Economic Freedom and Economic Growth Across U.S. States: A Spatial Panel Data Analysis

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Abstract

There is a substantial literature estimating the effect of economic freedom on economic growth. Most studies examine the relationship between freedom and growth for countries, while a few examine the relationship for U.S. states. Absent in the state–level literature is consideration of the presence of spatial spillovers affecting the freedom–growth relationship. Neglecting to account for spatial autocorrelation can bias estimation results and therefore inferences drawn. We find evidence of a spatial pattern in real per-capita GSP that affects non-spatial estimates of the freedom–growth relationship. Taking into account the direct and indirect effects of economic freedom on GSP, we find a 10 percent increase in economic freedom is associated with a 4.2 percent increase in GSP.

Keywords: spatial panel data model, spatial econometrics, economic freedom

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1 Introduction

The role that market-oriented institutions play in determining long-run economic growth has recently come to the forefront of the economics profession with the theoretical and empirical work of Acemoglu et al. (2005), which builds off the insights of economic historians such as North and Thomas (1970), North and Weingast (1989), and North (1990). In recent years the development of cross-country measures of institutions, such as the Economic Freedom of the World (EFW) index (Gwartney et al., 2015), has allowed scholars to analyze the relationship between institutions and growth using panel data methods over more recent and shorter time frames. Important early works in this literature include Easton and Walker (1997), Dawson (1998), Wu and Davis (1999), and Scully (2002), who largely find that economic freedom is positively associated with economic growth. The creation of the Economic Freedom of North America (EFNA) index (Stansel et al., 2014) has allowed scholars to test the economic freedom–growth relationship within the United States and these studies find similar results (Compton et al., 2011; Wiseman and Young, 2013).

A critical survey of the economic freedom–growth relationship by (De Haan et al., 2006, p.157) concluded that "there are strong indications that liberalization, i.e., an increase in the EF index, stimulates economic growth." Subsequent papers by Gwartney et al. (2006), Faria and Montesinos (2009), Williamson and Mathers (2011), and Rode and Coll (2012) also find a positive relationship between economic freedom and growth controlling for a diverse set of factors and over varying time periods and countries. Given the consistency of this subsequent literature, it is not surprising that a 2014 accounting of the entirety of the empirical literature citing the EFW by Hall and Lawson (2014) found only one paper suggesting that the EFW index is not robustly related to economic growth. The relationship between economic freedom and growth appears to be as strong as any empirical relationship given the wide variety of empirical specifications and approaches that have been used to test the hypothesis.

To this point, however, no scholars have accounted for spatial dependence in variables across countries or states when analyzing the economic freedom–growth relationship in a panel data setting. There are strong theoretical reasons based on Tiebout (1956) and yardstick competition (Brueckner and Saavedra, 2001) to think that economic policies are spatially related. Recent empirical work by Leeson and Dean (2009) and Leeson et al. (2012) shows that democracy and economic freedom spreads geographically across countries, i.e., that changes in a country's economic or political institutions "spill over" to nearby countries. Similarly, a number of papers using the EFNA as an explanatory variable find evidence of spatial dependence (Ashby, 2007; Hall and Sobel, 2008; Goetz and Rupasingha, 2009; Mulholland and Hernández-Julián, 2013) in cross-sectional analyses. Appropriately accounting for spatial dependence where it exists is important because the failure to do so can lead to incorrect conclusions, which is especially important for policy-relevant research (LeSage and Dominguez, 2012).

In this paper we make two contributions. The first is to the literature on economic freedom and economic growth. Ours is the first paper to deal with spatial dependence in the data by using spatial econometric techniques. We find evidence of spatial autocorrelation in real per-capita Gross State Product (GSP) across U.S. states. Failure to account for this spatial dependence means that non-spatial papers are providing incorrect estimates of the true marginal effects. Second, ours is the first paper in the burgeoning literature that uses the EFNA as an explanatory variable (Apergis et al., 2014; Heller and Stephenson, 2014; Cebula et al., 2015; Hoover et al., 2015; Hall et al., 2015) to employ spatial panel data econometric estimation techniques. In doing so we highlight how spatial panel models allow for the estimation of indirect or "spillover" effects of changes in explanatory variables. We find that after accounting for both the direct and indirect effects of state-level economic freedom on real per-capita GSP, a ten percent increase in economic freedom increases GSP by 4.2 percent.

