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Cluster Sample Inference with Very Few Groups¹

Johan Vikström²

Abstract

If the number of clusters equals the number of cluster-invariant regressors the usual clusters-specific standard errors cannot be computed. One important example is the difference in differences setting with two groups and two time periods. This paper introduces a new method to calculate how large the within cluster correlation of the model errors can be yet still enable OLS coefficients to retain statistical significance at a desired level. This sensitivity approach is applied to previous results regarding the effects of workers compensation benefits.

Keywords: Cluster effect; cluster robust; difference in difference; sensitivity; workers compensation.

JEL Codes: C12; C21; C23.

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1. Introduction

In some settings with grouped or clustered regressors there are at most as many clusters as there are coefficients of cluster-invariant regressors to estimate. Then the usual cluster-specific standard errors (e.g. `vce(cluster)` in Stata) cannot be computed. A common procedure in this case is to revert to the use of default or heteroskedastic-robust standard errors that ignore the potential efficiency loss due to clustering. In this paper we propose a method to calculate how large the within-cluster correlation of the model errors can be yet still enable OLS coefficients to retain statistical significance at a desired significance level. This sensitivity analysis approach can be viewed as being in the same spirit as for example Rosenbaum and Rubin(1983) and Rosenbaum (2004).

The new approach is applied to the results of Meyer *et.al.* (1995), who study the effects of increased workers compensation benefits using a difference-in-differences (DID) approach that contrasts the outcomes before and after a policy reform for a treatment and a control group. This DID setting with two groups and two time periods is a leading example of a situation in which the number of clusters equals the number of cluster-invariant regressors. Other cases arise with data from only a small number of villages, regions, municipalities or schools.

Previously design sensitivity analysis has been used to test whether an estimate is sensitive to some kind of selection bias. One example is sensitivity analysis with respect to the assumption of unconfounded treatment assignment. In this case, the sensitivity approach assesses how far one can deviate from the unconfoundedness assumption before changing the estimate by a certain pre-specified amount. In this paper, the sensitivity analysis is performed with respect to bias in the standard errors and not with respect to bias in the point estimate as in previous papers. This introduces a new type of sensitivity analysis.

The sensitivity approach complements the existing cluster inference methods. If the number of groups is small Donald and Lang (2007) propose to use data aggregated at the cluster level. Two alternatives are to use cluster bootstrap methods (Cameron et.al. (2008)) or two-stage minimum distance (Wooldridge (2006)). However, none of these approaches are applicable if the number of clusters equal the number of cluster-invariant regressors. This is most easily seen in the Donald and Lang (2007) framework, as it means that the number of aggregated observations equals the number of coefficients to estimate.

2. Model

Consider a linear model for the outcome y for individual i in time period t in group g

$$y_{igt} = x'_{igt}\beta + c_{gt} + \varepsilon_{igt}$$

$$e_{igt} = c_{gt} + \varepsilon_{igt} \quad (1)$$

where ε_{igt} is an individual time specific error, c_{gt} is a group common error term (cluster effect) that varies across groups and time, and x_{igt} represents the regressors. Under the usual exogeneity conditions OLS could be applied, and if the number of groups, G , is large fully robust inference could be applied, but if G is small the inference problem is more complicated (see e.g., Cameron and Miller (2015)). As an illustration consider a simple case with regressors that only vary by group and time:

$$y_{igt} = x'_{gt}\beta + c_{gt} + \varepsilon_{igt} \quad (2)$$

Taking group means we obtain

$$\bar{y}_{gt} = x'_{gt}\beta + \eta_{gt} \quad (3)$$

where $\bar{y}_{gt} = \sum_{s=1}^{n_{gt}} y_{sgt} / n_{gt}$ and $n_{gt} = c_{gt} + \left(\sum_{s=1}^{n_{gt}} \varepsilon_{sgt} / n_{gt} \right)$. Here, n_{gt} is the number of observations in group g in time period t). If $n_{gt} = n$ the pooled OLS estimator of eq.1 is identical to the between-groups estimator of eq.3.. From this we have that, if $c_{gt} \neq 0$, the OLS estimator is inconsistent if the number of groups, G , is small. Instead, Donald and Lang (2007) show that we have to rely on small-sample properties. If η_{gt} is i.i.d. normally distributed we can perform inference based on a t -distribution with $GT - K$ degrees of freedom, where T is the number of time periods and K the number of regressors.

The limit case is if the model is just-identified, that is if the number of cluster-invariant regressors equals the number of clusters. Following Donald and Lang (2007) the inference should then be based on a t -statistic with zero degrees of freedom, implying that no regular inference can be applied. Instead, this paper proposes to use sensitivity analysis as diagnostic tool in cases with just-identified linear models.

3. Sensitivity analysis for cluster samples

This section introduces the new sensitivity analysis. With only a few groups, one can use the standard OLS covariance matrix, $\hat{V} = \sigma^2 (X'X)^{-1}$, but notice that $\hat{V}$ only gives correct standard errors if $c_{gt} = 0$ for all g, t . This can be compared with the true, but unknown, covariance matrix

$$V = \sigma^2 (X'X)^{-1} X'CX (X'X)^{-1}, \quad (4)$$

with $E(ee') = \sigma^2 C = (\sigma_c^2 + \sigma_\epsilon^2)C$ where e is a vector collecting all e_{igt} .

