The Unemployment Invariant Hypothesis: Heterogenous Panel Cointegration Evidence From U.S. State Level Data

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ABSTRACT

We explore the long-run relationship between the unemployment rate and the labor force participation rates for U.S. over the period of 1976-2015. We use U.S. state level data and panel cointegration techniques that are robust to cross-sectional heterogeneity, cross-sectional dependency, omitted variable bias and endogeniety issues. We find evidence that on average these two variables are cointegrated and are inversely related. Similar to studies that employ U.S. country level data, this study further questions the empirical relevance of the unemployment invariant hypothesis for the case of the U.S.

Keywords: Unemployment Rate, Unemployment Invariant Hypothesis, Panel Cointegration
JEL Classifications: E24, J60

1. INTRODUCTION AND PROBLEM IDENTIFICATION

From macroeconomics theories, the unemployment invariance hypothesis posits that labor force participations rates do not affect long-run unemployment rates (Layard et al., 2005). However, the empirical evidence on this hypothesis are conflicting. For example, studies such as Osternholm (2010), Emerson (2011) and Kakinaka and Miyamoto (2012) documents a long-run relationship between unemployment and participation rates for the cases of Sweden, U.S. and Japan respectively. On the other hand, studies such as Tansel et al. (2016) find no supporting evidence.

Due to this inconsistency, we therefore revisit the debate by investigating the long-run relationship between unemployment rates and labor force participations. Understanding the nature of the relationship is important for not only theoretical modelling but also for policy formulation and implementation (Emerson, 2011).

We contribute to the debate by using U.S. state level data and recently developed panel unit root and cointegration techniques. Unlike time series analysis, the panel unit root tests and cointegration tests combines the information on time series with the information on cross-sectional units. The addition of cross-sectional variation to time series variation improves estimation efficiency (Levin et al., 2002). Futhermore, the methods used control for omitted variable bias and endogniety issues that might affect the long run relationship.

Using a balanced panel of annual observations for all states in the U.S. from 1976 to 2015, we find that on average unemployment rates and the labor force participation rates are cointegration and are negatively related. This further suggests that the theoretical unemployment invariant hypothesis might not hold in empirical studies, and cautions the use of unemployment invariant hypothesis in policy decision making. The rest of this paper is organized as follows: Section 2 describes the model and data, Section 3 includes the empirical analysis and Section 4 concludes.

2. MODEL AND DATA

Following the literature, the long-run relationship can be expressed as the following bivariate equation:

$$U_{it}=\alpha_i+\delta_i t+\beta L_{it}+e_{it} \tag{1}$$

Where by $i = 1, 2,…, N$ denotes state and $t = 1, 2,…, T$ denotes time. Equation (1) states that unemployment rate, U, in state i at

time t depends on state specific fixed effects, α_i, state specific trends, $\delta_i t$ and the labor force participation rate, L. And e_{it}, is the idiosyncratic error term. Considering that the short run effects and adjustments to the long-run are accommodated in the error term, e_{it}, the equation represents a long-run effect of changes in labor force participation rate (as measured by β).

We obtain annual data on unemployment and labor participation rates are from are from the U.S. Department of Labor (available at: http://www.bls.gov/home.htm), and the data covers the period of 1976-2015. All the are all seasonally adjusted.

3. EMPIRICAL ANALYSIS

3.1. Panel Unit Root Testing

For most macroeconomics data, it is reasonable to assume that the time series are non-stationary unit root processes. Thus, the first step in the empirical analysis involves pre-testing the variables to determine the order of integration. We verify the non-stationary of the variables by using the Im, Pesaran and Shin (2001) test (IPS), which controls for cross-sectional heterogeneity in the estimated coefficients. The augmented Dickey-Fuller (ADF) regression for the IPS can be expressed as follows:

$$\Delta x_{it} = z_{it}^{'}\gamma + \alpha_i \Delta x_{it-1} + \sum_{j=1}^{p_i}\varnothing_{ij}\Delta x_{it-j} + \upsilon_{it},\qquad(2)$$