Our paper proceeds as follows. As an excellent example of the recent literature, we follow Compton et al. (2011) in our choice of explanatory variables, including the use of the EFNA index as our measure of economic freedom.[1] After briefly describing the data, we describe spatial panel models. The following section presents our empirical results. We conclude with some thoughts on our results and the implications for the economic freedom-growth literature specifically and the economic freedom literature more generally.

2 Data and Econometric Approach

The model used in our estimations below mirrors that found in Compton et al. (2011), though ours includes state-level data from 1988 through 2013 and, because of the spatial techniques discussed below, omits data for Alaska and Hawaii. The dependent variable is the log of

[1]Compton et al. (2011) estimate both OLS and System GMM dynamic panel models, generally getting more significant results on the economic freedom variable in the OLS models. The overall economic freedom scores shows a significantly positive relationship with economic growth in their paper.

real per capita gross state product obtained from the Bureau of Economic Analysis (BEA)[2]. Independent variables obtained from the Census Bureau include education (percentage of the population 25 and older that graduated from college), percent black, and percent Hispanic. The percentage of the population living in metropolitan areas was obtained from the BEA Local Area CA1 Personal Income Summary table. Real per capita gross private domestic investment by state is the real (in 2009 dollars) national gross private domestic investment multiplied by the ratio of the state-to-national (nominal) personal income, divided by state population. The freedom index variable is the overall score at the state and local level (Table 3.4c in Stansel et al. (2014))[3]. Table 1 provides summary statistics for the data used.

A family of related spatial econometric models can be represented by the following[4]:

$$
\begin{aligned}
y_{it} &= \delta \sum_{j=1}^{N} w_{ij} y_{jt} + x_{it}\beta + \sum_{j=1}^{N} w_{ij} x_{ijt}\gamma + \mu_i + \lambda_t + u_{it} \\
u_{it} &= \rho \sum_{j=1}^{N} w_{ij} u_{it} + \varepsilon_{it}
\end{aligned}
\tag{1}
$$

where i is an index for the cross-sectional dimension (i.e. the spatial units, or states in the U.S.), with $i = 1 \ldots N$, and t is an index for the time dimension (i.e. the time periods), with $t = 1 \ldots T$. The dependent variable y_{it} is an observation on the dependent variable at i and t, x_{it} is a $(1 \times K)$ row vector of observations on the explanatory variables, and β is a matching $(K \times 1)$ vector of fixed but unknown parameters. The terms μ_i and λ_t represent space–and time–period fixed effects, respectively.

The additional terms in the above equation are what make the panel model a spatial econometric one. In particular, the model may contain a spatially lagged dependent variable or a spatial autoregressive process in the error term. In addition, there may be spatially weighted explanatory variables in the model. An important aspect of any spatial econometric model is the spatial arrangement of the units in the sample. In practice, this is accomplished by specifying a spatial weight matrix, W, The individual elements in the spatial weight matrix, w_{ij} , would equal "1" if observations i and j were "neighbors" (based on some metric) and "0" otherwise. Normally, a row stochastic weight matrix is used in a regression

[2]Since GSP is reported using SIC through 1997, and using NAICS from 1997 and later, we adjusted the earlier SIC values by multiplying them by the ratio of the 1997 values (1997 NAICS/1997 SIC). This follows Compton et al. (2011). Values are in 2009 dollars, adjusted using the GDP chain-type price index.

[3]Dataset at `http://www.freetheworld.com/`.

[4]Throughout this section we utilize the notation in Elhorst (2014b)

modeling context, which means that the rows of the spatial weight matrix sum to unity. This transformation of the spatial weight matrix provides for an intuitive explanation for the Wy and Wu terms. The Wy term can be thought of as a weighted average of the surrounding observations on the dependent variable, and Wu can be thought of as a weighted average of the surrounding error terms. Depending on the regression modeling context, both δ and ρ measure the extent of the spatial autocorrelation, in the dependent variable and the error term, respectively.