Let us initially consider the simplest case. Assume that ϵ is homoscedastic, $E(c_{gt}c_{gt'}) = 0$ for all t and all $g \neq g'$ and $E(c_{gt}c_{gt'}) = 0$ for all g and all $t \neq t'$. Further, assume that the regressors are constant within each group ($x_{igt} = x_{gt}$) and constant group size ($n_{gt} = n_g$). Then, from Klock (1981) we have, $V(\beta_j) = (1 + \rho(n-1))\hat{V}(\beta_j)$, where $\rho = \frac{\sigma_c^2}{\sigma_c^2 + \sigma_\epsilon^2}$ is the within-cluster correlation. Next, expressing the ratio between the two error term variances as $\sigma_c^2 = \gamma\sigma_\epsilon^2$ we have:

$$V(\beta_j) = \left(1 + \frac{\gamma}{1+\gamma}(n-1)\right)\hat{V}(\beta_j). \quad (5)$$

If the model is just-identified the data contains no information about γ . Instead, this paper proposes to use γ as a sensitivity analysis parameter. After estimating $\hat{\beta}_j$ using the disaggregated data, the sensitivity analysis amounts to assessing how much γ has to deviate from zero to change the standard errors by a pre-specified amount. If the results are insensitive to departures from the assumption of no within group correlation, this indicates that the results can be trusted, even if no proper inference could be performed.

One could also calculate how large the within-cluster correlation of the model errors can be yet still enable OLS coefficients to retain statistical significance at a desired

significance level. Formally, using standard textbook results, if $\gamma = 0$ and if $\sum n_{jt}$ is large $t = \left(\hat{\beta}_j / \sqrt{\hat{V}(\hat{\beta}_j)} \right) \sim t_{n_{GT}-K}$. Next, if $\gamma \neq 0$ and is known, and with normally distributed cluster errors $(c_{jt} \sim N(0, \sigma_c^2))$ we have $t = \left(\hat{\beta}_j / \sqrt{\left(1 + \frac{\gamma}{1+\gamma}(n-1) \right) \hat{V}(\hat{\beta}_j)} \right)$. Then, by setting $t = T_{NGT-K, 1-\alpha/2}$ where $T_{NGT-K, \nu}$ is the ν quantile of the t-distribution with $NGT - K$ degrees of freedom, and solving for γ ;

$$\gamma_{c,j} = \frac{\hat{\beta}_j^2 - t^2 \hat{V}(\beta_j)}{(n-1) \hat{V}(\beta_j) - \hat{\beta}_j^2 + t^2 \hat{V}(\beta_j)}, \quad (6)$$

so that $\gamma_{c,j}$ is the γ cut-off value that renders the coefficient of interest statistically insignificant at the $\alpha\%$ level. If $\gamma_{c,j}$ is unreasonably large, one can be confident that the null-hypothesis about zero effect can be rejected.

If the assumption of either $n_{gt} = n$ or $x_{igt} = x_{gt}$ do not hold the relationship between $\hat{V}(\beta_j)$ and $V(\beta_j)$ is more complicated. With one single regressor we have from e.g. Moulton (1986) that $V(\beta_j) / \hat{V}(\beta_j) = 1 + \left[V(n_{gt}) / \bar{n}_{gt} - 1 \right] \rho_x \rho$, where $\bar{n}_{gt}$ is the average group size and ρ_x the within-group correlation of x_{igt} . With more than one regressor one could use eq. 4, noting that C , has the familiar block-diagonal structure

$$C = \begin{pmatrix} C_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & C_{GT} \end{pmatrix}, \quad (7)$$

with $C_{GT} = \left[(1-p)I_{gt} + pJ_{gt} \right]$, where I_{GT} is an n_{gt} times n_{gt} identity matrix, and J_{gt} is an n_{gt} times n_{gt} matrix of ones. Then, using (4) we have $V(\hat{\beta}_j) = (\sigma_c^2 + \sigma_\epsilon^2) E_{jj} = (1+\gamma) \sigma_\epsilon^2 E_{jj}$,

where E_{jj} is the (j, j) element of $E \equiv (X'X)^{-1} X'CX (X'X)^{-1}$ with C defined as in (7)³. The

cut-off value, $\gamma_{c,j}$, is then found by numerically solving for γ in $T_{NGT-K,1-\alpha/2} = \frac{\hat{\beta}_a}{\sqrt{(1+\gamma)\hat{\sigma}_\epsilon^2 E_{jj}}}$

Correlation over time in the cluster effects. We now relax the assumption $E(c_{gt}c_{gt'}) = 0$, i.e. we allow for correlation over time in the cluster effects. Instead, we assume an AR(1) structure for $c_{gt} = \kappa c_{gt-1} + d_{gt}$, where d_{gt} is assumed to be a white noise series with mean zero and variance σ_d^2 . Further, let us assume that $|\kappa| < 1$ and make the natural extension of the basic sensitivity analysis and define $\sigma_d^2 = \gamma \sigma_\epsilon^2$. This gives two sensitivity parameters, γ and κ , instead of the single sensitivity parameter γ . To be clear, κ is interpreted as the first-order autocorrelation coefficient for c_{gt} , and γ as the relation between the variance of the group-time specific shock and the variance of the unobserved heterogeneity.

As before (4) still holds. Under the AR(1) assumption we can express C in terms of κ and γ . From the appendix we have $V(\hat{\beta}_j) = (1+\gamma)\sigma_\epsilon^2 F_{jj}$, where F_{jj} is the (j, j) element of $F \equiv (X'X)^{-1} X'CX (X'X)^{-1}$ with C defined as in (A.7)-(A-9). Based on this expression one can assess the sensitivity of the standard errors with respect to both the autocorrelation and the variance of the group-time specific shocks. As above, one may be interested in the cut-off values which renders a specific estimate insignificant. One way to achieve this is to solve for γ for a range of values of κ . The cut-off value, $\gamma_{c,j}(\kappa)$, for a given κ is found by

numerically solving for γ in $T_{NGT-K,1-\alpha/2} = \frac{\hat{\beta}_j}{\sqrt{(1+\gamma)\hat{\sigma}_\epsilon^2 F_{jj}}}$.