Where x_{it} is each variable of interest; $z_{it}^{'}$ represents deterministic terms, such as individual time trends and fixed effects; and p_i is lag length for each state. The null hypothesis for the IPS test is the unit root for all i (e.g., H_0: $\alpha_i = 0$), and the alternative is the presence of stationarity in at least one of the panels (e.g., H_0: $\alpha_i < 0$, $\forall_i = 1, 2, \ldots, N; \alpha_i = 0, i = N_1+1, N_2+2, \ldots, N$) The IPS test statistics combine individual unit root tests to obtain a panel-specific result.[1] The IPS test statistics are expressed as:

$$\Gamma_i = \frac{\sqrt{N}[\bar{t}_{NT} - \mu]}{\sqrt{v}},\qquad(3)$$

Where $\bar{t}_{NT}$ is the average of individual country ADF t-statistics; and μ and v are the mean and variance of the individual t-statistics, respectively. One drawback of the IPS test is that it does not control for cross-sectional dependence in the error term, such as common shocks. Indeed, for the state level data it is important to control for such dependence because U.S. state bourders are pourous and workers flow freely between states. Therefore, economic conditions in one state might easily affect employment rates or work force participation rates in another state.

There we use the Pesaran (2004) tests of crosss-sectional dependence and reported the results in Table 1.

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[1] Maddala and Wu (1999) and Choi (2001) propose other methods that control for cross-sectional heterogeneity: The Fisher-augmented Dickey-Fuller and the Fisher-Phillips–Perron tests. These tests are non-parametric tests for panel unit root, and the tests are based on combining individual P values from the individual unit root tests. The results from these tests, although not reported in this paper, are similar to those of IPS and provide similar conclusions. The main drawback of these tests is that they still do not control for cross-sectional dependence in the error term.

Table 1 reports the results from the Pesaran (2004) cross-sectional dependent tests. For both the data in levels and first difference, we reject the null hypothesis that both unemployment rates and labor force participation rates are independent across states. The results are similar for the data in first differences.

We then proceed with checking for the stationarity of the series using the cross-sectionally augmented IPS (CIPS), which is based on the cross-sectional augmented ADF (CADF) and controls for cross-sectional dependence (Pesaran, 2007). The CADF regression can be expressed as:

$$\Delta x_{it} = z_{it}^{'}\gamma + \alpha_i x_{it-1} + \sum_{j=1}^{p_i}\varnothing_{ij}\Delta x_{it-j} + \eta_i \bar{x}_{it-1} + \sum_{j=0}^{p_i}\varphi_{ij}\Delta\bar{x}_{it-j} + \xi_{it},\ (4)$$

Where is $\delta_i t + \beta_i L_{it} + b_{1i}\bar{U}_t +$ is the country mean of time series x_{it}.

The cross-sectionally augmented IPS is the average of the individual country CADF statistics and can be expressed as:

$$CIPS = N^{-1}\Sigma_{I=1}^{N}t_i \qquad(5)$$

where t_i is the OLS t-ratio of α_i in Equation (4), and the corresponding critical values are given by Pesaran (2007).

We report the panel unit root tests in Table 2.

Table 2 shows that unemployment rates and labor force participation rates are non-stationary in their level form especially when we control for the cross-sectional dependence in the error term. However for the first difference data Table 2 demonstrates that the differences of the series are stationary even at 5% significance levels. An implication is that these variables are integrated of the same order one, $I\ (1)$.

Table 1: Pesaran (2004) cross-sectional dependence test and average correction coefficients

Variables	CD-test	ρ	ρ*
Levels			
U_{it}	146.00	0.67	0.67
L_{it}	131.79	0.60	0.61
First differences			
ΔU_{it}	155.41	0.71	0.71
ΔL_{it}	59.03	0.27	0.28

Under the null hypothesis of cross-section independence CD~$N\ (0, 1)$

Table 2: Panel unit root tests

Variables	Deterministic terms	IPS statistic	CIPS statistic
Levels			
U_{it}	Constant, trend	−2.654***	−2.442
L_{it}	Constant, trend	−2.215	−2.37
First differences			
ΔU_{it}	Constant	−3.162***	−2.53***
ΔL_{it}	Constant	−2.993***	−2.716***

Four lags were selected to adjust for autocorrelation for each variable. The relevant 1% (5%, 10%) critical values for the *IPS* statistics is −2.44 (−2.36, −2.32) with an intercept and linear trend, and −1.81 (−1.73, −1.68) with an intercept. The relevant 1% (5%, 10%) critical values for the CIPS statistics is −2.72 (−2.60, −2.55) with an intercept and linear trend, and −2.23 (−2.11, −2.05) with an intercept. *** (**.*) indicates significant levels at 1% (5%, 10%) level, respectively