Given equation 1, special cases can be obtained by restricting parameters. For example, setting both $\rho = 0$ and $\gamma = 0$, we obtain a model that exhibits spatial dependence only in the dependent variable. This model is the spatial autoregressive (SAR) model which can be expressed mathematically as follows:

$$y_{it} = \delta \sum_{j=1}^{N} w_{ij} y_{jt} + x_{it}\beta + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

The spatial error model (SEM) arises when the restrictions $\delta = 0$ and $\gamma = 0$ are in effect, resulting in spatial dependence in the error term alone. The SEM model can be expressed mathematically as follows:

$$\begin{aligned} y_{it} &= \sum_{j=1}^{N} x_{it}\beta + \mu_i + \lambda_t + u_{it} \\ u_{it} &= \rho \sum_{j=1}^{N} w_{ij} u_{it} + \varepsilon_{it} \end{aligned} \tag{3}$$

Placing the restriction $\rho = 0$ results in the spatial Durbin model (SDM). The SDM allows for a spatially lagged dependent variable as well as spatially lagged independent variables. The spatially lagged independent variables are explanatory variables that are pre–multiplied by the spatial weight matrix and represent a weighted average of the surrounding values of the explanatory variables. In other words, the spatially weighted explanatory variables capture any spillover effects that may be present. The SDM model can be expressed as follows:

$$y_{it} = \delta \sum_{j=1}^{N} w_{ij} y_{jt} + x_{it}\beta + \sum_{j=1}^{N} w_{ij} x_{ijt}\gamma + \mu_i + \lambda_t + \varepsilon_{it} \tag{4}$$

The SAR model is used when one believes that there may be possible spatial autocorrelation in the dependent variable. It is important to note that the inclusion of the Wy term on the right hand side of the above equation introduces simultaneity bias and therefore the use of OLS as an estimation strategy will produce biased and inconsistent parameter estimates LeSage and Pace (2009). Therefore maximum likelihood estimation is used to estimate the parameters in the SAR model[5].

The SEM is utilized when one believes that there may be variables that are omitted from the model that are spatially correlated but that are uncorrelated with the included regressors. The conditions under which this spatial residual autocorrelation arises are nicely illustrated in a housing context by (Dubin, 1998, p. 304): "Housing prices are a prime example: clearly the location of the house will have an effect on its selling price. If the location of the house influences its price, then the possibility arises that nearby houses will be affected by the same location factors. Any error in measuring these factors will cause their error terms to be correlated." In the SEM, the OLS estimator is unbiased, but inefficient. SEM can also be efficiently estimated via maximum likelihood.

LeSage and Pace (2009) point out that SDM should be used when one believes that there are omitted variables in the model that are spatially correlated and these spatially correlated omitted variables are correlated with an included explanatory variable in the model. If these two conditions hold, the SDM is the most appropriate model. As indicated by equation 1 all three of these models may include space–and time–fixed effects; in our case we have state–and year–fixed effects. To determine whether such fixed effects are jointly significant, standard Likelihood Ratio (LR) tests can be performed. Further details regarding the estimation and use of spatial panel data models are contained in Elhorst (2014a).

3 Empirical Results

Many panel data models that examine the effect of economic freedom on growth (e.g., Compton et al. (2011)) include both state and year fixed effects. To determine if both types of

[5]Details regarding maximum likelihood estimation of spatial econometric models are contained in LeSage and Pace (2009).

these fixed effects should be included in our empirical specification, we conduct two likelihood ratio (LR) tests: one for the inclusion of state fixed effects and one for the inclusion of time (or in our case, year) fixed effects. The null hypothesis for the state fixed effects is $H_o : \mu_1, \mu_2, \ldots, \mu_n = 0$ and the results indicate that this null hypothesis should be rejected (LR: 2160.57, 48 df, p-value 0.0000). The null hypothesis for the year fixed effects is $H_o : \lambda_1, \lambda_2, \ldots, \lambda_t = 0$ and the results indicate that this hypothesis should also be rejected (LR: 513.55, 25 df, p-value 0.0000). Therefore, both state and year fixed effects are included in our models.

