perp'\beta_\perp)^{-1}$ is the factor loading matrix of the common trend.

Beveridge and Nelson (1981) showed that an integrated process can be represented in terms of non-stationary components and stationary components, in which the non-stationary component is a random walk with drift and the stationary component is covariance stationary. They interpreted the non-stationary component as the long run forecast of the series adjusted for its mean rate of change and the stationary component as a business cycle. Stock and Watson (1988) showed that cointegrated multiple time series share at least one common trend. In summary, the stationary or transitory component can be interpreted as temporary business cycle, whereas interpretation on non-stationary or permanent component is the long run forecast profile as a random walk with drift.

Impulse Response Analysis

Impulse response analysis of vector autoregressive systems is a useful tool to examine the interrelationships among the variables in dynamic models (Lütkepohl and Reimers, 1992). From this analysis, we investigate the effects of one standard deviation shock of one variable to the other variables. In a vector autoregressive systems, when we find an equilibrium relationship among the variables at some period, *t*, any exogenous shock to a variable leads to a new long-run equilibrium provided no further shocks occur.

For impulse response analysis, we first consider the *m*-dimensional vector autoregressive model and rewrite it as moving average (MA) representation

(5) $$Z_t = \mu + \sum_{j=0}^{\infty} \Psi_j \varepsilon_{t-j}$$

where $\Psi_0 = I_m$ and $\Psi_j = \sum_{i=1}^{j} \Psi_{j-i}\Phi_i$, $j = 1, 2, \cdots, \infty$ with $\Phi_i = 0$ for $i > p$. The elements of the Ψ_j represent the impulse response of the system.

We examine the orthogonalized impulse responses of the system and the errors are orthogonalized by Cholesky decomposition so that the covariance matrix of the resulting innovations is diagonal.

(6) $$Z_t = \mu + \sum_{j=0}^{\infty} \Theta_j e_{t-j}$$

where $\Theta_j = \Psi_j P$, $e_t = P^{-1}\varepsilon_t$, $E(e_t e_t') = I_m$, $PP' = \Omega$ and *P* is assumed to be a lower triangular matrix with positive diagonal elements (Lütkepohl, 1990). The elements of the Θ_j are impulse responses and Lütkepohl and Reimers (1992) explain that a one time impulse may have a permanent effect on the dynamic system, which will lead to a new long-run equilibrium.

Data

To date there have been few studies dealing with the cointegration analysis approach in regional science. To estimate the effects of job growth on the labor market, most studies use cross-sectional data, or lagged dependent variables as variables on the right hand side. The most common model regresses the changes in the population of a fixed year on the change in employment, labor force participation rates, or net migration rate: See Greenwood and Hunt (1984) and Summers (1986). Some models with the population as the dependent variable use the level of the employment / population ratio or employment as an independent variable. Bartik (1992) argued that models that use the levels variables might be biased by unobserved fixed effects of local areas. However, models that use the changes of variables also have a weak point, that is, they cannot predict variables in levels. To overcome these deficiencies, we use the cointegration analysis that allows us to estimate the long run equilibrium relationship in levels.

In this study we use three variables, population, labor force participation rate for population aged 18 and 64 and employment to examine the long run equilibrium relationship among these variables. The long run equilibrium relationship equation gives a unit change interpretation as in a general linear regression model. Our data are from the Office Forecast Council (OFC) in the state of Washington. We calculated the labor force participation rate by dividing civilian labor force by population aged 18 to 64. The scale of population and employment is 1000 people and that of labor force participation rate is percentage. The data series are observed at two different frequencies. The labor force participation rate and the employment are quarterly data for the period between 1969 and

1993. However, only annual data are available for the population variable because population is surveyed only on the second quarter of every year. Because the methods for cointegration analysis are applicable only to data with the same frequency (as far as we are aware of), we have two options to make the data frequencies the same. One is to use the second quarter data of the participation rate and employment in order to match the sampling frequency of the population data and these annual data are exhibited in Figure 1. The other is to estimate the quarterly values of population series using a similar interpolation method to Chow and Lin (1971).

We first focus on the annual data series, although the sample size is small. One may argue that the data over 25 years may not be long enough for a study of long-run equilibrium. However we could at least estimate the model with a long-run equilibrium restriction through model (3) and gain insight into the long-run behavior. Next we analyze the quarterly data using estimated quarterly population data and compare the two results.

Application of Cointegration Analysis to Annual Data

Let the vector Z_t consist of three variables, such that $Z_t = (p_t, r_t, e_t)'$, where p_t is the number of population, r_t is the labor force participation rate, and e_t is the employment at period *t*. As the data series in Figure 1 exhibit non-stationary behavior attributable to a unit root, we perform Dickey-Fuller (1979, 1981) test for unit root using the test statistics $\hat{\tau}_\tau$. The results summarized in Table 1 show that each of the three series is *I(1)*. That is, all three original series have a unit root and their first differenced series do not have a unit root.

The Choice of AR Order and Cointegrating Rank of Z_t

We now investigate if there is long-run equilibrium information among the components of Z_t, that is, if Z_t is cointegrated. To this end we consider a VAR model for Z_t as in (1). We examine an appropriate AR order based on the partial canonical correlation between W_t and W_{t-k} adjusted for $Z_{t-1}, W_{t-1}, \cdots, W_{t-k+1}$ (Ahn and Reinsel, 1990) and the Akaike Information Criterion (AIC). For a VAR (*p*) the partial canonical correlations between W_t and W_{t-k} are all zero, and thus $\Phi_k^* = 0$ for $k \geq p$. The results from partial canonical correlation analysis (PCCA) are summarized in Table 2 and Table 3. Table 2 indicates that the coefficient matrix Φ_i^* is significant until Φ_4^*. This means that the vector Z_t at a certain period is affected by the past five years history of the Z_t. Considering 25 observations of data, the VAR (5) model seems to be overfitted. Furthermore, the p-values (i.e. observed significance levels) are based on the large sample distribution. In contrast, as is Table 4, the minimum AIC is attained at lag 1, which in turn favors a VAR (1) of Z_t. For this reason, we consider tentatively an appropriate AR order to be between one and four in our model fitting.

We also need to determine cointegrating rank *r* through the rank of *C* matrix. Two test statistics, the trace statistic and the maximal eigenvalue statistic are used to determine the rank of *C* matrix. The Likelihood Ratio (LR) test statistic, $\Lambda = -n \sum_{j=r+1}^{m} \ln(1 - \hat{\rho}_j^2)$ is our trace statistic where $\hat{\rho}_j$ is the i-th largest partial canonical correlation between W_t and Z_{t-1} adjusted for $W_{t-1}, \cdots, W_{t-p+1}$. The null hypothesis of this trace statistic is that the cointegrating rank is at most *r* against the alternative hypothesis is that the cointegrating rank is *m*. The Likelihood Ratio (LR) test statistic, $\Lambda_{\max} = -n(1-\hat{\rho}^2_{r+1})$ is our maximal eigenvalue test statistic. The maximal eigenvalue test statistic evaluates the null hypothesis that the cointegrating rank is at most *r* against the alternative hypothesis is that the cointegrating rank is *r*+1. As there are no critical values available of these test statistics for small samples (as far as we are aware of), we generate percentiles of them through a Monte Carlo Simulation based on 50,000 replications for sample sizes N=25, 50, 75 and 100. The empirical percentiles along with the details of the simulation are in the appendix. Because the null hypothesis is rejected for larger values of the test statistics, upper percentiles are uses as critical values.

