Temporal and Spatial Effects of State and Local Taxes on Economic Growth

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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, we analyze the effect of both differences and levels of state and local taxes on state gross state product (GSP) growth. 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

Amid the national debate on corporate and individual income taxes, states across the nation are cutting tax rates hoping to stimulate long-term growth. In 2017 alone, states have undertaken measures to cut taxes: Tennessee and North Carolina have cut income taxes, California and New Jersey have cut sales taxes, and Arizona, New Mexico, North Carolina, Indiana, and DC have all cut corporate taxes. 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, 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.

The main empirical challenge in the tax and growth literature is the lack of a clear identification strategy that shows causal outcomes of increased taxes on state level growth. It is nearly impossible for researchers to isolate the effect of taxes from the effects of other factors, such as local labor market composition or political preferences. Although previous papers in the broader growth literature make use of longitudinal data to control for other state factors (Ojede and Yamarik, 2012; Reed, 2008; Gale et al., 2015), their estimates may still suffer from bias if growth is related to taxation through omitted variables.

Unfortunately, growth theories themselves are not explicit about specific factors that underlie the data-generating process for growth regressions, so researchers are faced with a large number of potential variables. The effects of different types of taxes, whether they be income, corporate, or sales taxes, vary widely within and across research depending on model specification and estimation strategy. The introduction of spatial econometrics has added another layer of complexity and differentiation in the literature on taxes and economic growth.

This paper builds on an existing, well-known empirical model to unify and analyze both spatial and aspatial estimations. 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 an 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 spillover 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 model dependent. This implies that results from new research on tax policy using unidentified regression analysis should be interpreted with caution.

2 Literature Review

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.

Ojede and Yamarik (2012) 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 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. 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).

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

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

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).

3.2.1 Spatial Weight Matrix

Spatial information is expressed as a spatial weight matrix $\mathbf{W}$ that summarizes spatial relations between n spatial units (states). Each spatial weight, ω_{ij}, reflects the spatial influence of state j on state i. $\mathbf{W}$ takes the following form:

$$\mathbf{W} = \begin{bmatrix} 0 & \omega_{1,2} & \dots & \omega_{1,n} \\ \omega_{2,1} & 0 & \dots & \omega_{2,n} \\ \vdots & \vdots & 0 & \vdots \\ \omega_{n,1} & \omega_{n,2} & \dots & 0 \end{bmatrix} \tag{6}$$

The ω is the specific weight as a function of a distance parameter, d_{ij}. In all cases of the given $\mathbf{W}$, the weight-matrix is row-normalized. We compare two types of distance measures, d_{ij}: queen contiguity and inverse distance weighting. For the first measure, only geographically contiguous states are assumed to have any influence on a neighbor's growth, and each contiguous state has the same amount of influence. Here,

$$\omega_{ij} = \begin{cases} \frac{I(d_{ij})}{\sum_{j=1}^{n} I(d_{ij})}, \text{ if } i \neq j \\ 0, \text{ otherwise} \end{cases} \tag{7}$$

where $I(d_{ij})$ is an indicator function that takes the value of 1 if states are contiguous and zero otherwise.

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:

$$\omega_{ij} = \begin{cases} \frac{d_{ij}^{-\alpha}}{\sum_{j=1}^{n} d_{ij}^{-\alpha}}, \text{ if } i \neq j \\ 0, \text{ otherwise} \end{cases} \tag{8}$$

where α is the decay parameter. The decay parameter in our estimation is set to one, and d_{ij} is the distance in miles to another state's population centroid. In this case, every other state has an effect on a state's growth, no matter how far away it is. A summary of the spatial weight matrices can be found in the appendix in Table 7.