Another factor that must be considered is the type of spatial econometric model to utilize, i.e. should one use the SAR, SEM, or SDM model? Elhorst (2010) has proposed a testing procedure that 1) uses the spatial Durbin model as the point of departure and 2) builds on the earlier work of Florax et al. (2003). The first step in the procedure is to use the standard Lagrange Multiplier (LM) tests to determine if the SAR or SEM model is appropriate. The LM Lag test is a test to determine if there is any omitted spatial autocorrelation in the dependent variable, while the LM Error test is designed to detect any residual spatial error correlation. Both of these tests are one–way tests in that they only take into account the specific type of spatial dependence being tested. Additionally, each of these test statistics is distributed under the null hypothesis of no spatial autocorrelation χ^2 with one degree of freedom. The robust varieties of these tests (i.e. the LM Lag Robust and LM Error Robust tests) are designed to take into account the other type of spatial dependence: i.e. the LM Lag Robust test takes into account the possible presence of spatial dependence in the error term while the LM Error Robust test takes into account the possibility of spatial dependence in the dependent variable. A rubric for determining the proper spatial econometric model is contained in Florax et al. (2003).

Table 2 contains results from the various LM tests and shows that the null hypothesis of no spatial correlation in the dependent variable or the error term can be safely rejected. Elhorst (2010), who has developed a more complete testing procedure, at this point recommends that the spatial Durbin model be estimated and that the two following hypotheses be tested via a likelihood ratio (LR) test:

$$H_o : \theta = 0 \tag{5}$$

$$H_o : \theta + \delta\beta = 0 \tag{6}$$

The first null hypothesis is a test to determine if the spatial Durbin model can be reduced to the SAR model and the second hypothesis tests whether the spatial Durbin model can be reduced to the SEM model. Both the first null hypothesis (LR 49.57, p-value 0.0000) and the second null hypothesis (LR 38.66, p-value 0.0000) can be rejected at the 1% level of significance. In this instance, Elhorst (2010) recommends that the spatial Durbin model be estimated and the null hypothesis $H_o : \delta = 0$ be tested. The results of this test indicate that the null hypothesis is rejected at the 1% level of significance ($\delta = -0.27$, t–stat -5.10, p–value 0.0000) and we conclude from our testing procedure that the spatial Durbin panel model is the most appropritate model to use in the empirical analysis[6].

The results of the SDM model are contained in Table 3. The first noteworthy result is that the spatial autocorrelation parameter δ is negative, with a value of -0.27 and statistically significant at the 1% level. This indicates a modest, although highly statistically significant, amount of spatial autocorrelation in our dependent variable. These results indicate that a simple panel data model that did not take into account the spatial dependence would lead to incorrect inferences.

Regression models that contain a spatially–lagged y variable (i.e. a $\rho W y$ term) have coefficients estimates that are not directly interpretable. We can formally represent this by writing the spatial Durbin model in reduced form as follows

$$y = \delta W y + X\beta + WX\gamma + \varepsilon \quad (7)$$

$$y = (I_n - \delta W)^{-1} (X\beta + WX\gamma) + (I_n - \delta W)^{-1} \varepsilon \quad (8)$$

$$S(W) = {}^{\partial y}\!/_{\partial x_r} = (I_n - \delta W)^{-1} (\beta + W\gamma) \quad (9)$$

The multiplication of the $S(W)$ matrix by our coefficient estimates results in an $N \times N$ matrix of effects estimates, whereby the diagonal elements represent the direct plus feedback effects and the off–diagonal elements represent the indirect or spillover effects[7]. Mathematically, we can express each of these partial derivative effects as follows:

[6] According to LeSage and Pace (2009) the SDM model is the only model that produces unbiased coefficient estimates under three other spatial econometric data generating processes.