4. Application

Meyer et al. (1995) (MVD, henceforth) study the effects of an increase in disability benefits (workers compensation) in the state of Kentucky. The reform, implemented on July 15, 1980, increased the maximum level at which the benefits could be collected from \$131 to

³ Note that σ_ϵ^2 can be estimated using the within group-time cell variation:

$$\sigma_\epsilon^2 = (nGT - GT)^{-1} \sum_{g=1}^G \sum_{t=1}^T \sum_{i=1}^n (y_{igt} - \bar{y}_{gt})^2$$

\$217 per week, which meant that previous high earners (over the new maximum level) experienced a 66% increase in their benefits, while the benefits for workers with previous low earnings (below the old ceiling) were unchanged. MVD analyze the effect of the increase using a DID estimator, which contrasts the difference in injury duration between before and after the reform for the treatment group (high income earners) and the control group (low income earners).

Table 1: Sensivity analysis estimates for the effects of workers compensation benefits

	Treated		Non-Treated		Differences		DID
	(High earnings)		(Low earnings)				
	Pre	Post	Pre	Post	[2-1]	[4-3]	[5-6]
	Period	Period	Period	Period			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Log duration	1.38	1.58	1.13	1.13	0.20	0.01	0.19
	(0.04)	(0.04)	(0.03)	(0.03)	(0.05)	(0.04)	(0.07)
Sample Size	1.233	1.161	1.705	1.527			
Sensitivity Analysis							
γ_c %5 [%10]					0.0026	-	0.00067
					[0.0041]		[0.00127]
$\sqrt{\gamma_c} * \sigma_{\varepsilon_c}$ %5 [%10]					0.0629	-	0.0335
					[0.0787]		[0.0461]

Notes: The results in the upper panel are taken from Meyer et al. (1995), their standard errors in parentheses. The outcome is mean log duration, censored after 42 months. The sensitivity analysis results in the lower panel is own calculations.

The upper panel of Table 1 restates MVD's results for the outcome mean log injury duration. The DID estimate of the treatment effect (Column 7) is statistically significant, but MVD ignore the cluster-sample issue and use regular OLS standard errors, so that their standard errors are biased downwards if there are any cluster effects. The model is just-identified, since if re-written as a regression model their DID model includes four cluster-invariant regressors and four clusters.

As an illustration consider sensitivity analysis under the assumption that the cluster-effects (group-time shocks) are uncorrelated between the groups as well as uncorrelated over time. From Table \ref{tab1} we have that the 5% level cut-off value for the DID estimate is 0.00067, which means that the variance of the group-time shocks is allowed to be 0.00067

times the variance of the unobserved individual heterogeneity before the treatment effect is rendered insignificant. At first glance it may seem difficult to assess whether this is an unreasonably large value. Table 1 therefore also reports these values recalculated as cut-off standard deviations for the group-time shocks $(\sqrt{\gamma_c} \sigma_\varepsilon)$. These cut-off values show that the standard deviation of the group-shocks is allowed to be 0.034 on the 5% level (0.046 on the 10% level). Column 1 and Column 3 show that the average log injury duration are 1.38 and 1.13 for the treatment group and the control group before the reform. Compared with these averages, the allowed standard deviation of the shocks is quite large. It is therefore fair to say that the conclusion that the treatment effect is significant is not sensitive to a reasonable departure from the independence (no-cluster) assumption.

5. Conclusions

This paper has introduced and implemented a new method to perform inference when the number of clusters equal the number of cluster-invariant regressors. Possible applications include the difference-in-differences setting with the two groups and two time periods.

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Appendix

In order to express C in terms of κ and γ use the well-known properties of an AR(1) process (under the assumption of $|\kappa| < 1$), and that $\sigma_d^2 = \gamma\sigma_\varepsilon^2$. Then:

$$\sigma_c^2 = E(c_{gt}c_{gt}) = \frac{\sigma_d^2}{1-\kappa^2} = \frac{\gamma\sigma_\varepsilon^2}{1-\kappa^2} \quad (\text{A.1})$$

And if $t \neq t'$

$$\text{Cov}(c_{gt}c_{gt'}) = E(c_{gt}c_{gt'}) = \kappa^{|t-t'|} \frac{\sigma_d^2}{1-\kappa^2} = \kappa^{|t-t'|} \frac{\gamma\sigma_\varepsilon^2}{1-\kappa^2} \quad (\text{A.2})$$

Thus if $t \neq t'$

$$E(e_{igt}e_{jgt}) = \sigma^2 = \sigma_c^2 + \sigma_\varepsilon^2 = \frac{\gamma\sigma_\varepsilon^2}{1-\kappa^2} + \sigma_\varepsilon^2 = \sigma_\varepsilon^2 \frac{1+\gamma-\kappa^2}{1-\kappa^2} \quad (\text{A.3})$$

Further, using (A.1) and (A.3) if $i \neq j$

$$E(e_{igt}e_{jgt}) = \sigma_c^2 \frac{\gamma\sigma_\varepsilon^2}{1-\kappa^2} = \sigma^2 \frac{\gamma}{1+\gamma-\kappa^2} \quad (\text{A.4})$$

Further, using (A.2) and (A.3) if $t \neq t'$

$$E(e_{igt}e_{jgt'}) = \kappa^{|t-t'|} \frac{\sigma_d^2}{1-\kappa^2} = \sigma^2 \kappa^{|t-t'|} \frac{\gamma}{1+\gamma-\kappa^2} \quad (\text{A.5})$$

And under assumption $E(c_{gt}c_{gt'}) = 0$, if $g \neq g'$

$$E(e_{igt}e_{jgt'}) = 0 \quad (\text{A.6})$$

From (A.3)-(A.6) we have (A.7)-(A.9).