3.2.2 Testing for Spatial Correlation

Moran's I test (Cliff and Ord, 1981) is used to detect spatial clusters in local dimensions. First, Moran's I is calculated:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \tag{9}$$

where n is the number of states, w_{ij} is a spatial weight, and x is the variable whose spatial distribution is being studied. Under the null hypothesis, the variable being analyzed is randomly distributed spatially (i.e. no spatial autocorrelation), and:

$$\begin{aligned} E[I] &= -\frac{1}{n-1} \\ V[I] &= E[I^2] - E[I]^2 \end{aligned}$$

with the z_I-score statistic is computed as:

$$z_I = \frac{I - E[I]}{\sqrt{V[I]}} \tag{10}$$

The results of the Moran's I test confirm global spatial correlation for most variables of interest, with the results for all variables found in Table 6 in the appendix.

3.2.3 Spatial Estimation Model

With spatial correlation confirmed, we now turn to the task of model selection. In the realm of spatial econometrics, there are three components of spatial spillovers: the spatial lag of the dependent variables (ρWy), a set of spatial lags of explanatory values (θWX), and the spatially autocorrelated error them (λWu). A full spatial model is given by:

$$\begin{aligned} y_t &= \rho W y_t + \beta X_t + \theta W X_t + \delta_t + \psi 1 + u_t \\ u_t &= \lambda W u_t + \epsilon_t \end{aligned} \tag{11}$$

where X includes the explanatory variables, δ are time effects, ψ are spatial effects, and W is an n x n row-stochastic spatial weight matrix. In the above specification, ρ represents the spatial autoregressive parameter and θ is the spatially lagged independent variables parameter. We utilize the bias corrected maximum likelihood approach described by Yu et al. (2008).[1]

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

For determining proper model selection, we use the general-to-specific approach of LeSage and Fischer (2008); LeSage and Pace (2009) for the rule of estimation.[2] This strategy starts with estimating a spatial Durbin model (SDM) that incorporates both the spatial lag of the dependent variables (ρWy) and spatial lags of explanatory values (θWX). Equation (5) is re-written as:

$$\Delta lny_{it} = \rho \sum_{j=1}^{N} \omega_{ij} \Delta lny_{jt} + \boldsymbol{X}'_{it}\beta + \sum_{j=1}^{N} \omega_{ij} \boldsymbol{X}'_{jt}\theta + \delta_t + \psi_i + \epsilon_{it} \tag{12}$$

where Δy_{it} and Δy_{jt} are the differenced growth rates of real GSP in state i and neighboring states j, respectively; $\boldsymbol{X_{it}}$ and $\boldsymbol{X_{jt}}$ are the tax and other control variables in states i and j; δ are time effects; ψ are spatial effects; and ω_{ij} is an element of the n x n row-stochastic spatial weight matrix.

This model is advantageous in that it nests most other models used in the growth literature. By later imposing restrictions on the parameters, we can determine the final spatial specification. For instance, 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. Finally, the imposition of the restriction where $\rho = 0$, $\theta = 0$ leads to a non-spatial least-squares growth regression model. We also test for spatial correlation in the error term. Since the spatial autocorrelation model (SAC) and SDM are non-nested models, we use information criteria to test the two models. The results of these tests can be found in Table 8. 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).

3.2.4 Interpreting Spatial Regression Coefficients

In spatial regression models, there is a feedback process that makes interpretation of the coefficients less straightforward than a non-spatial regression.[4] The direct

[2]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).

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

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

marginal effect is the effect on GSP growth from changes in 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. LeSage and Pace (2009) provide a means of calculating scalar summary measures of these two types of effects that arise from changes in the explanatory variables of an SDM.

We consider these impacts for the model in (13), using the $n \times n$ matrix defined in (14), which contains an index u to denote association of this matrix with parameters β_u and θ_u for the u^{th} explanatory variable in the matrix X.

$$y = \rho W y + \alpha + \beta X + \theta W X + \epsilon \tag{13}$$

$$S_u = (I_n - \rho W)^{-1}(I_n \beta_u + W \theta_u) \tag{14}$$

The impact from a change in the u^{th} variable in state i is $\frac{\partial y_i}{\partial x_{ju}}$, represented by the ijth element of the matrix S_u.

