Temporal and Spatial Effects of State Taxes on Economic Growth[1]

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Abstract

In this paper we estimate the relationship between the economic growth of states and taxes, modeling both the effects of states own taxes on growth over time and the fiscal spillover effects of taxes in neighboring states on their economic growth. Our research goes beyond the usual temporal tax-growth analysis in the literature to incorporate spatial spillovers. Using annual data for the states over the period 1999-2013 our estimation strategy divides the data into five-year periods to analyze the effect of both differences and levels of state taxes on state gross state product (GSP) growth. We specify a state production function for output and derive estimating equations that are empirically estimable. Our analysis includes consideration of each of the major state tax revenue sources: income (both personal and corporate), property, and sales taxes. While some previous studies have found strong inverse relationships between state taxes and economic growth, our results indicate that the temporal tax-growth relationship is sensitive to model specification and the time period of analysis. We extend the model to include spatial spillover effects using a spatial Durbin model in order to determine how neighboring states taxes may affect a states economic growth. Our results indicate that negative spillover effects are present in some cases, which we analyze for policy implications.

1. Introduction

The effect of taxes on economic growth has been the subject of many researchers. Empirical studies report mixed findings on whether state taxes are correlated with measures of state economic growth. Most of these studies – but not all – find evidence of a negative effect of taxes on various measures of state economic performance. The academic literature on taxes and growth also features a wide variety of methodologies and results. The effects of different types of taxes, whether they be

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[1]This draft paper has been prepared for presentation at the 110th Annual Conference on Taxation of the National Tax Association, Philadelphia, November 9-11, 2017.

income, corporate, or sales taxes, vary widely within and across research depending on model specification and estimation strategy. Spatial econometrics is a relatively new technique that is being applied to this area of research as well.

It is not just the results of these studies that differ. Policy makers have strong opinions on whether tax cuts encourage economic growth. This topic is the subject of debate in the press, between political candidates, and among advocacy groups. This is mostly due to the competing literature about what drives economic growth. Depending on the researcher's philosophical bent, the complexity of the economy creates an easy way for a theory to gain traction and find validation in the vast amounts of data. This is extended to dynamic scoring where tax cuts may be found to "pay for themselves" at least partially.

Growth literature also recognizes the impact of neighboring countries and states on one's own growth. With labor and capital being more mobile than ever, it would be erroneous to assume that an economy exists in isolation and not consider spill-over effects, in this case fiscal spillovers.

Due to the large number of specifications in the literature, we first chose to build on an existing model. Reed (2008) regresses state-level data on the percent change in real per capita personal income between five-year intervals. Reed models state growth using and extensive set of controls first established in Reed (2009). We essentially replicate and extend Reed's model using data from 1999 to 2013. We then incorporate spatial modeling to capture spatial effects. We also disaggregate the overall tax burden to identify which taxes have the most impact on growth. In this way, we can compare the results while using the same underlying data and model.

As in previous literature, we find that the relationship between taxes and economic growth is not stable and varies depending on model specification. This result extends to the spatial analysis; results are fragile and dependent upon model specification.

2. Review of the Literature

As previously noted, the literature on growth and taxation is broad. We present a review of the most relevant literature to this project below, but a comprehensive review of the literature can be found in Wasylenko (1999), Mazerov (2013), and McBride (2012). Abreu et al. (2004) and Döring and Schnellenbach (2006) provide a solid review of the spatial literature on growth. The work we review here consists of the most relevant work but is not, by far, an exhaustive list.

Non-spatial econometric strategies range from static panel estimators (fixed effects) on annual data, the use of longer-run cross-sectional data using OLS or Error

correction (EC) models, to using pooled mean group (PMG) strategies to look at both long-run and short-run economic growth. Ojede and Yamarik (2012) use a PMG to empirically test the effects of tax policy on state-level economic growth and find that property taxes lowered both short-run and long-run economic growth, sales taxes lowered long-run growth, and income taxes have no short-run or long-run impact. Reed (2008) and Gale et al. (2015) use panel data to estimate changes in tax revenues on growth by using a five-year differences model. Reed finds strong, negative, and robust effects of state taxes on growth using a regression of state-level data on the change in the log of real per capita personal income between five-year periods on the change in overall tax burden. Reed incorporates an extensive set of controls first established in Reed (2009). Later work by Gale et al. (2015) find that extending Reed's model by several time periods causes the coefficients on tax burden to become smaller and insignificant. They suggest that the sensitivity of the results raises the possibility that the coefficient estimates are not stable over time. They find that the effect of tax revenues on personal income growth changed dramatically between periods (sometimes even switching signs).

Spatial effects have been previously examined without the use of modern spatial econometric techniques. Reed and Rogers (2004) examine the effects of a 30 percent reduction in personal income taxes in New Jersey between 1994 to 1996. They find that the overall effect of the tax cut in New Jersey was small and not significant relative to neighbors. Goff et al. (2012) use a matching system that uses pairs of states based on their location to examine the effects of tax revenues on per capita GSP. They find that a one percentage point increase in the state tax burden reduces GSP per capita growth rates by 0.19 percentage points. However, these results are not robust to different specifications. Ljungqvist and Smolyansky (2014) analyze bordering states and what happens when one state changes a corporate tax rate. They report that increases in statutory corporate tax rates reduce employment and wages. However, this effect does not work in the opposite direction. Reductions in statutory corporate tax rates do not increase employment and wages, (with the exception of during recessions).