The trace statistic and the maximal eigenvalue statistic are shown in Table 5 for different AR orders and cointegrating ranks. For AR order 2, since we cannot reject rank 0 in both trace and maximal eigenvalue statistics, there does not exist a stationary long-run equilibrium relationship among the variables. Both statistics support rank 2 in AR 1 and AR 4 while they support rank 1 in AR order 3. For large sample, it is well known that the choice of the cointegrating rank is robust to the choice of the AR order. However, for small samples like ours, the cointegrating rank is sensitive to the choice of the AR order. Therefore, in order to find an appropriate AR order and a cointegrating rank, we fit models using these different choices of the AR order and the cointegrating rank, and check significance of each coefficient in Φ^*_i. Since the coefficients beyond Φ^*_2 are insignificant, we determined the AR order *p* of Z_t in equation (1) as three. That is, the VAR (3) and cointegrating rank 1 model is chosen for further analysis.

We fit the following ECM with AR order 3 and cointegrating rank 1 using Ahn and Reinsel (1990).

$$W_t = \delta + \alpha\beta' Z_{t-1} + \Phi_1^* W_{t-1} + \Phi_2^* W_{t-2} + \varepsilon_t , \tag{7}$$

and obtain estimates of the vector of constant term, $\hat{\delta}$ = [210.390, 234.152, 4066.116]′, the vector of speed of adjustment coefficient, $\hat{\alpha}$ = [-0.032, -0.038, -0.657]′, and the cointegrating vector $\hat{\beta}$ = [1, 75.815, -2.201]′. With a normalized population coefficient the long run equilibrium relationship is represented by

$$p_t = 6004.909 - 75.815\ r_t + 2.201\ e_t \tag{8}$$

This cointegrating combination adjusted for the mean is displayed in Figure 2. From the equation in (8), we can see that the long run relationship of a unit increase in the labor force participation rate (1%) is a decrease of 75,815 in population and the long run relationship of a unit change in employment (1000) is an increase of 2,201 in population.

Decomposition into Stationary and Non-Stationary Components

Using the decomposition method described in a previous section, we decompose our time series into stationary components and non-stationary components. Before interpreting stationary components and non-stationary components, we first overview the history of economic conditions in Washington from the beginning of 1970s to the beginning of 1990s.

The Washington State economy slumped in 1970-1973 and 1981-1983, whereas it expanded rapidly during the late 1970s and the late 1980s. Large population increases due to net migration occurred as a result of rapid economic expansions in Washington during the late 1970s and late 1980s. Net migration dropped when the state economy slumped in 1981-1983. In the beginning of the 1990s, California experienced net out-migration of over 400,000 persons per year. Washington received a significant amount of these Californian out-migrants. This factor contributed to relatively high levels of net migration for Washington during the early 1990s, even at a time when the state's economy slowed down significantly.

Figure 3 contains the plots of the stationary components for the population and labor force participation rate and Figure 4 depicts the stationary component of the employment. Surprisingly, the pattern of the stationary component of population is quite similar to that of labor force participation rate. Based on the above information about economic behavior in Washington, we find that the cyclical fluctuation of employment responds immediately to changing economic conditions in Washington. The response of population to changing economic conditions is about three or four years later than that of employment. This is supported by the Granger (1969) causality test results summarized in Table 6 and the impulse response analysis in the following section. Accordingly, the plot of three years delayed stationary components of population is similar to the stationary component of employment as in Figure 5.

It is interesting that the pattern of stationary component of employment and net migration which is defined as the difference between in-migration and out-migration is quite similar as shown in Figure 6. This indicates that the short run effect of employment corresponds with migration behavior, mainly in-migration for Washington. Figure 7 shows that the plot of three years delayed stationary components of population is similar to the plot of net migration. Like employment, the response of population to changing economic conditions is about three years later than that of net migration.

Consequently, in short run, with employment and net migration having same immediate pattern, they respond to changing economic conditions. We interpret the stationary component of employment as a reflection of the historical and cyclical economic conditions in Washington. The stationary components of population and labor force participation can be interpreted in relation to the historical employment and net migration patterns in Washington.

Figures 8 through 10 depict the original data series and their non-stationary component respectively. The pattern of the non-stationary components is very similar to that of all original series. These trends reflect long waves of socioeconomic change including the baby bust of the 1970s, the baby boom echo of the 1980s, considerable increase in the female labor force participation rate and gradual decline in male labor force participation rate. The slope of the non-stationary component of population around 1980 is steeper than that in 1970s, whereas the non-stationary component of labor force participation rate was relatively high in 1970s and began to decline in 1980, which is mainly caused by natural population increase (the excess of births over deaths) from 1980. From 1970 to 1995, the state's aggregate labor force participation rate increased from 61.5% to 70.1%. During this period, the male labor force participation rate gradually declined, while the female labor force participation rate rose significantly. This information allows us to interpret the non-stationary component of labor force participation rate as reflecting the increasing trend of labor force participation rate in Washington mainly due to a considerable increase in the female labor force participation. The fluctuations in the non-stationary component of labor force participation rate show that female labor force participation is also significantly affected by economic conditions.

Impulse Response Analysis

Figure 11 and 12 depict the impulse responses of the population, employment and labor force participation rate to a one standard deviation shock in employment. For all three variables, the impulse leads to a permanent increase provided no further shock occurs. In other words, they settle at different equilibrium value after a long period of time. Figure 11 shows a slower response of the population to changing economic conditions. In short run, the response of the population to a one standard deviation shock in employment lags several years that of employment. Figure 12 supports Bartik's and Yeo and Holland's findings. Note that Bartik found that 25% of the job growth from a shock to local job growth is reflected in increased local labor force participation rate in the long-run. Yeo and Holland found that the long-run effect of the job growth on labor force participation remains, although its effect is small. However, the analysis result does not support the Blanchard-Katz's finding - the long-run effect of the job growth on the labor force participation rate is negligible.

For the party who benefits from job growth, we suspect that most of new jobs are captured by in-migrants because the pattern of the stationary component of employment and net migration is quite similar and the impulse response of population is significantly higher than that of employment. Based on the report of Office of Financial Management in the state of Washington (1999), net migration accounts for about 60 percent of the state population growth in the past 25 years and most of the migrants are young workers with a long-term attachment to the labor force. Thus we suspect that a high proportion of increase in labor force participation rate is due to migration.

Estimation of Quarterly Population Data

Until now we analyze the three annual time series which have 25 observations respectively. Because the population, labor participation rate, and employment are related, we interpolate the annual population data using the quarterly labor participation rate and employment data applying a similar method in Chow and Lin (1971). Then we reanalyze the series using the quarterly observations and check whether both results are similar or not. Through the analysis of quarterly data, we gain insight into the dynamics of the quarterly population even though the total population is observed yearly. Chow and Lin (1971) introduced best linear unbiased interpolation and extrapolation of time series by related series. If we assume that the quarterly observations of the series to be estimated satisfy a multiple regression relationship, $p = X\gamma + u$ where population, p is 100×1, X is 100×3 matrix and u is a random error with mean 0 and covariance matrix V. The first column of X is one vector, second one is labor force participation rate, r and third one is employment, e. The vector of 25 annual observations of the dependent variable, subscripted by a dot which signifies being annual, satisfies the regression model

(9) $$p_{.} = Cp = CX\gamma + Cu = X_{.}\gamma + u_{.}$$

with $E u_{.} u_{.}' = V_{.} = CVC'$ and C being the 25×100 matrix that converts the 25 annual observations collected during the second quarter into 100 quarterly observations.