[7] Note that each explanatory variable will have an associated $N \times N$ matrix of effects estimates.

$$\text{Direct Effect: } \frac{\partial E\left(y_i\right)}{\partial x_i} = S(W)_{ii} \tag{10}$$

$$\text{Indirect Effect: } \frac{\partial E\left(y_i\right)}{\partial x_j} = S(W)_{ij} \tag{11}$$

The direct plus feedback effect is the marginal effect of a change in an independent variable at location i and how it affects the dependent variable at location i, while the indirect effect is how a change in an independent variable at location j affects the dependent variable at location i, where $i \neq j$.

Given the potentially large numbers of observations that can be analyzed, LeSage and Pace (2009) recommend several scalar summary measures of the direct and indirect effects.[8] The average direct effect is taken to be the average of the main diagonal of the $S\left(W\right)$ matrix, while the average total effects are the average of the row sums of the $S\left(W\right)$ matrix. The average indirect effects are the difference between the average total effects and the average direct effects.

The effects estimates calculated from a model that contains a spatially–lagged y variable provides a much richer set of results that can be analyzed compared to a non–spatial panel data model, which by assumption does not include any spillover effects as a consequence of the independence of observations assumption. Another advantage of using the SDM model is that the effects estimates are not constrained to have the same sign, which is not the case for the SAR model (Elhorst, 2010).

Table 3 contains the direct, indirect (or spillover), and total effects from the SDM panel data model. We first note that all of the explanatory variables have been transformed by taking logs, which facilitates the interpretation of the effects estimates as elasticities. We also note that we utilized a five–nearest–neighbor spatial weight matrix W in our empirical analysis as the average number of contiguous neighbors for U.S. states is five.

The top portion of Table 3 contains the direct effects, which measure how much the dependent variable changes in a state when a particular explanatory variable changes in that same state. The first thing to note that out of the six included explanatory variables, four of them are significant at the 1% level (i.e. investment, freedom, black, metro), one is significant at the 5% level (i.e. education), and one is not statistically significant, i.e. Hispanic. Our main variable of interest is the freedom variable, which measure the level of

[8]For example, in a county–level data setting, the $S\left(W\right)$ matrix would consist of a 3061×3061 matrix of effects.

economic freedom in each state. The results indicate that as the economic freedom index increases by 10%, GSP increases by 3.01%, which is fairly substantial. Our results lend additional credence to the idea that improvements in economic freedom are associated with increases in GSP. To put these changes in perspective, a ten percent increase in a state's economic freedom score would be like Oregon's economic freedom (6.6) increasing to that of Tennessee (7.2). While under a standard deviation in economic freedom, the corresponding increase in real per-capita GSP calculated at the mean is approximately $1200, or under 15% of a standard deviation.

While seemingly small, it is important to note that these are just the direct effects of an increase in economic freedom. Since economic freedom spills over to nearby states (likely because of yardstick or Tiebout competition), it is important to account for how an increase in one state's economic freedom affects neighboring states' real per-capita GSP. As mentioned earlier, one of the features of the spatial Durbin panel model is its ability to empirically estimate the indirect or spillover effects of changes in explanatory variables. Essentially. these spillover effects measure how changes in our explanatory variables affect the dependent variable (real per-capita GSP) of surrounding states. The middle portion of Table 3 shows the indirect or spillover effects of changes in our explanatory variables. It is important to note that the scalar summary used to calculate the indirect effects summarizes spillovers over all states in the sample. Thus the spillover falling on any one state is much smaller than the total indirect effect. From a viewpoint within a state, these spillover effects might not be directly relevant. From a macro perspective, however, the fact that increases in economic freedom in Oregon directly increase economic growth in Oregon *and* indirectly in other states is important.