Spatial econometric techniques have also been used throughout the regional econometrics literature. Unfortunately, most of these papers use one period (cross-sectional) spatial dependence models. Only recently have spatial econometric techniques been extended to panel data, and even fewer studies incorporate fiscal policy (in the form of taxation). Garrett et al. (2005) use a first-differenced model and find that increasing the tax revenue share of personal income decreases state growth rates, consistent across different spatial models. One advantage of their approach is that they allow for regional variation in spatial correlations. Kopczewska et al. (2017) show that

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taxes on labor and capital have a negative impact on GDP growth in a study of European countries in 2002-2011. Using a first-differenced model with dynamic spatial estimation, Segura (2017) shows contradictory effects of an increase in state taxation on growth, depending on the spatial specification. Atems (2015) extends the work of Ojede and Yamarik (2012) by incorporating a dynamic spatial Durbin model that shows a 0.37% decrease in growth from own-state and 0.94% spatial spillover effect for every 1% increase in state and local taxes.

The model specification derived in this paper complements Reed (2008). We use this well-known specification to add spatial spillover effects from neighboring states. In this way, we can compare and extend the results while using the same underlying data and model.

3. Methodology

3.1. Specification

Starting with a general version of a Cobb-Douglas production function, we assume that state GDP (Y_t) is determined by the following:

$$Y_t = A_t K_t^\alpha (L_t Q_t)^\beta \tag{1}$$

where K_t is capital, L_t is employment, Q_t is the efficiency of labor, and A_t represents other factors that would also affect state production.

Converting to per capita terms, we divide both sides by population size and manipulate the equation to get the form

$$\frac{Y_t}{N_t} = A_t \left(\frac{K_t}{N_t} \right)^\alpha \left(\frac{L_t}{N_t} \right)^\beta Q_t^\beta N_t^{(\alpha+\beta-1)} \tag{2}$$

Taking logs and differences yields:

$$\begin{aligned}
ln(y_t) - ln(y_L) = &\alpha[ln(k_t) - ln(k_L)] + \beta[ln(\ell_t) - ln(\ell_L)] \\
&+ (\alpha + \beta - 1)[ln(N_t) - ln(N_L)] \\
&+ [ln(A_t) - ln(A_L) + \beta[ln(Q_t) - ln(Q_L)]]
\end{aligned} \tag{3}$$

where $y_t = Y_t/N_t, k_t = K_t/N_t$, and $\ell_t = L_t/N_t$.

We incorporate the Reed (2008) estimation technique where L is equal to 4 years. According to Reed, using five-year interval data alleviates issues with minimizing errors from mis-specifying lag effects and reduces measurement error that may be present in the data that draws from different times of the year from multiple sources. The periods are non-overlapping (1999-2003, 2004-2008, and 2009-2013).

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Equation (3) can also be re-written as

$$\Delta lny_t = \alpha \Delta lnk_t + \beta \Delta ln\ell_t + (\alpha + \beta - 1)\Delta lnn_t + F_t \tag{4}$$

where $F_t = [ln(A_t) - ln(A_L) + \beta[ln(Q_t) - ln(Q_L)]$, and represents variables that are factors that affect the growth rate of productivity. Δ represents the change in a variable between periods $t - L$ and t. Since the variables A and Q are not observable, we replace them with a function of observables, $g(X, T)$.

The general specification of the model becomes

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\begin{aligned}
\Delta lny_{it} = {} & \beta_0 + \beta_1 \Delta lnk_{it} + \beta_2 \Delta ln\ell_{it} + \beta_3 \Delta lnn_{it} \\
& + \delta(\Delta T_{it}) + \lambda T_{i,t-L} \\
& + \gamma(\Delta X_{it}) + \kappa X_{i,t-L} \\
& + state_i + time_t + \epsilon_{it}
\end{aligned} \tag{5}
$$

where t$= 2003, 2008, 2013$ in the case of the five-year model, lny_{it} is the log of real GSP per capita, lnk_{it} is the log of real capital stock per capita, and $ln\ell_{it}$ is the log of employment, and lnn_{it} is the log of population. There are many variables that can serve as proxies for F_t. The variables ΔT_{it} and ΔX_{it} represent changes in taxes (T) and other explanatory variables (X) over the differenced period. The variables $T_{i,t-L}$ and $X_{i,t-L}$ are the initial levels of taxes and other explanatory variables for the period. These components that make up F_t can enter as both differenced and level variables. This makes sense intuitively because a factor of production is influenced by the initial level and persistent effects over time (particularly in the case of things like education or tax rates). As our measure of taxes, we use total tax burden, defined as the ratio of state and local tax revenues to GSP. This can be thought of as the "effective average tax rate." A decomposed tax burden, consisting of property, sales, personal income, and corporate income taxes are constructed in the same fashion.

3.2. Specification with Spatial Effects

The specification outlined in equation (5) works only if an economy exists in isolation. It ignores the influence of spillover effects to neighboring economies, which could be in the form of technological transfers, knowledge diffusion, or the accumulation of mobile factors. A simple plot of the 5-year differences in state growth rates shows that different regions grow or shrink together (see Figure 1). Moran's I test is used to detect spatial clusters in local dimensions:

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \tag{6}$$

Under the null hypothesis of no global spatial autocorrelation, the expected value of I is:

$$E(I) = -\frac{1}{N-1}$$

where $I > E(I)$ indicates positive spatial autocorrelation (similar regions exhibit similar values of X) or $I < E(I)$ indicates negative spatial autocorrelation (similar regions have dissimilar values of X). The results of the Moran's I test confirm global spatial correlation, with the results for all variables found in Table 6 in the appendix. With this in mind, we use the general-to-specific approach of LeSage and Pace (2009) for the rule of estimation. This allows for selection of spatial and panel components first, followed by variables selection. Estimation from specific to general (as advocated by Anselin (1988) and Elhorst (2010)) may create an environment where some variables may gain or loose significance under different specifications (Kopczewska et al., 2017). We start with a spatial Durbin model and incorporate the three components of spatial spillovers: the spatial lag of the dependent variables ($\rho W y$), a set of spatial lags of explanatory values ($\theta W X$), and the spatially autocorrelated error them ($\lambda W u$). By later imposing restrictions on the parameters and then using a test, we can determine the final spatial specification. We utilize the bias corrected maximum likelihood approach described by Yu et al. (2008).[2]