(10) $$C = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & \cdots & 0 & 0 & 0 & 0 \\ \vdots & & & & & & & & & & & \ddots & & & & \\ 0 & \cdots & & & & & & & & & & & 0 & 1 & 0 & 0 \end{bmatrix}$$

According to Chow and Lin (1971) the best linear unbiased estimator of quarterly population, p_q, that is from (9) is given by

(11) $$\hat{p}_q = X_q \hat{\gamma} + (V_{q.} V_{.}^{-1})\, \hat{u}_{.}$$

where $\hat{p}_q$ is quarterly estimates of population and $\hat{\gamma} = (X_{.}' V_{.}^{-1} X_{.})^{-1} X_{.}' V_{.}^{-1} p_{.}$ is the Generalized Least Squares (GLS) estimate of the regression coefficients using the 25 annual observations in the sample, $\hat{u}_{.} = [I - X_{.}(X_{.}' V_{.}^{-1} X_{.})^{-1} X_{.}' V_{.}^{-1}]p_{.} = p_{.} - X_{.}\hat{\gamma}$ is the 25×1 vector of residuals in the regression using annual data. However, instead of the generalized least squares estimate of γ, we use the estimate from the previous cointegration analysis of the annual data as the estimate of γ. When the cointegrating rank is more than one, the parameters of regression model for the GLS are not identifiable. Note that our cointegrating vector is $\hat{\beta}$ = [1, 75.815, -2.201]′, and the constant term in the model of $\hat{p}_{.}$ is 6004.119. As a result, $\hat{\gamma}$ = [6004.119, 75.815, -2.201]′.

The next step is to estimate the covariance matrix of residuals. The residuals of the cointegrating combination based on annual data follow a first-order autoregressive process $u_t = a\,u_{t-1} + v_t$ and the estimate of a, $\tilde{a}$ is 0.3549. Similar to Chow and Lin, a consistent estimate of a in $\hat{V}$ below is $\hat{a} = \sqrt[4]{\tilde{a}}$ = 0.5957 for our interpolation problem because $\tilde{a}$ is estimated by annual data. Therefore, the estimates of the covariance matrix of u_t for quarterly data is

$$(12) \qquad \hat{V} = \begin{bmatrix} 1 & \hat{a} & \hat{a}^2 & \cdots & \hat{a}^{99} \\ \hat{a} & 1 & \hat{a} & \cdots & \hat{a}^{98} \\ \hat{a}^2 & \hat{a} & 1 & \cdots & \hat{a}^{97} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \hat{a}^{99} & \hat{a}^{98} & \hat{a}^{97} & \cdots & 1 \end{bmatrix}$$

For the purposes of interpolation, we need

$$(13) \qquad V_{q.} V_{.}^{-1} = VC'(CVC')^{-1}$$

Using $\hat{V}$ as an estimator of V, we can estimate $\hat{p}_q$ in (11).

Application of Cointegration Analysis to Quarterly Data

Figure 13 plots the quarterly population and employment series and Figure 14 represents the quarterly labor force participation rate series. As previously described, the values of quarterly population series are estimated as described in the previous section.

As with the annual data analysis, we first performed the augmented Dickey-Fuller (1979, 1981) test to determine the order of integration of each time series data. Table 7 shows the results of the augmented Dickey-Fuller (ADF) test for the null hypothesis of a unit root for both original series and first differenced series. We can see that all three original series are nonstationary and their first differenced series are stationary.

Based on partial canonical correlation and the minimum AIC we choose an appropriate AR order and the results are summarized in Tables 8, 9 and 10. For the quarterly data case, partial canonical correlation supports AR(7) while the minimum AIC supports AR(2). The trace statistics and maximum eigenvalue statistics shown in Table 11 for different AR orders. Both statistics support rank 2 from AR(2) through AR(5) while they support rank 1 in AR order 1 and 7. For AR order 6 and 8, since we cannot reject rank 0 in both trace and maximal eigenvalue statistics, there does not exist a stationary long-run equilibrium relationship among the variables. Therefore, in order to find an appropriate AR order and a cointegrating rank, we fit models using these different choices of the AR order and the cointegrating rank, and we check significance of each coefficient in Φ_i^*. Since the coefficients are significant until Φ_6^*, we determined the AR order *p* of Z_t as seven. That is, the VAR(7) and cointegrating rank 1 model is chosen for further analysis. The AR order 7 in quarterly data analysis is to be comparable to AR(2) in annual data case which may be considered close enough to our choice of AR(3) in the section of annual data analysis. The rank 1 is same as the choice in annual data analysis.

We now fit an ECM with AR order 7 and 1 cointegrating vector as follows:

(14) $$W_t = \delta + \alpha\beta' Z_{t-1} + \sum_{i=1}^{6} \Phi_i^* W_{t-i} + \varepsilon_t ,$$

and obtain estimates of the vector of constant term, δ = [631.2077, 14.0121, 179.2476]′, the vector of speed of adjustment coefficient, α = [-0.1019, -0.0023, -0.0282]′ and the cointegrating vector β = [1, 77.5172, -2.2160]′. Finally, we can derive the long run equilibrium relation given by

(15) $$p_t = 5668.78 - 77.52\, r_t + 2.22\, e_t$$

The estimated coefficients of the long run equilibrium relationship are close to those of the annual data case. The interpretation is same as in the annual data analysis.

Figure 15 shows the plots of stationary components for the population and labor force participation rate and Figure 16 depicts the stationary component of employment. Although the stationary components plots of quarterly data are more cyclical than those of annual data, the cyclical fluctuations of quarterly data are almost identical with those of annual data for all three series. Therefore, we can put the same interpretations on stationary components as annual data. The plots of non-stationary components and their original series are shown in Tables 17 through 19. Each of them not only exactly follows the path of their original time series but also represent the same long waves and trends as annual data analysis. Interpretations on them are also same as those of the annual data analysis.

Since the sample size of annual series is small, we analyzed the series using a larger number of observations and checked for similarity of results. In both data series, analysis results were consistent and the estimated values of the parameters were close.

Conclusions

We proved that employment growth from new business investment causes increase in population in the state of Washington in spite of its beautiful environment and amenities. The causality does not operate in reverse way. This study found a long run equilibrium relationship among population, labor force participation rate and employment, in which population is positively related to employment and negatively related to labor force participation rate. The long run effect of a unit change of labor force participation rate (1%) is a decrease of 73,880 in population and the long run effect of a unit change in employment (1000) is an increase of 2,190 in population.

We decomposed the time series into stationary components and non-stationary components. The pattern of the stationary component of population is quite similar to that of labor force participation rate while that of employment shows a different fluctuation. From the decomposition, it was obvious that the pattern of stationary component of employment and net migration is quite similar, which means net migration is the short run, temporary response to employment change. The patterns of three years delayed stationary components of population are similar to that of employment and net migration, and the plots correspond to changing economic conditions. According to the change in economic conditions population responds three years later than employment and net migration. We interpreted the non-stationary component of labor force participation rate as reflecting the increasing trend of labor force participation rate in Washington mainly due to a considerable increase in the female labor force participation.