Of the six included explanatory variables, four are statistically significant: investment and % black population are significant at the 1% level, and freedom and % Hispanic population are significant at the 5% level. Again, our main variable of interest is the economic freedom index and the results indicate that as the economic freedom in a particular state increases by 10%, real per–capita GSP in *surrounding* states increases by 1.2%, on average. This is an important result for two reasons. First, this is the first study to use spatial panel data methods to estimate the relationship between economic freedom and GSP that correctly calculates the proper marginal effects of explanatory variables on growth. Second, we show that there are positive spillovers in economic freedom. That is, a state increasing economic freedom will not only affect real per capita GSP in the home state, but the effect of that increase will ripple across neighboring states. *Papers that utilize the state-level economic* *freedom index as an explanatory variable and do not control for spatial dependence are likely understating the true effect of economic freedom on the dependent variable.*

Finally, the bottom portion of Table 3 show the point estimates for the total effects, which are defined as the sum of the direct and indirect effects. The total effects are all statistically significant at the 1% level, with the exception of the education variable, which is significant at the 5% level. The total effect on the freedom variable has a point estimate of 0.42 which indicates that a 10% increase in the economic freedom index in the own and surrounding states increases GSP by 4.2%. Calculated at the mean real per-capita GSP, this means that a state like Oregon becoming as economically free as Tennessee would see $1706 in additional GSP per capita. Failure to account for the indirect effects of economic freedom on growth, even if spatial dependence were controlled for, would underestimate the total effect of increases in economic freedom of real per-capita GSP by approximately $500.

4 Conclusion

The purpose of this paper is to contribute to the literature on the economic freedom–growth relationship and the literature using state-level economic freedom as an explanatory variable. We do so by detecting the presence and estimating the magnitude of spatial effects in a common empirical model of freedom and growth. A number of spatial specification tests were conducted and the prevailing specification is the spatial Durbin model, which allows for spatial dependence in the dependent variable as well as allowing for the empirical estimation of spillover effects.

The empirical results from the spatial Durbin panel model are important for at least three reasons. First, we find evidence of a modest, although highly statistical significant level, of spatial autocorrelation which indicates that there is a spatial pattern in real per–capita GSP. Second, we find empirical evidence that as the economic freedom in a state increases, there is an increase in real per–capita GSP. Combined with the pre-existing literature on the economic freedom–growth relationship, there should be little doubt about the positive association between overall economic freedom and growth. As pointed out by Compton et al. (2011) and others, however, this might not be true of all components of economic freedom. Further attempts to look closer at how economic freedom contributes to growth should utilize spatial econometric approaches where possible in order to properly obtain the marginal effects of individual components. In addition, when the Durbin model is the appropriate model, the indirect effects should highlight important spillovers across states related to individual policies that are components of economic freedom. For example, state and local jurisdictions clearly mimic each other in tax policy (Hall and Ross, 2010; Duncan and Gerrish, 2014).

Third, for the growing number of papers using the EFNA as an explanatory variable, such as the large number of papers studying entrepreneurship (Hall and Sobel, 2008; Goetz and Rupasingha, 2009; Gohmann et al., 2008; Gohmann, 2012), it is important to note the ability to identify and measure the spillover effects of changes in explanatory variables. One of the hallmarks of spatial econometric panel data models is that they can empirically estimate these indirect effects. These spillover effects measure how changes in an explanatory variable in one state affects the dependent variable in surrounding states. Our empirical results indicate that as economic freedom in one state increases, there is an increase in the real per–capita GSP in surrounding states. For papers in the broader economic freedom literature, this suggests that increases in economic freedom could indirectly effect entrepreneurship, housing prices (Campbell et al., 2008), income inequality (Ashby and Sobel, 2008), or any number of other variables. Economists and policymakers should appropriately estimate these spillovers and account for them in policy proposals.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Real Per–Capita GSP	40627.35	8906.88	21772.36	69897
Education	0.24	0.05	0.12	0.39
Investment	6640.17	1716.95	3168.49	12587.59
Freedom	6.57	0.76	4.09	8.3
Black	0.1	0.1	0	0.37
Hispanic	0.08	0.09	0	0.47
Metro	0.74	0.19	0.29	1

Table 2: Lagrange Multiplier Test Results

LM Test	LM Test Value	p–value
LM Lag	3.9913	0.0457
LM Error	11.9729	0.0005
LM Lag Robust	0.2171	0.6413
LM Error Robust	8.1987	0.0042