Equation (5) can also be re-written as a full spatial model:

$$\Delta ln y_{it} = \rho W \Delta ln y_{jt} + \sum_{k=1}^{K} \beta X_{kit} + \sum_{k=1}^{K} \theta W X_{kit} + \delta_t + \psi_i + u_{it}$$

$$u_{it} = \lambda W u_{it} + \epsilon_{it}$$

(7)

where X includes all of the explanatory variables from the right-hand side of equation 5, δ are time effects, ψ are spatial effects, and W is an n x n row-stochastic spatial weight matrix.

To select a spatial model for the empirical estimation, we begin by estimating the spatial Durbin model (SDM). Using equation (7) without the error component, we test whether the model is actually a spatial autoregressive model (SAR) using the testing hypothesis $H_o : \theta = 0$. To test whether the SDM can be reduced to a spatial error model (SEM), we test the hypothesis $H_o : \theta = -\rho\beta$.[3] If both hypotheses are rejected, it can be assumed that the SDM is the best fit model. The results of these tests can be found in Table 8. We also test for spatial correlation in the error term.

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[2]This work is translated into Stata code by Belotti et al. (2016).

[3]See LeSage and Pace (2009) for an exposition.

Since the spatial autocorrelation model (SAC) and SDM are non-nested models, we use information criteria to test the two models. For the spatial ρ parameter in the final model, a positive value indicates clustering of similar states and common reactions. A negative value corresponds with competition between states – the so-called "backwash" effect – where there is an outflow of resources from one state to another (Kao and Bera, 2013).

$$
\mathbf{W} = \begin{bmatrix}
0 & \omega_i(d_{12}) & \ldots & \omega_i(d_{1N}) \\
\omega_i(d_{21}) & 0 & \ldots & \omega_i(d_{2N}) \\
\vdots & \vdots & 0 & \vdots \\
\omega_i(d_{N1}) & \omega_i(d_{N2}) & \ldots & 0
\end{bmatrix} \tag{8}
$$

The ω is the specific weight given a distance parameter, d_{ij}. In the above specification, ρ represents the spatial autoregressive parameter and σ is the spatially lagged independent variables parameter.

We compare two types of distance measures, d_{ij}: contiguity and a physical distance measure. In all cases of the given $\mathbf{W}$, the weight-matrix is row-normalized. For the first measure, only bordering states are assumed to have any influence on a neighbor's growth, and each bordering state has the same amount of influence. The second measure is an inverse distance weight. This is found using population centroids from the 2010 Decennial Census (U.S. Census Bureau, 2010). By using the inverse, those states closest to the centroid have higher weights that decay with distance. In this case, every other state has an effect on a state's growth, no matter how far away it is. The decay parameter is one: $d_{it} = 1/miles$. A summary of the spatial weight matrices can be found in the appendix in Table 7.

4. Data

The model is estimated using data for the 48 contiguous U.S. states over the 1999-2013 period. Table 4 in the appendix lists the variable names, description, and sources. Summary statistics are listed in Table 5.

4.1. Dependent Variable

The dependent variable is the change in the natural log of real gross state output per capita from $t-L$ to t for each state where L is the 4-year difference. This variable is calculated starting with data on real GDP by state from the Bureau of Economic Analysis's Regional Database and divided by the respective state's population in the relevant year.

4.2. Explanatory Variables

The tax variables are the primary explanatory variables of interest. Following Reed (2008) and Gale et al. (2015), our tax variables are the total state and local tax revenue in a given state and year as a share of GSP. As a starting point, we first examine total tax burden and then incorporate decomposed tax revenue – namely property, sales, individual income, and corporate income taxes.[4][5]

One difficult part of modeling state-level growth is the lack of data on state-level capital stock. The Bureau of Economic Analysis (2015) only provides capital stock estimates for the nation. Garofalo and Yamarik (2002) develop a method to estimate state capital stock by apportioning total capital stock using

$$k_{i,j,t} = \left[\frac{y_{i,j,t}}{Y_{i,t}} \right] K_{i,t} \tag{9}$$

$$k_{j,t} = \sum_{i=1}^{19} k_{i,j,t} \tag{10}$$

where i represents the nineteen different one-digit private NAICS industries, j represents the state, and t is the time script. Lower case levels refer to amounts for the state and uppercase levels refer to the BEA totals for industry. We use the identical procedure to calculate state-level capital stock for 1999-2013. These estimates apportion the capital stock based on state GSP.

Other control variables are replicated as in Reed (2008).[6] These are used as a benchmark for comparison across model specifications. These include population, educational attainment, percentage of the population that is female, that is white, and that is of working age, union membership, and industrial diversity (see below). They also include the proportions of GSP devoted to agriculture and mining, as well as the initial level of a state's own GSP. The descriptions and data sources for these variables can be found in Tables 4 and 5 in the appendix.

We construct a measure of industrial diversity to include in the model with an

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[4]Local data are not available for 2001 and 2003, so the averages of the preceding and following years was used.

[5]These series are collected from the State & Local Government Finance data collected by the US Census. Property tax, individual income taxes and corporate taxes are taken from the T01, T40, and T41 series respectively, while the sales tax includes sales and gross receipts (T09, T10, T11, T12, T13, T14, T15, T16, and T19).