The *average direct effect* is constructed as an average of the diagonal elements of S_u. This is a scalar representation of individual direct effects that include feedback influences that arise as a result of changes in a state's own u^{th} variable passing through neighbors and then back to itself. The *average indirect effect* is constructed using an average of the off-diagonal elements of S_u. The off-diagonal row elements are first averaged, and then an average of these averages is taken. These are considered true spillover effects – a measure of how changes in another state's u^{th} variable affect own state growth. Lastly, the *average total effect* is the sum of both average indirect and direct effects.

4 Data

The model is estimated using data for the 48 contiguous U.S. states over the 1999-2013 period. We discuss our variables below; Table 1 in the appendix lists the variable names, description, and sources. Summary statistics are listed in Table 2.

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 gross state product (GSP) 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. We first examine total tax burden and then incorporate decomposed tax revenue into our specification – namely property, sales, individual income, and corporate income taxes.[5][6]

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 to each state using

$$k_{i,j,t} = \left[\frac{y_{i,j,t}}{Y_{i,t}}\right] K_{i,t} \tag{15}$$

$$k_{j,t} = \sum_{i=1}^{19} k_{i,j,t} \tag{16}$$

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.

Other control variables are replicated as in Reed (2008).[7] 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 1 and 2 in the appendix.

We construct a measure of industrial diversity to include in the model with an index based on the 19 private NAICS industries using the following:

$$Diversity_i = \sum_j \left(\frac{GSP\ in\ Industry_j}{Total\ GSP}\right)^2 \tag{17}$$

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

[6] 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).

[7] These variables are taken directly from Reed's best SIC specification.

where j is each state's industry GSP.

5 Estimation Results

5.1 Model without spatial effects

Table 3 summarizes the initial results of the total 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 may have differential affects 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 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 is rather uninteresting. It shows varying effects across revenue sources, with most being weakly negative. The only exception are 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). It is important to note that the coefficients report the effect of an increase in tax revenue equal to 1 percent of personal income. This increase represents a very different percentage change in each tax source. For instance, if corporate revenues average about 0.4 percent of GSP and personal income taxes average 2 percent, a corporate tax rate coefficient of 8 implies that a 10 percent increase in corporate taxes (from 0.40 to 0.44 percent of GSP) would raise the growth rate by 0.32 percentage points. Likewise, a 10 percent increase in income taxes (from 2.0 to 2.2 percent of GSP) would raise the cumulative growth rate by 0.40 percentage points if the income tax coefficient were 2.0.

5.2 Model with spatial effects

Direct, indirect, and total effects are reported for both the total tax burden and the decomposed tax specifications in Tables 4 and 5, respectively. Table 4 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 specification is the spatial Durbin model (SDM).[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 5 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 is correlated with a decrease in 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

[8]Test statistics can be found in Table 8.

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 research presents new results for the impact of tax revenues on overall real state growth. We build on the model constructed by Reed (2008), who shows that tax revenues negatively and significantly impacted real state growth 19701999. Replication of his results over the 1999-2013 time period, we show that the results are not robust to an extension of the time period similar to Gale et al. (2015). We also find spatial results using the same underlying data and model differ from current work that has found significant, negative effects of increased tax revenues on growth. We also show that revenues from different taxes have different effects on GSP. These results undermine claims that there is a robust and consistent impact of tax revenues on state growth.

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. The introduction of spatial econometrics into the literature on taxation has helped in this regard, however there is room for improvement.

In terms of policy, economic recessions not only cause the tax bases of many states to shrink, but also create an increased demand for government services. This can create significant fiscal stress for states, making state-level tax reform politically feasible. When considering tax policy changes, this paper should serve as a cautionary tale to policy makers and researchers within tax analysis circles. Researchers do a disservice to policy makers and individuals affected by tax policy when they produce causal evidence based on inappropriate models or those lacking a reliable identification strategy. These estimates should be interpreted with caution.