$$C = \begin{pmatrix} C_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & C_G \end{pmatrix} C_g = \begin{pmatrix} C_{11} & \dots & C_{T1} \\ \vdots & \ddots & \vdots \\ C_{1T} & \dots & C_{TT} \end{pmatrix}, \quad (\text{A.7})$$

with if $t = t'$

$$C_{tt'} = \left[\left(1 - \frac{\gamma}{1 + \gamma - \kappa^2} \right) I_{gt} + \frac{\gamma}{1 + \gamma - \kappa^2} l_{gt} l_{gt}' \right] \quad (\text{A.8})$$

and if $t \neq t'$

$$C_{tt'} = \kappa^{|t-t'|} \frac{\gamma}{1 + \gamma - \kappa^2} l_{gt} l_{gt'}' \quad (\text{A.9})$$



**Do Regional Differentials in Economic Freedom Yield Regional
Unemployment Rate Differentials in the U.S.? A Brief Exploratory Note
Adopting Panel Data Analysis**

Richard J. Cebula¹

Abstract

This study empirically investigates the hypothesis that the higher the degree of economic freedom in a state, the lower the unemployment rate in that state, other thing held the same. This hypothesis is based on the principle that greater economic freedom leads to greater real economic growth, which in turn reduces the unemployment rate. The framework studied consists of a panel dataset for the 50 U.S. states representing the period 2000 to 2012, a period which includes the Great Recession, as well as years prior to and following the Great Recession. The model estimated in this study includes for each state, in addition to a measure/index of overall economic freedom, control variables for the percentage of the population that is black, the percentage of the population that is Hispanic/Latin, the female labor force participation rate, and the percent of the population (age 25 and older) with at least a high school diploma. A number of state fixed-effects and dynamic panel data estimations are provided, all of which yield the finding that the greater the level of overall economic freedom, the lower the unemployment rate.

Keywords: State unemployment rate; economic freedom

JEL Codes: J10; J70; C23.

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1. Introduction

A number of scholarly articles have examined the effects of greater levels of economic freedom on the growth rate of real income, real GDP, and real GDP per capita. The clear pattern of findings in this literature is that there exists a positive and statistically significant impact of economic freedom on all of these measures of real economic growth (Heckelman and Stroup, 2000; Dawson, 2003; Arora and Vamvakidis, 2006; Gwartney, et al., 2006; Clark and Lawson, 2008; Hall et al., 2010; Ashby et al., 2013; Belasen and Hafer, 2013; Bennett and Vedder, 2013; Cebula and Mixon, 2013; Cebula and Mixon, 2014). In effect, this influence of economic freedom on economic growth is based on the economics principle that a greater degree of overall economic freedom, through the promotion of greater freedom from excessive government size, greater freedom from taxation, enhanced property rights, and greater labor market freedom, acts to encourage entrepreneurship and yield more efficiently operating labor, commodity, and financial markets.

Following in principle a study of 29 OECD nations for the 2003-2007 period by Cebula, Foley, and Capener (2015), the present study focuses on a parallel, yet different, potential impact of a greater degree of economic freedom, namely, lower unemployment rates. Arguably, greater economic growth resulting from greater economic freedom should lead to a reduced unemployment rate. More specifically, the present study investigates the hypothesis that the *higher* the overall level of economic freedom in state j within the U.S., the higher the pace of economic activity in the state and hence the *lower* the unemployment rate in the state, *ceteris paribus*.

This study seeks to investigate this hypothesis in terms of the impact of state-level economic freedom differentials on interstate unemployment-rate differentials in the U.S. in the following ways: (a) through the adoption of a state-level panel dataset for estimation purposes, one that includes data beginning with the year 2000; (b) by extending the analysis through the year 2012, thereby making the analysis relatively current, using a dataset that represents the study period 2000-2012; and (c) by using panel data analysis to study whether higher overall levels of economic freedom in a state, by increasing the efficiency of economic transactions in general within a state, act to reduce the overall unemployment rate in the state. This study adopts the overall economic freedom index by state for the U.S. generated by Stansel et al. (2015).

A basic model/framework is provided in Section 2 of the study. Section 3 of the study

provides the empirical model, a description of the data, and initial empirical results, whereas Section 4 provides further empirical evidence, indeed, what amounts to robustness testing. Finally, conclusions and an overview of the results are provided in Section 5. Interestingly, in all of the estimates, the state-level unemployment rate is found to be negatively and statistically significantly associated with greater economic freedom.

2. Background and the Initial Specification

The conventional wisdom is that individuals possess “economic freedom” when the property they acquire without the use of force, fraud, or theft is protected from physical invasion by others and they are free to use, exchange, or give away their property so long as their actions do not violate the identical rights of other persons. Therefore, “...an index of economic freedom should in theory reflect the degree to which rightly acquired property is protected and individuals are engaged in voluntary transactions” (Gwartney, Lawson, and Block, 1996, p. 12). Ruger and Sorens (2009, p. 1) similarly offer the definition of individual economic freedom as being “...the ability to dispose of one’s own life, liberty, and justly acquired property however one sees fit, so long as one does not coercively infringe on another’s ability to do the same.” Clearly, those economies that are the “freest” are those that operate with a minimal degree of government interference and instead depend upon the process of free choice and the efficiency of markets to answer the basic economic questions of what to be produced, how it is to be produced, how much is produced, and the price(s) at which the market will clear. Clearly, to the extent that governments impose restrictions on these choices, there is less economic freedom (Stansel, Torra, and McMahon, 2015, p. 1). Typically, the greater the degree of economic freedom, the more successfully and efficiently markets perform and the greater the prosperity created through private enterprise. These outcomes from greater freedom accelerate economic growth, which in turn creates opportunities for yet further success. It is hypothesized in this study that the greater the overall level of economic freedom in a state, the more efficiently and more productively the commodity markets, labor markets, and other markets of that state economy will operate, and hence the lower the unemployment rate in that state will be, *ceteris paribus* (Bennett, 2016; Feldman, 2007; Garrett and Rhine, 2011; Hall et al., 2013; Heller and Stephenson, 2014; and Stansel, 2013). Alternatively stated, a greater degree of economic freedom in a state implies an economic-political environment that is more conducive to research and development (R&D),

innovation, the pursuit of new ideas, products and services, risk-taking, and entrepreneurship in general (Cebula, et al., 2015). Hence, the greater the degree of economic freedom, the lower the unemployment rate is likely to be.