[6] These variables are described in Table 3, column 2 (best SIC specification) of Reed (2008).

index based on the 19 private NAICS industries using the following:

$$Diversity_i = \sum_j \left(\frac{GSP\ in\ Industry_j}{Total\ GSP} \right)^2 \tag{11}$$

where j is each state's industry GSP.

5. Estimation Results

5.1. Five-year differences non-spatial model

Table 1 summarizes the initial results of the tax burden on state growth using Reed's five-year differencing technique. In the first column, there are no other explanatory variable besides the tax burden (both differenced and initial level) as well as the Δlny, Δlnk, $\Delta ln\ell$, and Δlnn variables. The second column reports the same results with controls included. Different taxes, however, may have different effects on growth. We test this by decomposing taxes into four categories: property taxes, personal income taxes, corporate income taxes, and sales taxes. In columns three and four, we report the findings with and without controls. All estimations include both time and state fixed effects.

We find that the total tax burden in initial levels is positive and significant. For a 1 percentage point increase of state GSP taken as tax revenue at the initial point (4 years ago), cumulative growth of real GSP over four years was increased by 1.57 percent. This is equivalent to a 0.34 percent increase per year. The differenced tax burden is weakly negative but not significant. This is in direct contrast to Reed, who found that – both in differences and levels – tax burden has a negative, robust effect on state output growth. However, when compared to Gale et al. (2015), who extended Reed's model by several time periods, they find initial levels insignificant with positive effects of changes on tax burden over the 1996-2006 period (roughly the same period as this study). They suggest that the sensitivity of the results raises the possibility that the coefficient estimates are not stable over time.

The decomposed tax data shows varying effects across revenue sources. Most are weakly negative, with the exception of corporate tax rates. We find a strongly positive effect of corporate tax rates, similar to Gale et al. (2015), who find the initial level of corporate tax rates correspond with an approximately 7 log-point percentage increase in GSP (depending on specification).

5.2. Model with spatial effects

Due to the nature of spatial regression models, there is a feedback process that makes interpretation of the coefficients less straightforward than a non-spatial regression. The direct marginal effect is the effect on GSP growth from changes in

Table 1: Regression Results – Non-Spatial Panel

	(1)	(2)	(3)	(4)
Δ lnk	0.536***	0.529***	0.541***	0.456***
	(7.63)	(5.89)	(7.37)	(4.71)
Δ lnl	0.651***	0.624***	0.582**	0.471*
	(3.54)	(2.76)	(2.61)	(2.00)
Δ lnn	-0.901***	-0.942**	-0.672***	-0.417*
	(-5.39)	(-4.63)	(-2.78)	(-1.71)
Δ Tax Burden	-0.323	-0.323		
	(-0.98)	(-0.80)		
Tax Burden	1.974***	1.574***		
	(3.11)	(3.12)		
Δ Property Tax			-1.167	-0.659
			(-0.90)	(-0.47)
Property Tax			1.635	2.401
			(0.89)	(1.26)
Δ Sales Tax			-1.035	-1.795
			(-0.72)	(-1.18)
Sales Tax			0.980	-0.356
			(0.55)	(-0.19)
Δ Individual Income Tax			-0.906	-0.797
			(-0.67)	(-0.66)
Individual Income Tax			-1.183	-0.0945
			(-0.55)	(-0.05)
Δ Corporate Income Tax			2.926	1.538
			(1.03)	(0.59)
Corporate Income Tax			9.490*	4.453
			(1.68)	(0.76)
Controls	No	Yes	No	Yes
R^2	0.822	0.857	0.813	0.856
N	144	144	144	144

t-statistics in parentheses calculated with robust standard errors.

Summary statistics reported in Table 5 in the appendix.

* p<0.10, **p<0.05, *** p<0.01

the explanatory variables of the state itself, while indirect marginal effects are the changes in GSP growth due to the mutual spatial spillovers between the state and its neighbors. These effects are reported for both the total tax burden and the decomposed tax specifications in Tables 2 and 3, respectively.[7]

Table 2 summarizes the initial results of the tax burden on state growth using Reed's five-year differencing technique with the addition of spatial spillovers. This estimation contains controls, time, and state effects. After performing the tests outlined in the methodology section, we find the correct model is the SDM. (Test statistics can be found in Table 8.) Since much of the previous literature is conducted in first-differences and our five-year differences suffers from a small sample size, these estimates are provided as a means of comparison with the five-year differences model. While the 5-year estimates in the non-spatial model had positive coefficients for the initial tax burden, we find that adding spatial effects causes this variable to become insignificant and vary with specification. The total effect of the difference in tax burden (Δ tax burden) are negative and significant in three of the four spatial specifications: both 1-year contiguity and distance specifications as well as the 5-year distance measure. GSP growth falls by approximately 0.35 percent per year in the first-differenced model and falls by approximately 1.59 percent over the five-year period (or 0.32 percent per year). This total effect is driven by the direct effect in most cases.

Table 3 summarizes the results of the decomposed tax burden effects on growth. Property taxes are consistently negative and significant across specifications, with a state's own effects contributing a larger share of the total effect in most specifications. An increase of one percentage point in initial property tax revenue per GSP decreases state growth across specifications by 1.2% per year in the 1-yr model and 4.41% (0.88% per year) in the 5-yr model. Similar to the non-spatial model, differences in sales tax have a significant, negative own-state effect on growth, however this effect is confounded by spillovers and the total effect is only weakly negative. Overall, changes to individual income tax collection (in both differences and levels) vary with specification, but tend to be negative or weakly negative in both direct and indirect effects. Consistent with the non-spatial findings, differences in and levels of corporate taxes have a positive effect on GSP growth, although it is a somewhat weaker effect and changes subject to the specification.