3.2. Panel Cointegration Tests

After establishing that the series are integrated in the same order, the next step is to test for the presence of the long-run equilibrium relationship between labor force participation rates and unemployment rates. The panel cointegration literature suggests several methods; however, we employ a two-step residual-based cointegration test procedure suggested by Pedroni (1999; 2004). The first step involves estimating the long-run relationship regression separately for each state:

$$U_{it} = \alpha_i + \delta_i t + \beta_i L_{it} + e_{it} \tag{6}$$

The second step involves testing the stationary of the residuals from Equation (6). The null hypothesis is that there is no cointegration, and Pedroni (1999; 2004) has proposed seven test statistics. The first four test statistics are within-dimension statistics based on pooling the autoregressive coefficients across countries, restricting the autoregressive parameters to be homogeneous across countries. The remaining three test statistics are between-dimension statistics based on individually estimating the autoregressive coefficients for each country, thus allowing for cross-sectional heterogeneity.

One notable drawback of the Pedroni (2004) procedure is that it does not consider the potential cross-sectional dependence in the error term. Holly et al. (2001) and Banerjee and Carrion-i-Silvestre (2011) propose a two-step cointegrated procedure based on Pesaran (2006) common correlated effects (CCE) estimator, which controls for cross-country dependence in the error term. The step involves estimating a cross-sectionally augmented co-integration regression for each state i, such as:

$$U_{it} = \alpha_i + \delta_i t + \beta_i L_{it} + b_{1i} \bar{U}_t + b_{2i} \bar{L}_t + e_{it} \tag{7}$$

The cross-country averages of unemployment and labor force participation rates, $\bar{U}_t = N^{-1} \sum_{I=1}^{N} U_{it}$ and $\bar{L}_t = N^{-1} \sum_{I=1}^{N} L_{it}$, respectively, serves as the unobserved factors. The second step involves computing a CIPS statistics for the residuals from the individuallong-runrelation(e.g., $Residulas = U_{it} - (\hat{\alpha}_i + \hat{\delta}_i t + \hat{\beta}_i L_{it})$.

Table 3 includes both of the cointegration tests. In both cases we reject the null hypothesis that the two variables are independent

Table 3: Panel cointegration tests

Pedroni (1999; 2004) cointegration test statistics	
The dependent variable is U_{it}	
Panel v statistic	9.27***
Panel PP rho statistic	−7.02***
Panel PP t-statistic	−6.79***
Panel ADF t-statistic	−7.69***
Group PP rho-statistic	−3.59***
Group PP t-statistic	−5.91***
Group ADF t statistic	−8.41***

CIPS statistics for the residuals of the CCE long-run relationship−2.73***. For the Pedroni (1999; 2004) tests all test statistics are distributed N (0, 1) under a null of no cointegration. The relevant 1% critical values for the CIPS statistics is−2.72 for model with an intercept and linear trend. *** (**.*) Indicates rejection of the null of a no cointegration at 1% (5%, 10%) level respectively. ADF: Augmented Dickey-Fuller, PP: Phillips-Perron, CCE: Common correlated effects

and therefore we conclude that there is a long-run relationship between unemployment and labor force participation rates. These results are consistent with studies that use U.S. country level data such as Emerson (2011).

3.3. Long-run Relationship

To estimate the long-run effect of the labor force participation rate on the unemployment rate, we use the between-group mean panel dynamic ordinary least square (DOLS) estimator, which allows for estimation of cross-sectional heterogeneity in the estimated coefficients (Pedroni, 2001). The procedure involves the inclusion of leads and lags, as well as of current values of the first differences labor force participation rate variable in Equation (1). This is intended to control for possible endogeneity and serial correlation. Thus, Equation (1) can be rewritten as:

$$U_{it} = \alpha_i + \delta_i t + \beta L_{it} + \sum_{j=-q}^{q} \varnothing_{ij} \Delta L_{it-j} + \epsilon_{it}, \tag{8}$$

Where is $\varnothing_{ij}$ a vector of coefficients of leads and lag differences. An advantage of the DOLS procedure is that the estimated coefficients are unbiased and consistent, even in the presence of endogenous regressors. The panel-DOLS ($\hat{\beta}^*_{PDOLS}$) estimates are obtained using the following formula:

$$\hat{\beta}^*_{PDOLS} = \left[\frac{1}{N} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} Z_{i,t} Z'_{i,t} \right)^{-1} \left(\sum_{t=1}^{T} Z_{i,t} \widetilde{U_{i,t}} \right) \right]_1 \tag{9}$$