There are several well-known measures (indices) of economic freedom, including those by generated by Gwartney, Lawson, and Hall (2013), the Heritage Foundation (2013), and Stansel, Torra, and McMahon (2015). The *Economic Freedom of North America Index (EFNA)*, as most recently generated by Stansel, Torra and McMahon (2015), is the oldest and possibly best established/known of the state-level indices of economic freedom for the U.S. Accordingly, this study adopts the *EFNA* economic freedom index by state generated by Stansel, Torra, and McMahon (2015, Table 3.4c), whose state-level form conforms to the other state-level data considered in this study. The subnational (state-level) index for each of the 50 states in the U.S. (*EFNA*) consists of ten variables which are divided into three equally weighted components, as follows: Area 1, Size of Government; Area 2, Takings and Discriminatory Taxation; and Area 3, Labor Market Freedom. Alternatively stated, the overall economic freedom index consists of three equally weighted component freedoms: government spending freedom; freedom from government taxes; and labor market freedom. For simplicity and in the interest of space constraints, the reader is referred to Stansel, Torra, and McMahon (2014, Chapter 3; 2015, Chapter 3) and to Stansel (2013, pp. 4-8) for a detailed description and explanation of the computation of the overall economic freedom index and the variables used in that computation. It is observed that these indices in Stansel, Torra, and McMahon (2015, Table 3.4c) are both geographically comparable and comparable over time. They assume values between 0.0 and 10.0, with higher index values corresponding to greater economic freedom. It is hypothesized in this study that EGB_{jt} is an increasing function of $ECONFREE_{jt}$, other things held the same.

Given the emphasis in this study on economic freedom, in this eclectic framework, the fundamental hypothesis of this Section of the study is that the percentage unemployment rate in state j ($UNEMPLRATE_j$) depends inversely upon the overall level of economic freedom in state j ($ECONFREEDOM_j$), *ceteris paribus*, as well as upon a number of control variables ($CONTROL_j$), as follows:

$$UNEMPLRATE_{jt} = f(ECONFREEDOM_{jt}, CONTROL_{jt}), \quad (1)$$

where it is hypothesized that:

$$fECONFREEDOM_{jt} < 0, \quad (2)$$

where $UNEMPLRATE_{jt}$ is the level of the average unemployment rate of the civilian labor force in state j in year t , expressed as a percent; $ECONFREEDOM_{jt}$ refers to the average value of the overall economic freedom measure (index) in state j in year t ; and $CONTROL_{jt}$ refers to the values of control variables in state j in year t to be included in the empirical estimates. The hypothesized negative sign on $fECONFREEDOM_{jt}$ is not only compatible with (Gwartney et al., 1996, p. 12) but also with prior empirical studies by Bennett (2016), Feldman (2007), Garrett and Rhine (2011), Hall et al. (2013), Heller and Stephenson (2014), and Stansel (2013).

Table 1. Variables and data source

Variable	Data Source/s
$UNEMPLRATE_{jt}$	U.S. Census Bureau (2002, Table 572; 2006, Table 581; 2010, Table 580), U.S. Census Bureau (2012).
$ECONFREEDOM_{jt}$	Stansel et al. (2015, Table 3.4c)
$BLACK_{jt}$	U.S. Census Bureau (2002, Table 34; 2006, Table 16; 2010, Table 19), U.S. Census Bureau (2012).
$HISP_{jt}$	U.S. Census Bureau, 2002, Table 34; 2006, Table 16; 2010, Table 19), U.S. Census Bureau (2012), Pew Research Center (2013).
$FLFPR_{jt}$	U.S. Census Bureau (2002, Table 572; 2006, Table 581; 2010, Table 580), U.S. Census Bureau (2012).
$HSPLUS_{jt}$	U.S. Census Bureau, 2002, Table 212; 2006, Table 318; 2010, Table 228), U.S. Census Bureau (2012).

The control variables included in the analysis are, as follows: the percentage of the population in state j that is Black/Afro-American ($BLACK_{jt}$); the percentage of the population that is Hispanic/Latin ($HISP_{jt}$); the percentage female labor force participation rate ($FLFPR_{jt}$); and the percentage of the population age 25 years and older that has earned a high school diploma or higher degree. The variable $BLACK_{jt}$ is included in the analysis to control for the fact that the average unemployment rate of Blacks in the U.S. economy, 11.631%, was *greater* over the study period than the overall unemployment rate, 6.308% (Council of Economic Advisors, 2013, Table B-42). Similarly, the variable $HISP_{jt}$ is included in the model in order to control for the fact that the average unemployment rate of Hispanics/Latinos, 8.1%, was *greater* over the study period than the overall unemployment rate, 6.308% (Council of Economic Advisors, 2013, Table B-42). Finally, the control variable $FLFPR_{jt}$ is included in the analysis to reflect the fact that the average unemployment rate of females in the U.S. economy, 6.015%, was *lower* over the

study period than the overall unemployment rate, 6.308% (Council of Economic Advisors, 2013, Table B-42). Based on these data, it is expected (*ceteris paribus*, in each case) that the unemployment rate in state j is an increasing function of $BLACK_{jt}$ and $HISP_{jt}$ and a decreasing function of $FLFPR_{jt}$.