While the work of some previous studies has found strong inverse relationships between state taxes and economic growth, our results indicate that the temporal

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[7]See LeSage and Pace (2009) or Elhorst (2010) for a detailed explanation of interpreting parameter estimates in spatial regression models.

Table 2: Spatial Effects – Total Tax Burden

	1-year differences in lny		5-year differences in lny	
	Contiguity	Distance	Contiguity	Distance
Direct Effects				
Δlnk	0.461***	0.473***	0.496***	0.544***
	(7.65)	(8.11)	(6.78)	(11.38)
Δlne	0.644***	0.623***	0.703***	0.438***
	(5.17)	(4.82)	(3.55)	(3.06)
Δlnn	-0.382***	-0.495***	-1.137***	-0.547***
	(-2.60)	(-3.27)	(-3.71)	(-3.28)
Δ Tax burden	-0.331**	-0.508***	0.244	-0.800**
	(-2.51)	(-3.73)	(0.57)	(-2.10)
Tax burden	0.158	-0.0603	0.549	0.0572
	(0.89)	(-0.98)	(1.25)	(0.30)
Indirect Effects				
Δlnk	-0.0963**	-0.466***	-0.0843	-0.280**
	(-2.05)	(-3.14)	(-0.82)	(-1.96)
$\Delta ln\ell$	0.0451	-0.0187	-0.0501	0.420
	(1.63)	(-0.07)	(-0.24)	(0.85)
Δlnn	-0.0269	-1.846	0.521	-0.298
	(-1.41)	(-0.96)	(1.32)	(-0.55)
Δ Tax burden	-0.0264	0.119	-1.099	-0.789
	(-1.25)	(0.43)	(-1.07)	(-1.32)
Tax burden	0.0123	-0.688**	-0.849	0.294
	(0.73)	(-2.09)	(-0.90)	(0.58)
Total Effects				
Δlnk	0.364***	0.00668	0.412***	0.264**
	(9.09)	(0.05)	(3.83)	(1.99)
$\Delta ln\ell$	0.689***	0.605**	0.653**	0.858*
	(5.53)	(2.54)	(2.24)	(1.76)
Δlnn	-0.409***	-2.341	-0.616*	-0.845*
	(-2.65)	(-1.20)	(-1.68)	(-1.71)
Δ Tax burden	-0.357**	-0.389*	-0.856	-1.589***
	(-2.43)	(-1.69)	(-1.01)	(-2.99)
Tax burden	0.171	-0.748**	-0.300	0.351
	(0.90)	(-2.13)	(-0.28)	(0.67)
Spatial ρ	0.0674*	0.709***	-0.165	-1.222***
	(1.68)	(17.49)	(-1.37)	(-3.78)
N	768	768	144	144

z statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

tax-growth relationship is sensitive to model specification and the time period of analysis. This finding also extends to spatial effects; although tax burden and its decomposed elements (in both differences and levels) often enters weakly negative into the estimation, it is very fragile to changes in the model.

6. Conclusion

Our analysis can be used to identify the temporal circumstances under which stronger effects of state taxes on growth have been observed, and those contexts in which weaker effects can be expected. Furthermore, our spatial analysis can be used to identify key fiscal spillovers among states affecting their growth. While the work of some previous studies has found strong inverse relationships between state taxes and economic growth, our results indicate that the temporal tax-growth relationship is sensitive to model specification and the time period of analysis. This finding also extends to spatial effects; although tax burden (in both differences and levels) often enters weakly negative into the estimation, it is very fragile to changes in the model.

With this in mind, policy makers should consider that the relationship between the economic growth of states and taxes depends on many different factors. This includes the activity of neighboring states, such as regional tax competition, surrounding state wealth, and neighbors' investments in both physical and human capital. For instance, a state may not be able to attract firms by lowering taxes if it is surrounded by states with few amenities and poor labor mobility. Ultimately, the effects of changes in taxation may depend on the particular environment within and surrounding each state.