The impulse responses of population, employment and labor force participation rate to a one standard deviation shock in employment show permanent increase effects. They settle at different equilibrium value after long term periods. The response of the labor force participation rate to an impulse in employment supports Bartik's (1993) and Yeo and Holland's (2000) findings. Obviously the result is the opposite of Blanchard and Katz's (1992) finding that the long-run effect of job growth on the labor force participation rate is negligible. With regard to the party who benefits from job growth, we suspect that most of new jobs are captured by in-migrants because the pattern of the stationary component of employment and net migration is quite similar and the impulse response of population is significantly higher than that of employment.

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Appendix: Simulated Critical Values of Trace and Maximal Eigenvalue Statistics

The limiting distributions of the trace statistic and the maximal eigenvalue statistic are the distributions of the trace and the maximal eigenvalue of

$(\int_0^1 B_d(u)\, dF_d(u)')' \, (\int_0^1 F_d(u)\, F_d(u)' du)^{-1} \, (\int_0^1 F_d(u)\, dB_d(u)')$ where $B_d(u)$ is a d-dimensional standard Brownian motion and $F(u) = B_d(u) - \int_0^1 B_d(u) du$ except that the first component of $F(u)$ is replaced by $u - 1/2$. Johansen and Juselius (1990) obtain percentiles of these limiting distribution for large samples. As we have small samples, we obtain percentile of the test statistics for small samples by the Monte Carlo simulation. We generate d – dimensional random walk processes $Z_t = \delta + Z_{t-1} + a_t,\ t = 1, 2, \cdots, T$ with $Z_0 = 0$ and $\delta = (1, 0, \cdots, 0)'$, for T = 25, 50, 75, 100 by generating pseudo normal random vectors using the RNMVM subroutine of IMSL. Then the trace and the maximal eigenvalue of

$(\sum_{t=1}^{T} a_t \overline{Z}'_{t-1})(\sum_{t=1}^{T} \overline{Z}_{t-1}\, \overline{Z}'_{t-1})^{-1}(\sum_{t=1}^{T} a_t \overline{Z}'_{t-1})$ are obtained. Based on 50,000 replications, empirical percentiles are found for both of them, and summarized in Appendix Table 1 through Appendix Table 4.

Appendix Table 1. Approximate Percentile for the Likelihood Ratio Test Statistics (N=25)

Percentile	Dimension (d)				
	1	2	3	4	5
Maximal Eigenvlaue					
0.5%	0.00004	1.42981	3.93426	6.78453	9.66753
1.0%	0.00015	1.64167	4.37563	7.32553	10.32730
2.5%	0.00101	2.03539	5.01974	8.14859	11.36024
5.0%	0.00424	2.44003	5.62131	8.96674	12.31856
10.0%	0.01647	3.00563	6.48126	9.98689	13.51820
25.0%	0.10502	4.18508	8.13431	11.99077	15.71175
50.0%	0.46383	5.91077	10.38015	14.56163	18.58978
75.0%	1.35892	8.18468	13.14124	17.63905	21.95750
90.0%	2.78245	10.74697	16.10984	20.92439	25.47419
95.0%	3.91309	12.53843	18.12781	23.09275	27.85367
97.5%	5.11654	14.17930	20.01540	25.09178	29.94946
99.0%	6.70548	16.27223	22.35285	27.82176	32.59093
99.5%	7.90031	17.82954	24.05824	29.49785	34.41322
Trace					
0.5%	0.00004	1.62647	6.52724	14.09257	23.97993
1.0%	0.00015	1.89255	7.08891	15.13858	25.51736
2.5%	0.00101	2.31970	8.09212	16.70702	27.62989
5.0%	0.00424	2.78528	9.04793	18.13896	29.48413
10.0%	0.01647	3.40366	10.27750	19.85534	31.78334
25.0%	0.10502	4.74187	12.59891	23.13847	35.92636
50.0%	0.46383	6.65841	15.69164	27.24903	41.05999
75.0%	1.35892	9.13119	19.27318	31.85716	46.72605
90.0%	2.78245	11.88870	22.96488	36.50669	52.38039
95.0%	3.91309	13.74282	25.49179	39.56074	55.80202
97.5%	5.11654	15.47996	27.75425	42.30320	59.14228
99.0%	6.70548	17.60849	30.57262	45.53668	63.09720
99.5%	7.90031	19.40523	32.54868	47.89322	65.89034

Appendix Table 2. Approximate Percentile for the Likelihood Ratio Test Statistics (N=50)

Percentile	Dimension (*d*)				
	1	2	3	4	5
Maximal Eigenvalue					
0.5%	0.00003	1.60173	4.50424	7.76128	11.24278
1.0%	0.00014	1.82863	4.97812	8.41453	11.92691
2.5%	0.00096	2.24829	5.66422	9.25936	12.98668
5.0%	0.00380	2.69933	6.35332	10.14989	13.96017
10.0%	0.01544	3.29527	7.23627	11.25670	15.25155
25.0%	0.10389	4.53566	8.97271	13.31228	17.56072
50.0%	0.46311	6.38063	11.30755	16.03700	20.60944
75.0%	1.33167	8.78246	14.20011	19.30281	24.15729
90.0%	2.73195	11.45368	17.31815	22.67434	27.77574
95.0%	3.88797	13.31947	19.30800	24.92246	30.34614
97.5%	5.10702	15.07210	21.30513	27.07455	32.63307
99.0%	6.76562	17.29564	23.83428	29.77200	35.51581
99.5%	8.04663	18.94029	25.64621	31.92806	37.36833
Trace					
0.5%	0.00003	1.81377	7.42487	16.51869	28.46244
1.0%	0.00014	2.07676	8.10612	17.51137	29.97954
2.5%	0.00096	2.57172	9.18935	19.16154	32.13519
5.0%	0.00380	3.07097	10.19017	20.70302	34.15465
10.0%	0.01544	3.72021	11.49826	22.56016	36.59861
25.0%	0.10389	5.09344	13.94564	25.98156	41.05484
50.0%	0.46311	7.13814	17.14346	30.27136	46.37817
75.0%	1.33167	9.73327	20.89473	35.14136	52.34282
90.0%	2.73195	12.56556	24.76696	40.05743	58.32362
95.0%	3.88797	14.52383	27.31449	43.24551	62.02025
97.5%	5.10702	16.47635	29.69501	46.05951	65.39952
99.0%	6.76562	18.72430	32.79377	49.75564	69.58170
99.5%	8.04663	20.46693	34.89926	52.00483	72.14625

Appendix Table 3. Approximate Percentile for the Likelihood Ratio Test Statistics (N=75)