Table 2. Descriptive Statistics

Variable	Mean	Standard Deviation
$UNEMPRATE_{jt}$	6.308	1.342
$ECONFREEDOM_{jt}$	6.925	0.604
$BLACK_{jt}$	9.988	9.497
$HISP_{jt}$	8.920	9.424
$FLFPR_{jt}$	60.781	4.300
$HSPLUS_{jt}$	84.21	4.60

Interestingly, Bennett (2016) and other related studies have suggested that the unemployment rate might *also* be affected by educational attainment (the higher the mean overall level of educational attainment, the lower the unemployment rate). In the effort to reflect educational attainment, we adopt the *de facto* control variable $HSPLUS_{jt}$, defined here as the percentage of the population in state j in year t age 25 years and older with *at least* a high school diploma, where it is expected that the unemployment rate is a decreasing function of $HSPLUS_{jt}$, *ceteris paribus*.

Accordingly, the model in equations (1) and (2) becomes the following:

$$UNEMPRATE_{jt} = f(ECONFREEDOM_{jt}, BLACK_{jt}, HISP_{jt}, FLFPR_{jt}, HSPLUS_{jt}), \quad (3)$$

where it is hypothesized that:

$$UNEMPRATE_{jt} = f_{ECONFREEDOM_{jt}} < 0, f_{BLACK_{jt}} > 0, f_{HISP_{jt}} > 0, f_{FLFPR_{jt}} < 0, f_{HSPLUS_{jt}} < 0 \quad (4)$$

Table 3. Correlation Matrix

	$ECONFREEDOM_{jt}$	$BLACK_{jt}$	$HISP_{jt}$	$FLFPR_{jt}$	$HSPLUS_{jt}$
$ECONFREEDOM_{jt}$	1.000				
$BLACK_{jt}$	0.082	1.000			
$HISP_{jt}$	-0.022	-0.140	1.000		
$FLFPR_{jt}$	0.215	-0.435	-0.231	1.000	
$HSPLUS_{jt}$	-0.020	-0.426	-0.141	0.496	1.000

State Fixed-Effects Estimation Results

The data sources for the variables in the analysis are provided in Table 1. Descriptive statistics can be found in Table 2. For the interested reader, the correlation matrix for the explanatory variables is provided in Table 3; clearly, as shown in Table 3, there are no noteworthy multicollinearity problems. In this section of the study, the Fixed-Effects Model, (as opposed to the Random Effects Model), as suggested by the Hausman (1978) test, is adopted. The Hausman (1978) specification test suggests that the Random Effects Model estimator is inconsistent. Since the fixed effects estimates are always consistent, only the fixed-effects results are reported. The Effects Specification is Cross-section Fixed (dummy variables). In all estimates, the standard errors are white corrected.

Before providing the estimation analysis, the issue of cross-section dependency is broached. Omay (2014) discusses three categories of panel data analysis, namely, Type 1 (Large N and Small T), Type 2 (Small N and Large T), and Type 3 (Large N and Large T). As observed by Omay (2014, p. 19), Pesaran (2004) initially proposed a cross-section dependency test. The Pesaran (2004) study proposes simple tests of error cross section dependence, which are applicable to a variety of panel data models. Applying the latter analysis to the present data-set yields the conclusion that there is no evidence of a cross-section dependency problem.

Estimating equation (3) in *linear* form by cross-section (state) fixed-effects yields the results shown in column (a) of Table 4. In column (a), all five of the estimated coefficients exhibit the hypothesized signs, with all five being statistically significant at the 1% level. In addition, the F -statistic is statistically significant at the 1% level. Finally, the R^2 is 0.79 whereas the adjusted R^2 is 0.71, so that the model explains approximately three-fourths of the variation in the dependent variable.

According to these cross-section fixed-effects results, the unemployment rate in state j ($UNEMPRATE_{jt}$) is an increasing function of (is positively associated with) both the percentage of the population in the state that is Black ($BLACK_{jt}$) and the percentage of the population in the state that is Hispanic/Latin ($HISP_{jt}$). In addition, the unemployment rate in state j is a decreasing function of (is negatively associated with) the female labor force participation rate in the state ($FLFPR_j$), the percentage of the adult population (age 25 and older) with at least a high school diploma in the state ($HSPLUS_{jt}$), and the index of economic freedom in the state

(*ECONFREEDOM_{jt}*). Thus, the findings in this initial estimation provide empirical support for the hypothesis that the unemployment rate is a decreasing function of the level of economic freedom.

Table 4. State Fixed-Effects Estimation Results

Dependent Variable	<i>UNEMPRATE_{jt}</i>	<i>Log (UNEMPRATE_{jt})</i>	<i>Log (UNEMPRATE_{jt})</i>
Explanatory Var.	(a)	(b)	(c)
Constant	41.05	9.88	45.99
<i>ECONFREEDOM_{jt}</i>	-2.211*** (-6.76)	-0.483*** (-9.59)	
<i>BLACK_{jt}</i>	0.411*** (2.69)	0.062** (2.27)	
<i>HISP_{jt}</i>	0.257*** (5.21)	0.055*** (5.36)	
<i>FLFPR_{jt}</i>	-0.292*** (-6.35)	-0.065*** (-7.53)	
<i>HSPLUS_{jt}</i>	-0.113*** (-3.08)	-0.025*** (-3.45)	
<i>Log (ECONFREEDOM_{jt})</i>			-3.697*** (-11.38)
<i>Log (BLACK_{jt})</i>			0.275** (2.05)
<i>Log (HISP_{jt})</i>			0.906*** (7.05)
<i>Log (FLFPR_{jt})</i>			-3.566*** (-6.73)
<i>Log (HSPLUS_{jt})</i>			-5.365*** (-5.66)
Weighted Statistics:			
<i>F</i>	10.03***	11.74***	11.52***
<i>R</i> ²	0.79	0.81	0.81
Adj. <i>R</i> ²	0.71	0.74	0.74

Note: Terms in parentheses are *t*-values. White cross-section corrected standard errors and *t*-values. ***Indicates statistically significant at 1% level; **indicates statistically significant at the 5% level, and *indicates statistically significant at the 10% level.