Table 3: Spatial Effects – Decomposed Tax Burden

		1-year differences in lny		5-year differences in lny	
		Contiguity	Distance	Contiguity	Distance
Direct Effects	Δ Prop Tax	-3.318***	-3.511***	-1.910**	-1.842*
		(-6.09)	(-7.13)	(-2.33)	(-1.91)
	Prop Tax	-0.0845	-0.0434	-0.938	0.00118
		(-0.23)	(-0.12)	(-0.69)	(0.01)
	Δ Sales Tax	-2.298***	-2.261***	-1.822**	-1.579**
		(-4.09)	(-3.76)	(-2.33)	(-2.09)
	Sales Tax	0.00504	0.000928	-1.037	0.269
		(0.02)	(0.00)	(-0.99)	(0.97)
	Δ Ind Inc Tax	-1.412*	-1.392*	0.0515	-0.862
		(-1.95)	(-1.92)	(0.06)	(-0.89)
	Ind Inc Tax	-0.374	-0.308	-4.242***	0.0123
		(-0.81)	(-0.72)	(-2.84)	(0.05)
	Δ Corp Inc Tax	1.655**	1.504*	3.221*	-0.846
		(2.29)	(1.94)	(1.81)	(-0.43)
	Corp Inc Tax	1.151	0.930	13.73***	-0.897
		(1.31)	(1.17)	(3.95)	(-0.72)
Indirect Effects	Δ Prop Tax	-0.229*	-7.179***	0.551	-5.989
		(-1.71)	(-3.07)	(0.30)	(-1.12)
	Prop Tax	-1.135***	-1.850	-3.473	-2.756**
		(-2.94)	(-1.20)	(-1.50)	(-2.18)
	Δ Sales Tax	-0.163	-2.001	2.239	-4.320
		(-1.54)	(-0.62)	(1.02)	(-0.90)
	Sales Tax	0.00114	2.078	8.350***	2.326*
		(0.05)	(0.64)	(2.99)	(1.84)
	Δ Ind Inc Tax	-0.0962	-5.135**	3.004*	-4.217
		(-1.23)	(-2.46)	(1.65)	(-0.84)
	Ind Inc Tax	-0.0266	-3.113	4.106	-0.395
		(-0.66)	(-1.39)	(1.58)	(-0.26)
	Δ Corp Inc Tax	3.304*	7.468**	3.609	12.40
		(1.95)	(2.33)	(0.97)	(0.98)
	Corp Inc Tax	0.0934	-1.875	-2.436	-5.849
		(0.95)	(-0.75)	(-0.35)	(-0.78)
Total Effects	Δ Prop Tax	-3.548***	-10.69***	-1.359	-7.831
		(-6.17)	(-4.59)	(-0.75)	(-1.35)
	Prop Tax	-1.220***	-1.894	-4.410*	-2.755**
		(-2.74)	(-1.38)	(-1.88)	(-2.13)
	Δ Sales Tax	-2.461***	-4.262	0.416	-5.899
		(-4.01)	(-1.28)	(0.20)	(-1.16)
	Sales Tax	0.00619	2.079	7.313***	2.596*
		(0.02)	(0.64)	(2.62)	(1.94)
	Δ Ind Inc Tax	-1.508*	-6.527***	3.056	-5.079
		(-1.95)	(-3.15)	(1.39)	(-1.01)
	Ind Inc Tax	-0.401	-3.421	-0.136	-0.383
		(-0.81)	(-1.52)	(-0.05)	(-0.23)
	Δ Corp Inc Tax	4.958**	8.972***	6.829	11.56
		(2.44)	(2.72)	(1.64)	(0.86)
	Corp Inc Tax	1.245	-0.946	11.29	-6.745
		(1.30)	(-0.39)	(1.44)	(-0.83)
	Spatial ρ	0.0634*	0.379***	-0.244*	-1.181***
		(1.69)	(4.60)	(-1.84)	(-4.53)
	N	768	768	144	144

z statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

References

Abreu, M., De Groot, H. L. and Florax, R. J. (2004), Space and growth: a survey of empirical evidence and methods, Technical report, Tinbergen Institute Working Paper No. TI 04-123/3.

Anselin, L. (1988), 'Model validation in spatial econometrics: a review and evaluation of alternative approaches', *International Regional Science Review* **11**(3), 279–316.

Atems, B. (2015), 'Another look at tax policy and state economic growth: The long-run and short-run of it', *Economics Letters* **127**, 64–67.

Belotti, F., Hughes, G. and Piano Mortari, A. (2016), 'Spatial panel data models using stata'.

Bureau of Economic Analysis (2015), 'National economic accounts, Table 3.1ES Current-Cost Net Stock of Private Fixed Assets by Industry', U.S. Department of Commerce.

Döring, T. and Schnellenbach, J. (2006), 'What do we know about geographical knowledge spillovers and regional growth?: A survey of the literature', *Regional Studies* **40**(03), 375–395.

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

Elhorst, J. P. (2017), 'Spatial Panel Data Analysis', pp. 2050–2058.
URL: *https://spatial-panels.com/wp-content/uploads/2017/07/Elhorst-Spatial-Panel-Data-Analysis-Encyclopedia-GIS-2nd-ed_Working-Paper-Version.pdf*

Gale, W. G., Krupkin, A. and Rueben, K. (2015), 'The relationship between taxes and growth at the state level: New evidence', *National Tax Journal* **68**(4), 919–942.

Garofalo, G. A. and Yamarik, S. (2002), 'Regional convergence: Evidence from a new state-by-state capital stock series', *Review of Economics and Statistics* **84**(2), 316–323.

Garrett, T. A., Wagner, G. A. and Wheelock, D. C. (2005), Regional Disparities in the Spatial Correlation of State Income Growth, Technical report, The Federal Reserve Bank of St Louis.
URL: *http://research.stlouisfed.org/wp/2005/2005-061.pdf*

Goff, B., Lebedinsky, A. and Lile, S. (2012), 'A matched pairs analysis of state growth differences', *Contemporary Economic Policy* **30**(2), 293–305.

Kao, Y.-H. and Bera, A. K. (2013), Spatial regression: The curious case of negative spatial dependence, *in* 'VII World Conference of The Spatial Econometric Association'.

Kopczewska, K., Kudła, J. and Walczyk, K. (2017), 'Strategy of Spatial Panel Estimation: Spatial Spillovers Between Taxation and Economic Growth', *Applied Spatial Analysis and Policy* **10**(1), 77–102.

LeSage, J. P. and Fischer, M. M. (2008), 'Spatial growth regressions: Model specification, estimation and interpretation', *Spatial Economic Analysis* **3**(3), 275–304.

LeSage, J. and Pace, R. K. (2009), *Introduction to Spatial Econometrics*.

Ljungqvist, A. and Smolyansky, M. (2014), 'To cut or not to cut? on the impact of corporate taxes on employment and income', National Bureau of Economic Research.

Mazerov, M. (2013), 'Academic research lacks consensus on the impact of state tax cuts on economic growth', *Center on Budget and Policy Priorities, June* **17**.

McBride, W. (2012), 'What is the evidence on taxes and growth?', *Tax Foundation* **207**.

Ojede, A. and Yamarik, S. (2012), 'Tax policy and state economic growth: The long-run and short-run of it', *Economics Letters* **116**(2), 161–165.