Table 3: Spatial Durbin Panel Model Results

Direct	Coefficient	t-stat	p–value
Education	0.127569	2.613939	0.011921**
Investment	0.670240	20.996196	0.000000***
Freedom	0.301430	11.753020	0.000000***
Black	0.030403	3.019623	0.004046***
Hispanic	-0.009219	-1.397000	0.168839
Metro	0.775383	9.685133	0.000000***
Indirect	Coefficient	t-stat	p–value
Education	0.100372	1.024705	0.310639
Investment	-0.177150	-3.269141	0.001999***
Freedom	0.117765	2.475664	0.016879**
Black	0.049500	3.124965	0.003015***
Hispanic	-0.031321	-2.449736	0.017995**
Metro	-0.029847	-0.254231	0.800403
Total	Coefficient	t-stat	p–value
Education	0.227940	2.213172	0.031674**
Investment	0.493090	9.674570	0.000000***
Freedom	0.419195	8.811886	0.000000***
Black	0.079903	5.591613	0.000001***
Hispanic	-0.040541	-3.006138	0.004200***
Metro	0.745536	7.200112	0.000000***
Spatial Autocorrelation δ	-0.27	-5.103893	0.000000***
R^2	0.9783		
Observations	1200		

*** significant at the 1% level ** significant at the 5% level * significant at the 10% level

References

Acemoglu, D., Johnson, S., and Robinson, J. A. (2005). Institutions as a fundamental cause of long-run growth. *Handbook of Economic Growth*, 1:385–472.

Apergis, N., Dincer, O., and Payne, J. E. (2014). Economic freedom and income inequality revisited: Evidence from a panel error correction model. *Contemporary Economic Policy*, 32(1):67–75.

Ashby, N. J. (2007). Economic freedom and migration flows between us states. *Southern Economic Journal*, pages 677–697.

Ashby, N. J. and Sobel, R. S. (2008). Income inequality and economic freedom in the us states. *Public Choice*, 134(3-4):329–346.

Brueckner, J. K. and Saavedra, L. A. (2001). Do local governments engage in strategic propertytax competition? *National Tax Journal*, pages 203–229.

Campbell, N. D., Jauregui, A., and Heriot, K. C. (2008). Housing prices and economic freedom. *Journal of Private Enterprise*, 23(2):1.

Cebula, R. J., Foley, M., and Hall, J. C. (2015). Freedom and gross in-migration: an empirical study of the post-great recession experience. *Journal of Economics and Finance*, pages 1–19.

Compton, R. A., Giedeman, D. C., and Hoover, G. A. (2011). Panel evidence on economic freedom and growth in the united states. *European Journal of Political Economy*, 27(3):423–435.

Dawson, J. W. (1998). Institutions, investment, and growth: New cross-country and panel data evidence. *Economic Inquiry*, 36:603–619.

De Haan, J., Lundström, S., and Sturm, J.-E. (2006). Market-oriented institutions and policies and economic growth: A critical survey. *Journal of Economic Surveys*, 20(2):157–191.

Dubin, R. A. (1998). Spatial autocorrelation: a primer. *Journal of housing economics*, 7(4):304–327.

Duncan, D. and Gerrish, E. (2014). Personal income tax mimicry: evidence from international panel data. *International Tax and Public Finance*, 21(1):119–152.

Easton, S. T. and Walker, M. A. (1997). Income, growth, and economic freedom. *American Economic Review*, 87(2):328–332.

Elhorst, J. P. (2010). Applied spatial econometrics: raising the bar. *Spatial Economic Analysis*, 5(1):9–28.

Elhorst, J. P. (2014a). *Spatial econometrics: from cross-sectional data to spatial panels*. Springer.

Elhorst, J. P. (2014b). Spatial panel data models. In *Spatial Econometrics*, pages 37–93. Springer.

Faria, H. J. and Montesinos, H. M. (2009). Does economic freedom cause prosperity? an iv approach. *Public Choice*, 141(1-2):103–127.

Florax, R. J., Folmer, H., and Rey, S. J. (2003). Specification searches in spatial econometrics: the relevance of hendrys methodology. *Regional Science and Urban Economics*, 33(5):557–579.