The cross-section fixed-effects estimation results for equation (3) expressed in *semi-log* form are summarized in column (b) of Table 4. Clearly, these findings are qualitatively very similar to those shown in column (a) of the Table. In particular, in column (b), all five of the estimated coefficients exhibit the hypothesized signs, with four being statistically significant at the 1% level and the fifth being statistically significant at the 5% level. Finally, again, the *R*² is 0.81 whereas the adjusted *R*² is 0.74, so that the model explains approximately three-fourths of

the variation in the dependent variable. Thus, in this estimation, the unemployment rate in a state is an increasing function of the percent of its population that is black and the percent of its population that is Hispanic/Latin, whereas the unemployment rate in state j is a decreasing function of the female labor force participation rate, the percent of the population age 25 and older with at least a high school diploma, and the index of economic freedom. Hence, there is further support for the hypothesis that greater economic freedom leads to a lower unemployment rate. Indeed, if the economic freedom index were elevated by one unit, say from 6.0 to 7.0, then the unemployment rate (other things held the same) would presumably decline by 48.3%.

Finally, there are the results for the log-log specification shown in column (c) of Table 4. These findings are qualitatively consistent with both the results in column (a) and column (b) of Table 4. All five of these estimated *elasticity* values exhibit the hypothesized signs, with four being statistically significant at the 1% level and the fifth being statistically significant at the 5% level. In addition, the R^2 is 0.81 whereas the adjusted R^2 is 0.74, so that the model explains approximately three-fourths of the variation in the dependent variable. More specifically, the unemployment rate in state j is an increasing function of the percentage of the population in the state that is Black, such that a 1% higher value for the variable $BLACK_{jt}$ is found on average to *elevate* the unemployment rate in state j by 0.275%. In addition, the unemployment rate in state j is an increasing function of the percentage of the population in the state that is Hispanic/Latin, such that a 1% higher value for the variable $HISP_{jt}$ is found on average to *elevate* the unemployment rate in state j by 0.906%. Furthermore, the unemployment rate in state j is found to be a decreasing function of the female labor force participation rate in state j . In this case, a 1% higher value for the variable $FLFPR_{jt}$ is found on the average to *diminish* the unemployment rate in state j by 3.566%. The unemployment rate in state j is also found to be a decreasing function of the percentage of the population age 25 years and older with at least a high school degree, such that a 1% higher value for the variable $HSPLUS_{jt}$ is found to reduce the unemployment rate in state j by 5.365%. Finally, and of greatest interest in terms of the objective of the present study, the unemployment rate in state j is found once again to be a decreasing function of the level of the overall economic freedom index in the state. In the case of this variable, the finding is that a 1% increase in the value of the economic freedom index in state j would be expected to *reduce* the unemployment rate in the state by 3.697%.

3. Dynamic Panel Data Estimates

In this section of the study, dynamic panel data estimates of the model are provided. In particular, we explore the impact of economic freedom (and the other specified factors) on the unemployment rate in state j , $UNEMPRATE_{jt}$, using Generalized Method of Moment/Dynamic Panel Data Estimations, i.e., the Panel GMM EGLS (cross-section weights) method. This econometric framework is adopted so as to address issues related to potential endogeneity of the explanatory variables in the model (Anderson and Hsiao, 1981; Arellano and Bond, 1991; Blundell and Bond, 1998). The Effects Specification is Cross-section Fixed (dummy variables). In all estimates, the standard errors are white corrected.

The Panel GMM EGLS (cross-section weights) estimation of the model in linear form is provided in column (a) of Table 5. As shown, the estimated coefficients on all five of the explanatory variables exhibit the hypothesized signs, with four once again being statistically significant at the 1% level; only the coefficient on the $FLFPR_{jt}$ variable fails to be statistically significant at the 10% level. Qualitatively, with the exception of variable $FLFPR_{jt}$, these results parallel those presented in the three cross-section fixed-effects estimates found in Table 4. Thus, the dynamic panel data estimation results in column (a) of Table 4 can be interpreted as implying that the unemployment rate in state j is an increasing function of the percentage of the population in the state that is Black ($BLACK_{jt}$) and the percentage of the population in the state that is Hispanic/Latin ($HISP_{jt}$). Furthermore, the unemployment rate in state j can be interpreted as being a decreasing function of the female labor force participation rate in state j ($FLFPR_{jt}$), the educational attainment variable ($HSPLUS_{jt}$), and the degree of economic freedom in state j ($ECONFREEDOM_{jt}$). Naturally, the lattermost result is of greatest interest since it is in effect the focal point variable of this study.

In column (b) of Table 5, the Panel GMM EGLS (cross-section weights) estimation of the model in *semi-log* form is provided. As in column (a) of Table 5, the estimation results are consistent (at the 1% statistical significance level) with the hypothesized negative relationship between the state-level unemployment rate on the one hand and the state-level measure of overall economic freedom on the other hand, ($ECONFREEDOM_{jt}$), as well as compatible with the hypothesized signs and significance levels on the control variables ($BLACK_{jt}$, $HISP_{jt}$, and $HSPLUS_{jt}$) over the study period. In particular, three of the five estimated coefficients shown in column (b) of Table 5 exhibit the expected signs and are statistically significant at the 1% level

while a fourth exhibits the expected sign and is statistically significant at the 2% level.² As in Table 4 and in column (a) of the present Table, then, evidence on behalf of a significant negative impact of economic freedom on the unemployment rate is obtained.