Reed, W. R. (2008), 'The robust relationship between taxes and us state income growth', *National Tax Journal* pp. 57–80.

Reed, W. R. (2009), 'The determinants of us state economic growth: A less extreme bounds analysis', *Economic Inquiry* **47**(4), 685–700.

Reed, W. R. and Rogers, C. L. (2004), 'Tax cuts and employment in new jersey: Lessons from a regional analysis', *Public Finance Review* **32**(3), 269–291.

Segura, J. (2017), 'The effect of state and local taxes on economic growth: A spatial dynamic panel approach', *Papers in Regional Science* **96**(3), 627–645.
URL: *http://doi.wiley.com/10.1111/pirs.12221*

U.S. Census Bureau (2010), 'Centers of population by state', https://www.census.gov/geo/reference/centersofpop.html. (accessed March 27, 2017).

Wasylenko, M. (1999), 'Taxation and economic development: The state of the economic literature', *Public Administration and Public Policy* **72**, 309–328.

Yu, J., De Jong, R. and Lee, L.-f. (2008), 'Quasi-maximum likelihood estimators for spatial dynamic panel data with fixed effects when both n and t are large', *Journal of Econometrics* **146**(1), 118–134.

Appendix

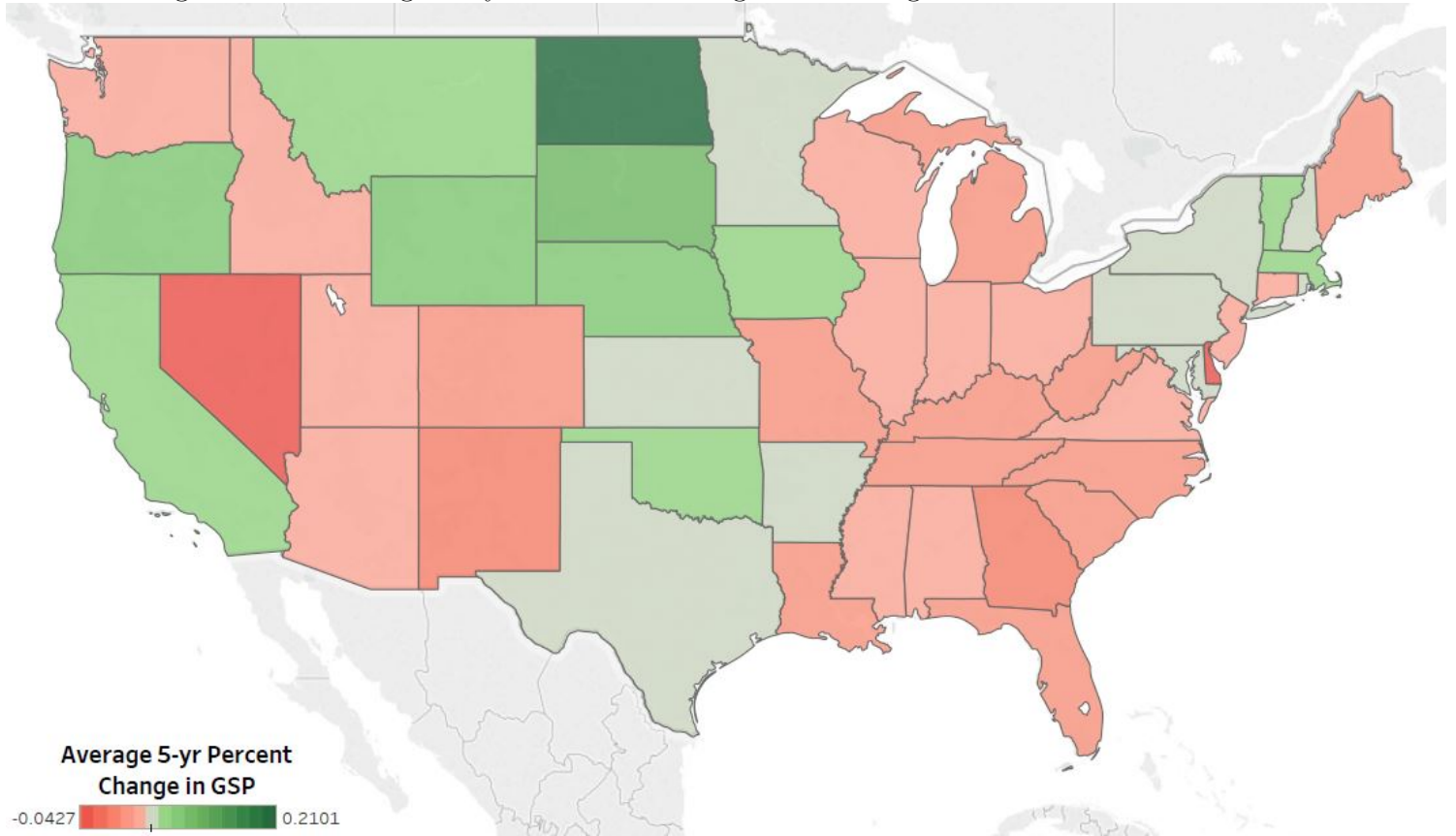Figure 1: Clustering of 5-year differences in growth throughout the US.

Table 4: List of Control Variables

Variable	Description
Education	Percentage of population (aged 25 and above) who have completed a Bachelor's degree (Source: Census)
Working Population	Percentage of the population aged 16 and older (Source: BLS)
White	Percentage of population that is white (Source: Census)
Female	Percentage of population that is female (Source: Census)
Population	Log of total population (source: Census)
Agriculture	Share of total earnings earned in Agriculture, forestry, fishing, and hunting industry, GSP by state (Source: BEA)
Mining	Share of total earnings earned in Mining industry, GSP by state; Source: BEA
Union	Percentage of population who are union members; Source: BLS for 2000-2013, Unionstats for 1997-99
Diversity	Measure of industrial diversity (See equation 11.)