Goetz, S. J. and Rupasingha, A. (2009). Determinants of growth in non-farm proprietor densities in the US, 1990–2000. *Small Business Economics*, 32(4):425–438.

Gohmann, S. F. (2012). Institutions, latent entrepreneurship, and self-employment: An international comparison. *Entrepreneurship Theory and Practice*, 36(2):295–321.

Gohmann, S. F., Hobbs, B. K., and McCrickard, M. (2008). Economic freedom and service industry growth in the united states. *Entrepreneurship Theory and Practice*, 32(5):855–874.

Gwartney, J., Lawson, R., and Hall, J. (2015). *Economic Freedom of the World: 2015 Annual Report*. Fraser Institute, Vancouver.

Gwartney, J. D., Holcombe, R. G., and Lawson, R. A. (2006). Institutions and the impact of investment on growth. *Kyklos*, 59(2):255–273.

Hall, J., Harger, K., and Stansel, D. (2015). Economic freedom and recidivism: Evidence from US states. *International Advances in Economic Research*, 21(2):155–165.

Hall, J. C. and Lawson, R. A. (2014). Economic freedom of the world: An accounting of the literature. *Contemporary Economic Policy*, 32(1):1–19.

Hall, J. C. and Ross, J. M. (2010). Tiebout competition, yardstick competition, and tax instrument choice: Evidence from ohio school districts. *Public Finance Review*, 38(6):710–737.

Hall, J. C. and Sobel, R. S. (2008). Institutions, entrepreneurship, and regional differences in economic growth. *American Journal of Entrepreneurship*, 1(1):69–96.

Heller, L. R. and Stephenson, E. (2014). Economic freedom and labor market conditions: Evidence from the states. *Contemporary Economic Policy*, 32(1):56–66.

Hoover, G. A., Compton, R. A., Giedeman, D. C., et al. (2015). The impact of economic freedom on the black/white income gap. *American Economic Review*, 105(5):587–92.

Leeson, P. T. and Dean, A. M. (2009). The democratic domino theory: An empirical investigation. *American Journal of Political Science*, 53(3):533–551.

Leeson, P. T., Sobel, R. S., and Dean, A. M. (2012). Comparing the spread of capitalism and democracy. *Economics Letters*, 114(1):139–141.

LeSage, J. and Pace, R. K. (2009). *Introduction to spatial econometrics*. CRC Press, Boca Raton.

LeSage, J. P. and Dominguez, M. (2012). The importance of modeling spatial spillovers in public choice analysis. *Public Choice*, 150(3-4):525–545.

Mulholland, S. E. and Hernández-Julián, R. (2013). Does economic freedom lead to selective migration by education. *Journal of Regional Analysis & Policy*, 43(1):65–87.

North, D. C. (1990). *Institutions, institutional change and economic performance*. Cambridge University Press.

North, D. C. and Thomas, R. P. (1970). An economic theory of the growth of the western world. *Economic History Review*, 23(1):1–17.

North, D. C. and Weingast, B. R. (1989). Constitutions and commitment: the evolution of institutions governing public choice in seventeenth-century england. *Journal of Economic History*, 49(4):803–832.

Rode, M. and Coll, S. (2012). Economic freedom and growth: Which policies matter the most? *Constitutional Political Economy*, 23(2):95–133.

Scully, G. W. (2002). Economic freedom, government policy and the trade-off between equity and economic growth. *Public Choice*, 113(1-2):77–96.

Stansel, D., Torra, J., and McMahon, F. (2014). *Economic Freedom of North America 2014*. Fraser Institute, Vancouver.

Tiebout, C. M. (1956). A pure theory of local expenditures. *Journal of Political Economy*, 64(5):416–424.

Williamson, C. R. and Mathers, R. L. (2011). Economic freedom, culture, and growth. *Public Choice*, 148(3-4):313–335.

Wiseman, T. and Young, A. T. (2013). Economic freedom, entrepreneurship, & income levels: Some us state-level empirics. *American Journal of Entrepreneurship*, (1):104–124.

Wu, W. and Davis, O. A. (1999). The two freedoms, economic growth and development: An empirical study. *Public Choice*, 100(1-2):39–64.