Table 6. Additional Dynamic Panel Estimation Results

Dependent Variable	<i>UNEMPRATE_{jt}</i>	<i>Log (UNEMPRATE_{jt})</i>	<i>Log (UNEMPRATE_{jt})</i>
Explanatory Var.	(a)	(b)	(c)
Constant	2,31	46,18	58,1
<i>ECONFREEDOM_{jt}</i>	-14.2*** (-10.26)	-2.79*** (-7.26)	
<i>BLACK_{jt}</i>	-0.831** (-2.05)	-0.141* (-1.94)	
<i>HISP_{jt}</i>	0.142* (1.69)	0.02 (1.20)	
<i>FLFPR_{jt}</i>	-0.579*** (-9.64)	-0.119*** (-6.23)	
<i>HSPLUS_{jt}</i>	0.112 (1.22)	0.025 (1.18)	
<i>UNION_{jt}</i>	-6.47** (-9.59)	-1.27*** (-6.82)	
<i>Log (ECONFREEDOM_{jt})</i>			-16.6*** (-4.86)
<i>Log (BLACK_{jt})</i>			0.256 (0.85)
<i>Log (HISP_{jt})</i>			0.663** (2.49)
<i>Log (FLFPR_{jt})</i>			-5.82*** (-2.96)
<i>Log (HSPLUS_{jt})</i>			-2.645 (-1.21)
<i>Log (UNION_{jt})</i>			-18.77*** (-5.33)

Note: Terms in parentheses are *t*-values. White cross-section corrected standard errors and *t*-values. ***Indicates statistically significant at 1% level; **indicates statistically significant at the 5% level, and *indicates statistically significant at the 10% level.

Finally, there is the Panel GMM EGLS (cross-section weights) *log-log* estimation in column (c) of Table 5. In this estimation, the unemployment rate in a state is an increasing

² The estimated coefficient on the *FLFPR_{jt}* variable is not statistically significant at the 10% level, as in column (a) of Table 5.

function of the percent of its population that is black and the percent of its population that is Hispanic/Latin, while being a decreasing function of the female labor force participation rate, the percent of the population age 25 and older with at least a high school diploma, and the index of economic freedom. Thus, there is further support for the hypothesis that greater economic freedom leads to a lower unemployment rate. Indeed, a 1% increase in economic freedom is found to exercise a 5.34% reduction in the unemployment rate. In principle, this persistent finding of the effect of economic freedom in the present study is compatible with the earlier studies by Bennett (2016), Feldman (2007), Garrett and Rhine (2011), Hall et al. (2013), Heller and Stephenson (2014), and Stansel (2013).

Table 6. Additional Dynamic Panel Estimation Results

Dependent Variable	<i>UNEMPRATE_{jt}</i>	<i>Log (UNEMPRATE_{jt})</i>	<i>Log (UNEMPRATE_{jt})</i>
Explanatory Var.	(a)	(b)	(c)
Constant	2,31	46,18	58,1
<i>ECONFREEDOM_{jt}</i>	-14.2*** (-10.26)	-2.79*** (-7.26)	
<i>BLACK_{jt}</i>	-0.831** (-2.05)	-0.141* (-1.94)	
<i>HISP_{jt}</i>	0.142* (1.69)	0.02 (1.20)	
<i>FLFPR_{jt}</i>	-0.579*** (-9.64)	-0.119*** (-6.23)	
<i>HSPLUS_{jt}</i>	0.112 (1.22)	0.025 (1.18)	
<i>UNION_{jt}</i>	-6.47** (-9.59)	-1.27*** (-6.82)	
<i>Log (ECONFREEDOM_{jt})</i>			-16.6*** (-4.86)
<i>Log (BLACK_{jt})</i>			0.256 (0.85)
<i>Log (HISP_{jt})</i>			0.663** (2.49)
<i>Log (FLFPR_{jt})</i>			-5.82*** (-2.96)
<i>Log (HSPLUS_{jt})</i>			-2.645 (-1.21)
<i>Log (UNION_{jt})</i>			-18.77*** (-5.33)

Note: Terms in parentheses are *t*-values. White cross-section corrected standard errors and *t*-values. ***Indicates statistically significant at 1% level; **indicates statistically significant at the 5% level, and *indicates statistically significant at the 10% level.

4. Concluding Observations

This study empirically investigates the hypothesis that the higher the degree of economic freedom in a state, the lower the unemployment rate in that state, *ceteris paribus*. This hypothesis is based on the principle that greater economic freedom leads to greater real economic growth, which in turn reduces the unemployment rate. The framework studied consists of a panel dataset for the 50 U.S. states representing the period 2000 to 2012, a period which includes the Great Recession, as well as years prior to and following the Great Recession. The model estimated in this study includes for each state, in addition to a measure/index of overall economic freedom, control variables for the percentage of the population that is black, the percentage of the population that is Hispanic/Latin, the female labor force participation rate, and the percent of the population (age 25 and older) with at least a high school diploma.

A number of state fixed-effects and dynamic panel data estimations are provided, all of which yield the finding that the greater the level of overall economic freedom, the lower the unemployment rate. Indeed, as a further illustration of the resiliency of the economic freedom variable, the model is expanded to include a potentially important additional *control* variable, namely, *UNION_{jt}*, the percent of the state population in state *j* in year *t* that is unionized. As shown in Table 6, the economic freedom variable is negative and highly statistically significant across estimations.

Arguably, as observed in Section 4, these results, which are in principle consistent with earlier studies, including those by Bennett (2016), Clark and Lawson (2008), and Stansel (2013), provide further evidence that societies that make a serious commitment to elevating economic freedom poise themselves to reap a variety of substantive benefits, including, in this case, lower unemployment rates. Clearly, the issue at hand is sufficiently important as to require further modeling, e.g., consideration of amenities (Deller, 2009) or entrepreneurship (Stough and Nijkamp, 2007), and empirical investigations using alternative data-sets.

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