In this case, $Z_{i,t}$ is 2(k+1)1 vector of repressors $Z_{i,t} = \left[L_{it} - \bar{L}_i, \Delta L_{it-k}, \ldots, \Delta L_{it+k} \right]$, and $\widetilde{U_{i,t}} = U_{i,t} - \bar{U}_i$. A bar over a variable denotes a mean and the subscript 1 outside the brackets indicated the first elements of the vector used to obtain the pooled slope coefficient. Notice that the expression following the summation is over I is similar to the typical DOLS estimator and the between estimator can be calculated as the average of the individual state DOLS estimator such that:

$$\hat{\beta}^*_{PDOLS} = \frac{1}{N} \sum_{i=1}^{N} \hat{\beta}^*_{D,i}$$

Where by $\hat{\beta}^*_{D,i}$ is the conventional DOLS estimator applied to each state. The associated t-statistic for the vector group-mean estimator can be constructed as:

$$t_{\hat{\beta}^*_{PDOLS}} = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} (\hat{\beta}^*_{D,i} - \beta) \left(\frac{1}{\hat{\sigma}_i^2} \sum_{t=1}^{T} (U_{i,t} - \bar{U}_i)^2 \right)^{-1/2}. \tag{10}$$

Where $\hat{\sigma}_i^2$ is the long-run variance of the residuals from the DOLS regression and $\hat{\beta}^*_{D,i}$ is the conventional DOLS estimator. This t-statistic is standard normal as both N and T approach infinity.

The DOLS results, reported in Table 4, show that unemployment and labor force participation rates are inversely related. One

implication is that the discouraged-worker effect is more dominant than the added-worker effect in the U.S. In addition, we also report the CCE estimates and find that the negative relationship still holds. Thus, these results do not support the unemployment invariant hypothesis.

To demonstrate cross-state heterogeneity, we plot the long-run effects of labor force participations rates on unemployment rates in Figures 1 and 2 in the Appendix for the results from using DOLS and CCE estimates, respectively. The individual reasons for the sign and magnitude of the state-level effects are complex, and their investigation is left for future work. However most, states experience a negative relationship between the two variables. Some states such as Massichussits and West Virginia, changes signs of the long run relationship, suggesting that the sign of individual states's relationship is sensitive to estimation methodology.

3.4. Causality

Though the DOLS does not require that regressors be exogenous, and the co-integration implies long-run Granger-causality in at least one direction, the causality might run in either direction. As a result, to test the direction of the long-run causality and the short-run dynamics between the variables, we enter the residuals from the individual DOLS of the long-run relationship:

$$Ec_{it} = U_{it} - \left[\hat{\alpha}_i + \hat{\delta}_i t + \hat{\beta}_i L_{it} \right], \qquad (11)$$

As an error-correcting term into a simple panel error correcting model (VECM) in the form:

Table 4: The long-run effect of labor force participation rate on unemployment rate

The dependent variable is U_{it}	
DOLS	**CCE**
−0.18***	−0.11**
(−6.91)	(−2.05)

The t-statistics in parenthesis. All regressions include one trend. The DOLS includes two leads and two lags. *** (**.*) Indicates significant at 1% (5%, 10%) levels, respectively. CCE: Common correlated effects, DOLS: Dynamic ordinary least square

Table 5: Vector-error-correction model, long-run causality and short run dynamic

Independent variables	Dependent variables	
	ΔU_{it}	ΔL_{it}
Ec_{it-1}	−0.0096	−0.088***
	(−0.68)	(−9.74)
ΔL_{it-1}	−0.20***	
	(−4.73)	
ΔU_{it-1}		−0.13***
		(−7.59)
ΔU_{it-2}		0.088***
		(5.01)
Constant	1.77	6.27***
	(1.81)	(9.87)

t-statistics are in parenthesis, *** (**.*) indicates rejection of the null of a no co-integration at the 1% (5%, 10%) level respectively. We obtain the maximum number of lag to be 1 by using a general to specific procedure. Thus we dropped the insignificant short-run dynamics according to the lowest t-statistics

$$\begin{bmatrix} \Delta U_{it} \\ \Delta L_{it} \end{bmatrix} = \begin{bmatrix} c_{1i} \\ c_{2i} \end{bmatrix} + \sum_{j=1}^{k} \Gamma_j \begin{bmatrix} \Delta L_{it-j} \\ \Delta U_{it-j} \end{bmatrix} + \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} Ec_{it-1} + \begin{bmatrix} \varepsilon_{1i} \\ \varepsilon_{2i} \end{bmatrix} \qquad (12)$$