Percentile	Dimension (*d*)				
	1	2	3	4	5
Maximal Eigenvalue					
0.5%	0.00003	1.63901	4.67199	8.17382	11.81339
1.0%	0.00014	1.86057	5.13029	8.76932	12.52080
2.5%	0.00089	2.32952	5.85775	9.68410	13.67224
5.0%	0.00377	2.78503	6.55061	10.55737	14.66208
10.0%	0.01539	3.38550	7.47707	11.67953	15.93704
25.0%	0.10124	4.66352	9.25674	13.79160	18.34714
50.0%	0.45375	6.53659	11.68857	16.59844	21.42519
75.0%	1.29805	8.96161	14.62513	19.92667	25.03569
90.0%	2.70085	11.71267	17.79558	23.41607	28.78642
95.0%	3.88506	13.58790	19.98903	25.77393	31.27003
97.5%	5.02929	15.35159	22.00989	27.96831	33.59522
99.0%	6.64227	17.56786	24.37812	30.59566	36.44074
99.5%	7.85819	19.19528	26.17358	32.67455	38.71803
Trace					
0.5%	0.00003	1.84403	7.75475	17.29445	30.31911
1.0%	0.00014	2.13503	8.47254	18.42401	31.72412
2.5%	0.00089	2.64100	9.54190	20.05646	34.00915
5.0%	0.00377	3.14814	10.56431	21.59355	36.08253
10.0%	0.01539	3.82784	11.92262	23.50947	38.49759
25.0%	0.10124	5.23631	14.41665	27.03851	42.98341
50.0%	0.45375	7.29913	17.69560	31.45857	48.46593
75.0%	1.29805	9.90742	21.54545	36.41562	54.48727
90.0%	2.70085	12.83130	25.52504	41.36847	60.43302
95.0%	3.88506	14.78765	28.20539	44.58499	64.28394
97.5%	5.02929	16.66736	30.51981	47.51479	67.77034
99.0%	6.64227	19.04277	33.58242	51.19997	71.98624
99.5%	7.85819	20.74977	35.59242	53.38948	75.02776

Appendix Table 4. Approximate Percentile for the Likelihood Ratio Test Statistics (N=100)

Percentile	Dimension (*d*)				
	1	2	3	4	5
Maximal Eigenvalue					
0.5%	0.00004	1.67272	4.86716	8.42402	12.12611
1.0%	0.00016	1.92763	5.30395	9.01527	12.88516
2.5%	0.00102	2.36671	6.01055	9.94244	13.98926
5.0%	0.00409	2.81071	6.71689	10.82655	15.04403
10.0%	0.01642	3.42829	7.63680	11.95442	16.34207
25.0%	0.10442	4.74110	9.41590	14.09169	18.78874
50.0%	0.46182	6.64446	11.90220	16.95947	21.91651
75.0%	1.34371	9.11060	14.88195	20.34630	25.51195
90.0%	2.72685	11.89154	18.05243	23.80437	29.35646
95.0%	3.86727	13.80669	20.22749	26.17239	31.95017
97.5%	5.06370	15.61507	22.28753	28.39861	34.24622
99.0%	6.67854	18.05861	24.83264	31.25117	37.41772
99.5%	7.98117	19.72457	26.51534	33.21503	39.73579
Trace					
0.5%	0.00004	1.93994	7.98728	17.87842	30.91952
1.0%	0.00016	2.19770	8.68079	18.86298	32.58025
2.5%	0.00102	2.68338	9.79212	20.60548	34.82240
5.0%	0.00409	3.18215	10.81532	22.17563	36.92950
10.0%	0.01642	3.88215	12.11687	24.05310	39.48685
25.0%	0.10442	5.34922	14.66622	27.61961	44.03326
50.0%	0.46182	7.41130	18.02354	32.14189	49.71305
75.0%	1.34371	10.08132	21.92179	37.19312	55.73866
90.0%	2.72685	13.04835	25.97027	42.14549	61.81979
95.0%	3.86727	15.10072	28.57504	45.45506	65.75732
97.5%	5.06370	17.07017	31.02484	48.35427	69.29696
99.0%	6.67854	19.42227	34.09746	52.05660	73.78222
99.5%	7.98117	21.19068	36.45694	54.72538	76.74147

Table 1. ADF Unit Root Test Results for Level Series and First Differenced Series (N = 25)

Description	Level Series			First Differenced Series		
Variable	p_t	a_t	e_t	p_t	a_t	e_t
$\hat{\tau}_\tau$	-2.380	-2.587	-2.817	-3.246	-5.533	-3.516
P-Value	0.378	0.289	0.206	0.030	0.000	0.017

Table 2. LR test statistics of Test of H0: The Canonical Correlations in the Current Row and All That Follow are Zero (N = 25)

Number	AR(2)	AR(3)	AR(4)	AR(5)
1	0.233 (0.008)	0.233 (0.056)	0.173 (0.169)	0.094 (0.000)
2	0.738 (0.318)	0.569 (0.167)	0.607 (0.444)	0.521 (0.013)
3	0.946 (0.352)	0.973 (0.573)	0.931 (0.464)	0.977 (0.502)

Numbers in parenthesis are P-values.

Table 3. Squared Partial Canonical Correlations (N = 25)

Number	AR(1)	AR(2)	AR(3)	AR(4)
1	0.820	0.685	0.591	0.715
2	0.467	0.220	0.415	0.348
3	0.029	0.054	0.027	0.069

Table 4. Akaike Information Criterion for Autoregressive Models (N=25)

Lag=0	Lag=1	Lag=2	Lag=3	Lag=4	Lag=5	Lag=6	Lag=7
502.70	465.20	472.10	479.71	492.07	504.16	484.24	475.19

Table 5. Trace Statistics and Maximal Eigenvalue Statistics (N = 25)

$H_0(r)$	Statistic				5% Significance Level
	AR 1	AR 2	AR 3	AR 4	
Trace Statistic					
2	0.55	0.20	1.00	0.10	3.91309
1	15.86	5.81	9.70	14.01	13.74282
0	58.67	18.84	28.63	38.35	25.49179
Maximal Eigenvalue Statistic					
2	0.22	0.27	0.92	0.11	3.91309
1	15.31	5.61	8.70	13.91	12.53843
0	42.81	13.03	18.93	24.34	18.12781

Table 6. Granger Causality Test Results (N=25)

Null Hypothesis:	Obs	F-Statistic	Probability
Lags: 1			
POP does not Granger Cause EMP	24	0.05701	0.81359
EMP does not Granger Cause POP		40.3320	2.7E-06
Lags: 2			
POP does not Granger Cause EMP	23	0.46044	0.63823
EMP does not Granger Cause POP		9.13324	0.00183

Table 7. ADF Unit Root Test Results for Level Series and First Differenced Series (N = 100)

Description	Level Series			First Differenced Series		
Variable	p_t	r_t	e_t	p_t	r_t	e_t
$\hat{\tau}$	-2.199	-3.009	-3.047	-4.616	-5.968	-4.614
P-Value	0.485	0.135	0.125	0.002	0.000	0.000

Table 8. LR test statistics of Test of H0: The Canonical Correlations in the Current Row and All That Follow are Zero (N = 100)

Number	AR(2)	AR(3)	AR(4)	AR(5)	AR(6)	AR(7)	AR(8)
1	0.343 (0.000)	0.744 (0.003)	0.721 (0.002)	0.876 (0.335)	0.736 (0.008)	0.722 (0.007)	0.855 (0.333)
2	0.714 (0.000)	0.950 (0.360)	0.976 (0.742)	0.995 (0.986)	0.909 (0.135)	0.927 (0.260)	0.982 (0.879)
3	0.963 (0.069)	0.979 (0.181)	0.995 (0.509)	0.999 (0.988)	0.989 (0.363)	0.997 (0.670)	0.999 (0.870)

Numbers in parenthesis are P-values

Table 9. Squared Partial Canonical Correlations (N = 100)

Number	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)	AR(6)	AR(7)	AR(8)
1	0.283	0.226	0.304	0.297	0.207	0.150	0.261	0.148
2	0.085	0.163	0.179	0.169	0.155	0.101	0.085	0.053
3	0.000	0.027	0.017	0.008	0.011	0.013	0.004	0.007