Table 5: Summary Statistics*

Variable	Mean	Std. Dev.	Minimum	Maximum
Δlny^1	3.73	6.29	-20.16	29.91
Δlnk^2	8.34	9.66	-22.69	56.93
$\Delta ln\ell^3$	3.21	4.50	-9.14	21.22
Δlnn^4	3.70	2.93	-4.42	22.50
Δ Tax Burden[5]	0.49	2.06	-6.25	7.55
Tax Burden	7.25	1.70	2.94	12.35
Δ Property Tax	0.09	0.28	-1.13	1.12
Property Tax	2.62	0.92	0.90	5.30
Δ Sales Tax	.003	0.23	-0.95	0.77
Sales Tax	3.03	0.90	0.67	5.04
Δ State Corp Income Tax	-0.01	0.14	-0.57	0.53
State Corporate Income Tax	0.29	0.18	0	1.11
Δ State Ind Income Tax	-0.02	0.24	-0.92	0.96
State Ind Income Tax	1.81	0.96	0	4.19
Δ Education	1.20	1.72	-3.10	6.80
Education	25.65	4.85	14.60	38.70
Δ White	-1.64	3.77	-17.26	35.96
Δ Female	-0.09	0.40	-2.61	1.98
Population (1,000s)	5984	6934	480	37000
Δ Agriculture	0.07	0.50	-3.70	3.72
Agriculture	1.33	1.41	0.10	8.99
Δ Mining	0.03	1.10	-10.76	8.38
Δ Union	-0.55	0.98	-4.26	3.52
Diversity	25.63	10.72	9.31	76.96
lny_{t-4}	10.68	0.18	10.27	11.15

[1]Δ lny is the percent change in real Per Capita GSP (2009 dollars).

[2]Δ lnk is the percent change in net private fixed assets (2009 dollars).

[3]Δ lnℓ is the percent change in total employment.

[4]Δ lnn is the percent change in total population.

[5] Tax Burden is the ratio of total state and local tax revenues over total state GSP.

* Variables denoted with a Δ correspond to the five-year difference in the variable over the period, and the variable itself is the value of the variable at the initial level of the five-year period.

Table 6: Global spatial autocorrelation

| | Moran's I | | | | |
Variables	I	E(I)	sd(I)	z	p-value*
Δlny	0.023	-0.007	0.009	3.27	0.001
Δlnk	0.033	-0.007	0.009	4.28	0.000
$\Delta ln\ell$	0.074	-0.007	0.009	8.66	0.000
Δlnn	0.125	-0.007	0.009	14.06	0.000
Δ Tax burden	-0.002	-0.007	0.01	0.57	0.286
Tax burden	0.019	-0.007	0.009	2.76	0.003
ΔProp Tax	0.011	-0.007	0.009	1.87	0.031
Prop Tax	0.166	-0.007	0.009	18.29	0.000
Δ Sales Tax	-0.001	-0.007	0.009	0.64	0.260
Sales Tax	0.073	-0.007	0.009	8.41	0.000
Δ Ind Inc Tax	0.007	-0.007	0.009	1.50	0.067
Ind Inc Tax	-0.002	-0.007	0.009	0.49	0.312
Δ Corp Inc Tax	-0.005	-0.007	0.009	0.25	0.401
Corp Inc Tax	0.066	-0.007	0.009	7.81	0.000
Δ Edu	0.02	-0.007	0.009	2.85	0.002
Edu	0.129	-0.007	0.009	14.35	0.000
Δ % white	0.005	-0.007	0.009	1.28	0.101
Δ % female	0.005	-0.007	0.009	1.28	0.100
% female	0.305	-0.007	0.009	33.19	0.000
Δ % Ag	0.028	-0.007	0.009	4.00	0.000
% Ag	0.152	-0.007	0.009	17.27	0.000
Δ % Mining	-0.008	-0.007	0.008	-0.17	0.433
Δ % Union	0.003	-0.007	0.009	1.05	0.146
Diversity	0.035	-0.007	0.009	4.50	0.000

*1-tail test

Table 7: Summary of Spatial Weight Matrices

Contiguous		**Inv Distance**[1]	
Matrix	Description	Matrix	Description
Dimensions	48x48	Dimensions	48x48
Values		Values	
min	0	min	0
min>0	0.125	min>0	0.0031991
mean	0.0208333	mean	0.0208333
max	1	max	0.235876

[1]Distances based on 2010 Census population centroids.

Table 8 : Tests for Specification Issues

	Total Tax Burden				Decomposed Tax Burden			
	Contiguous		Distance		Contiguous		Distance	
	test stat	p-value	test stat	p-value	test stat	p-value	test stat	p-value
1-year differences								
Wald Test SAR	5.18	0.023	255.36	0.000	18.29	0.000	243.38	0.000
Wald Test SEM	4.83	0.028	31.12	0.009	19.10	0.000	45.1	0.000
SDM AIC	4560		4410		4492		4630	
SDM BIC	4467		4238		4242		4463	
SAC AIC	4544		4543		4676		4600	
SAC BIC	4455		4455		4546		4484	
5-year differences								
Wald Test SAR	39.68	0.000	47.47	0.000	72.87	0.000	114.28	0.000
Wald Test SEM	41.47	0.000	39.62	0.001	59.03	0.000	93.17	0.000
SDM AIC	736		617		731		587	
SDM BIC	531		406		454		308	
SAC AIC	802		805		804		785	
SAC BIC	743		745		727		708	