To this end, c_{1i}s are fixed effects; Ec_{it-1} is the error-correction term that captures the error in or the deviation from the equilibrium; therefore, α_1 and α_2 are the adjustment coefficients that capture the extent to which U and L respond from the long-run or equilibrium relationship, respectively. Hall and Milne (1994) demonstrate that a significant error-correcting term suggests long-run granger causality, and, thus, long-run endogeneity and a non-significant adjustment coefficient imply long-run Granger non-causality from the independent variable to the dependent variable.

Table 5 resorts the results from this analysis. Based on these results we conclude that changes in unemployment rates leads to changes in labor force participation rates, because according the error correction term statistically significant for the model that uses changes in labor force participation rates. This is sufficient condition for the weak-causality test suggested by Hall and Milne (1994).

4. CONCLUSION

We employ homogenous and heterogeneous panel cointegration techniques to a pool of the 50 states in the U.S. for the period of 1976-2015. We find evidence that unemployment rates and labor force participation rates are inversely. Therefore, similar to Emerson (2011) the empirical evidence does not support invariant hypothesis for the case of the U.S.

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APPENDIX

Figure 1: Dynamic ordinary least square estimates of the long-run relationship between labor force participation rates and the unemployment rates. The dependent variable is the unemployment rate
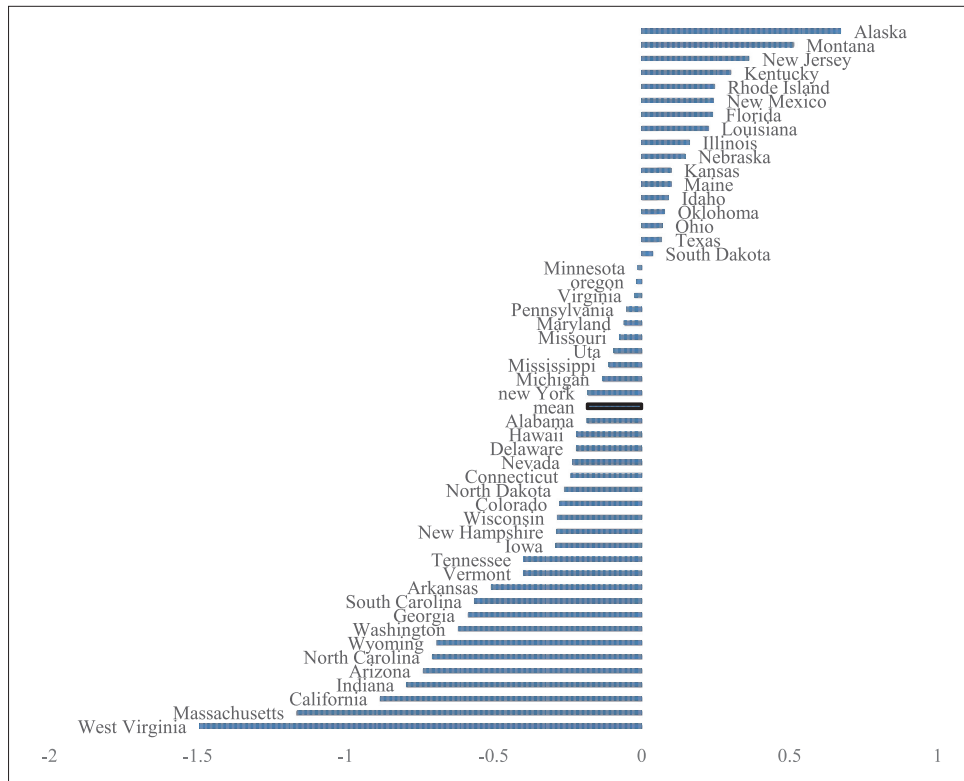
Figure 2: Common correlated effects estimates of the long-run relationship between labor force participation rates and the unemployment rates. The dependent variable is is the unemployment rate