Table 10. Akaike Information Criterion for Autoregressive Models (N=100)

Lag=0	Lag=1	Lag=2	Lag=3	Lag=4	Lag=5	Lag=6	Lag=7
1966.70	1333.22	1290.57	1296.99	1303.94	1313.57	1321.66	1335.10

Table 11. Trace Statistics and Maximal Eigenvalue Statistics (N = 100)

H_0 (r)	Statistic								5% Significance Level
	AR 1	AR 2	AR 3	AR 4	AR 5	AR 6	AR 7	AR 8	
Trace Statistic									
2	0.011	2.747	1.696	0.853	1.136	1.308	0.424	0.665	3.86727
1	8.852	20.535	21.398	19.359	18.001	12.005	9.306	6.071	15.10072
0	42.106	46.120	57.667	54.563	41.189	28.209	39.589	22.138	28.57504
Maximal Eigenvalue Statistic									
2	0.011	2.747	1.696	0.853	1.136	1.308	0.424	0.665	3.86727
1	8.841	17.788	19.702	18.506	16.866	10.697	8.883	5.406	13.80669
0	33.254	25.585	36.269	35.204	23.188	16.204	30.282	16.066	20.22749

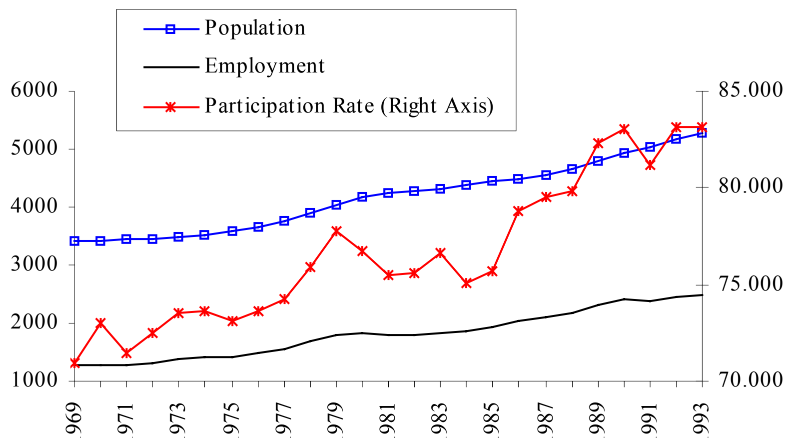

Figure 1. Time Series Plot for Annual Data

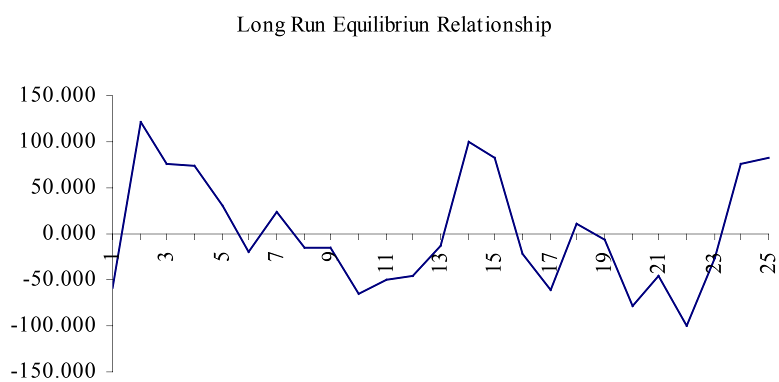

Figure 2. Long Run Equilibrium Relationship of the series

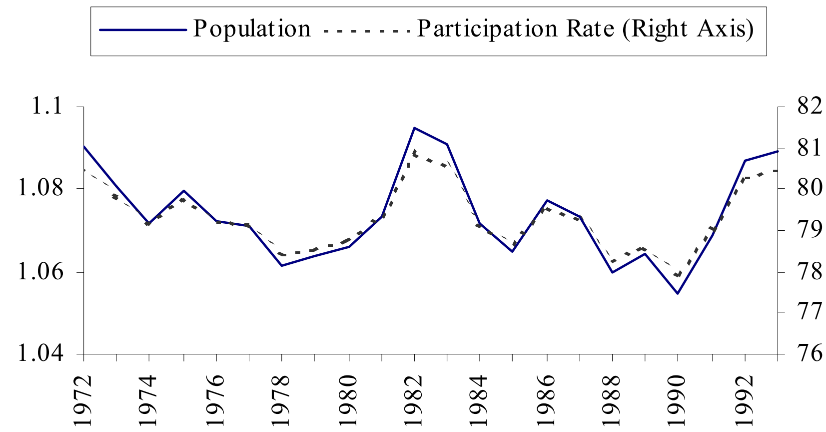

Figure 3. Stationary Component of Population and Participation Rate (N=25)

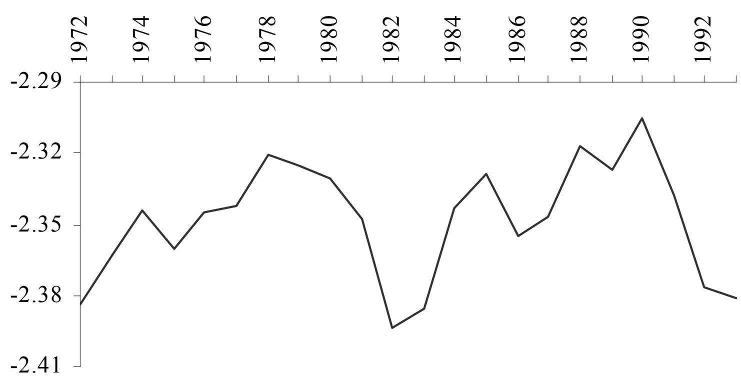

Figure 4. Stationary Component of Employment (N=25)

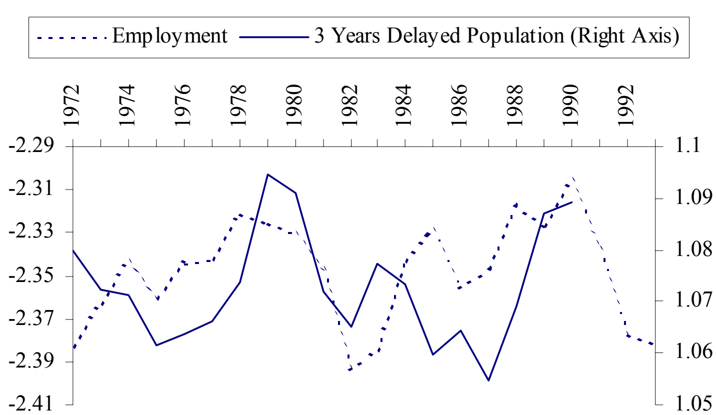

Figure 5. Stationary Component for 3 Years Delayed Population and Employment (N=25)

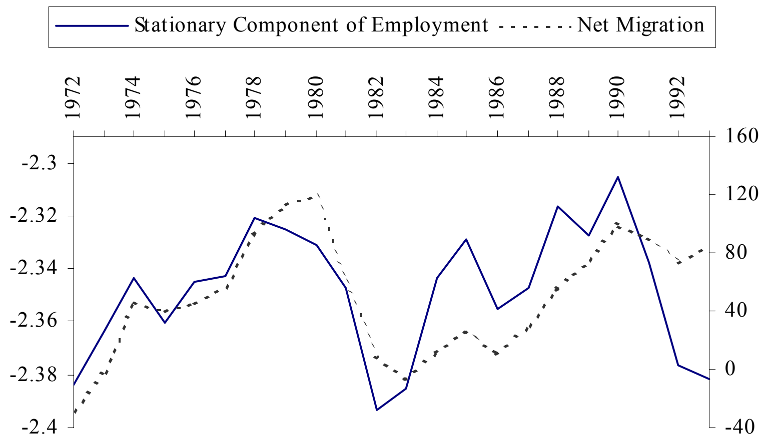

Figure 6. Stationary Component of Employment and Net Migration (N=25)

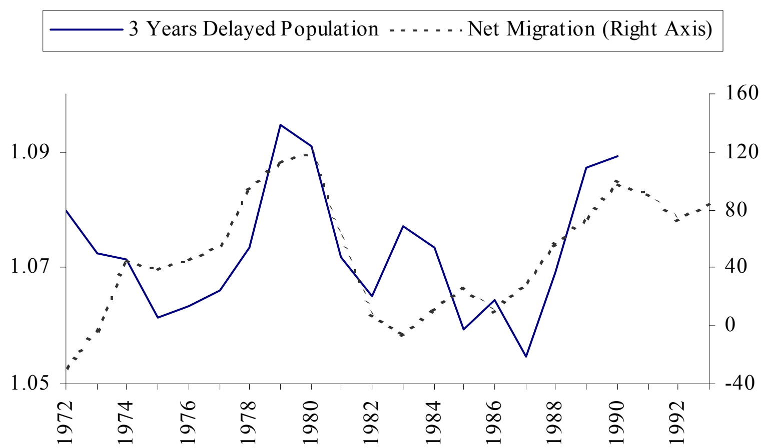

Figure 7. Stationary Component of 3 Years Delayed Population and Net Migration (N=25)

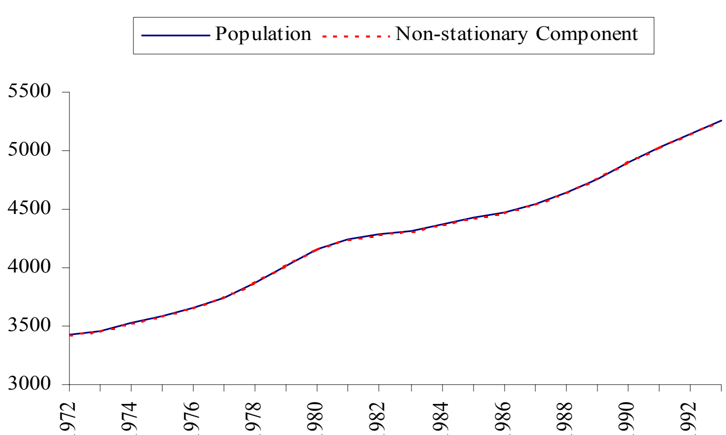

Figure 8. Non-stationary Component of Population (N=25)

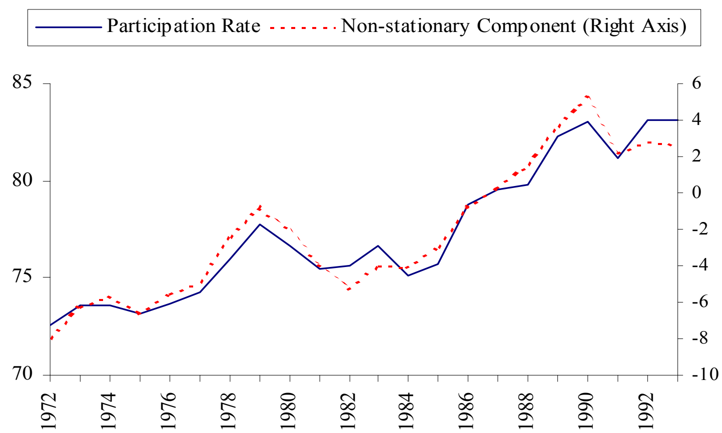

Figure 9. Non-stationary Component of Labor Force Participation Rate (N=25)

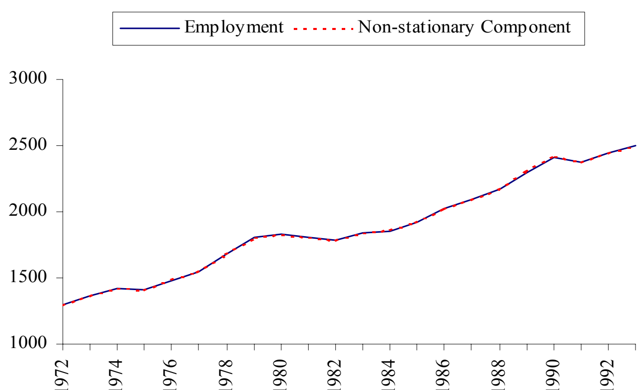

Figure 10. Non-stationary Component of Employment (N=25)

Figure 11. Impulse Response of Population and Employment to Employment

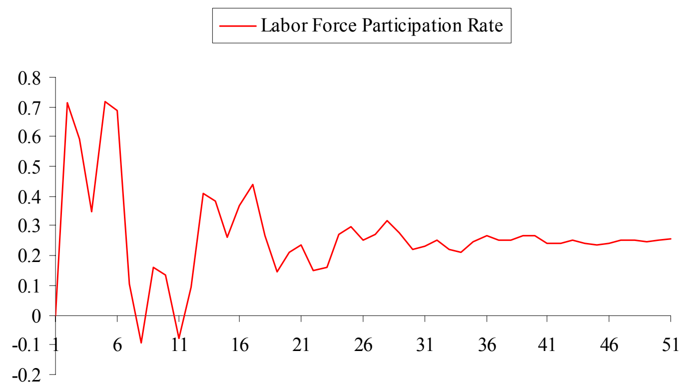

Figure 12. Impulse Response of Labor Force Participation Rate to Employment

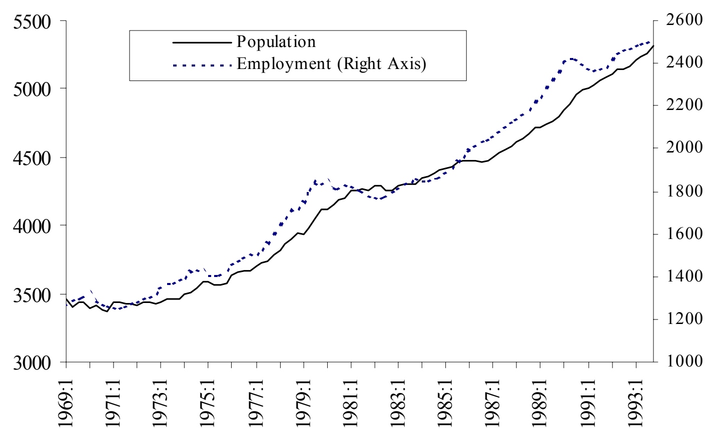

Figure 13. Population and Employment Series Plot for Quarterly Data

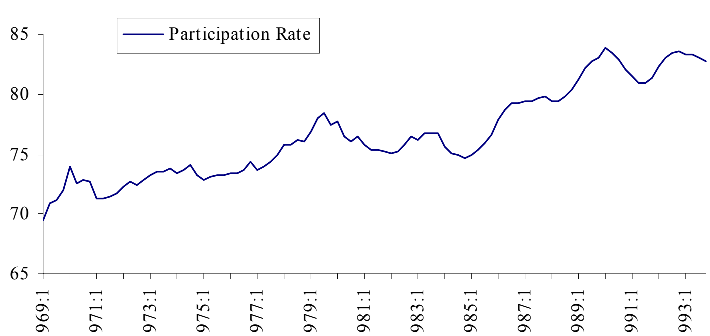

Figure 14. Labor Force Participation Rate Series Plot for Quarterly Data

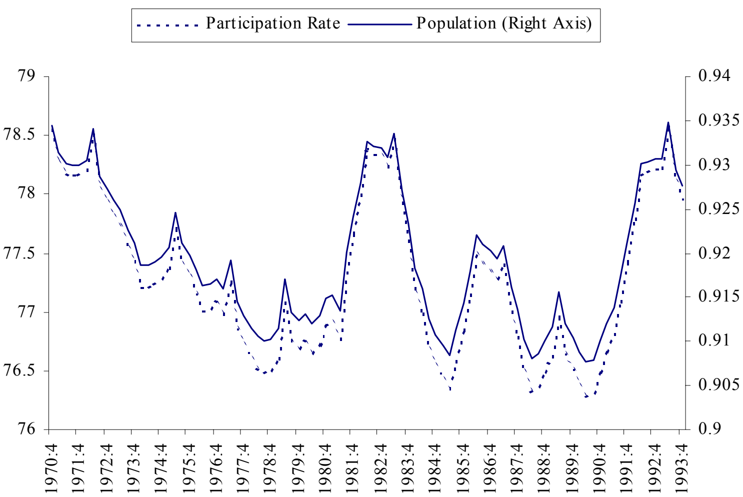

Figure 15. Stationary Component of Population and Participation Rate (N=100)

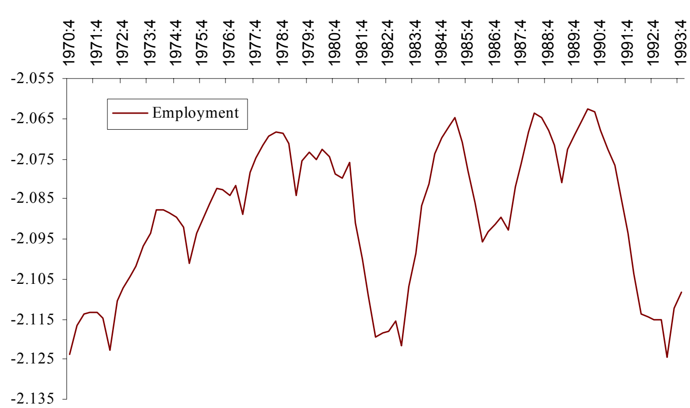

Figure 16. Stationary Component of Employment (N=100)

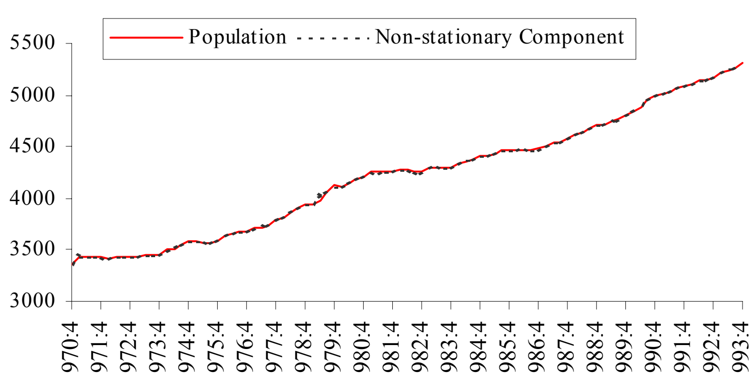

Figure 17. Non-stationary Component of Population (N=100)

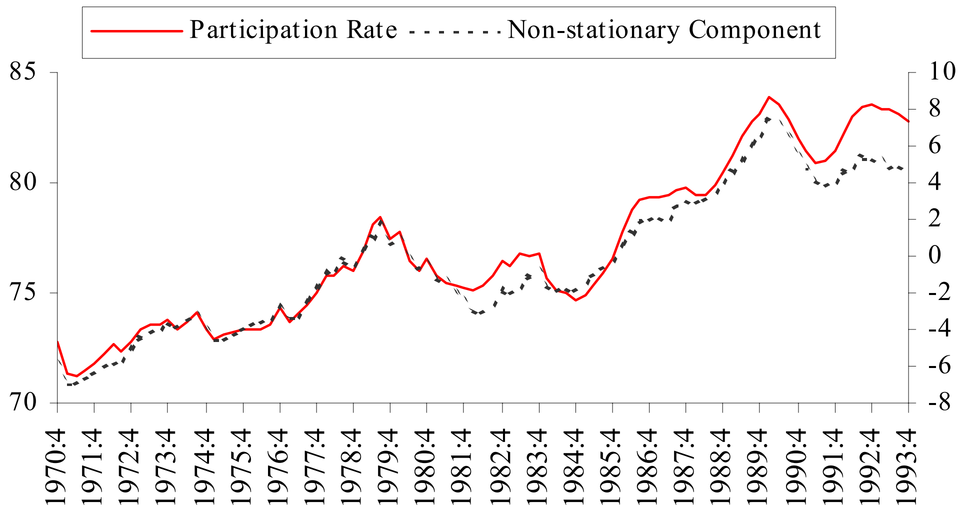

Figure 18. Non-stationary Component of Labor Force Participation Rate (N=100)

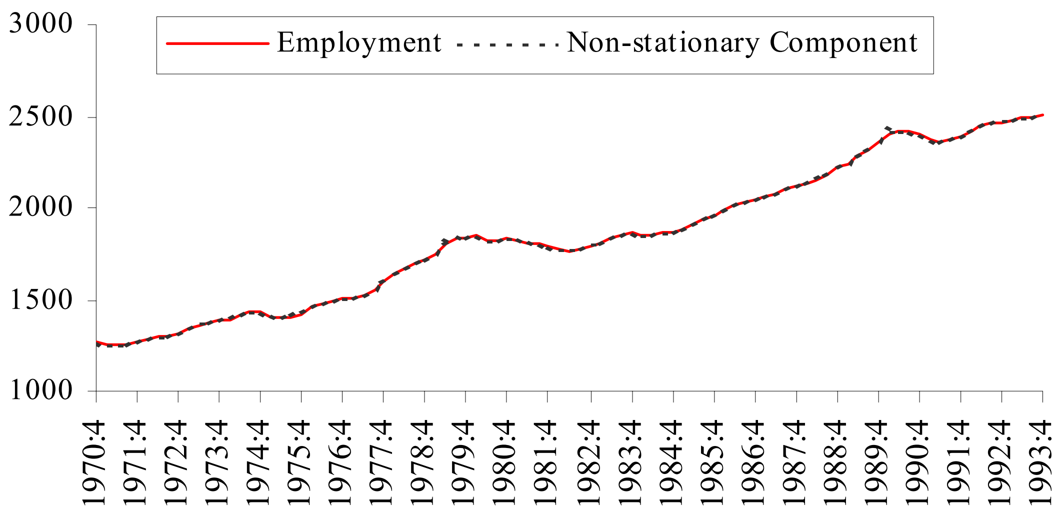

Figure 19. Non-stationary Component of Employment (N=100)