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Appendix

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

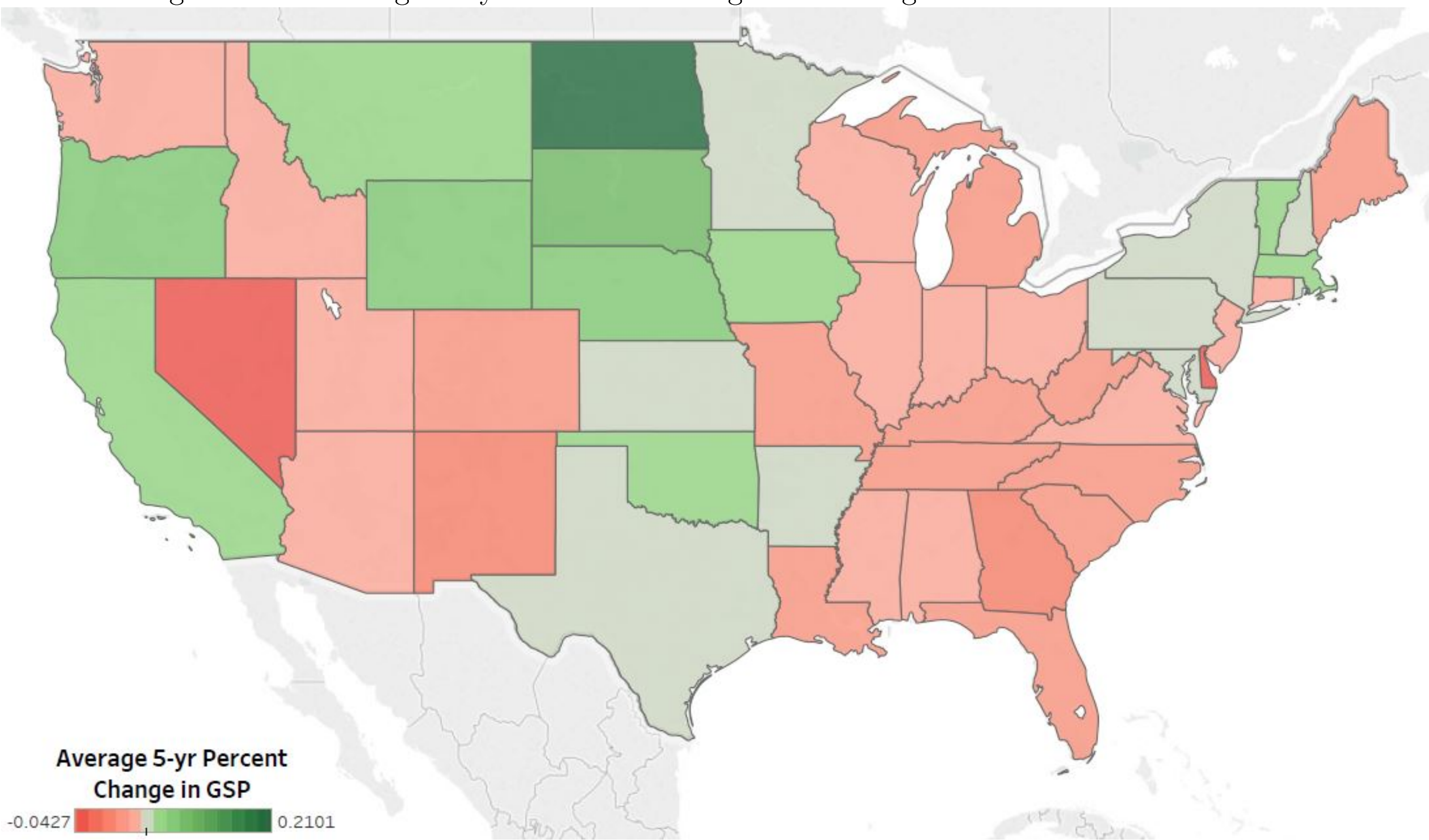

Table 1: List of Control Variables

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 17.)

Table 2: 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 $\ln\ell$ 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 3: Regression Results – Non-Spatial Panel

	(1)	(2)	(3)	(4)
Δlnk	0.536***	0.529***	0.541***	0.456***
	(7.63)	(5.89)	(7.37)	(4.71)
$\Delta ln\ell$	0.651***	0.624***	0.582**	0.471*
	(3.54)	(2.76)	(2.61)	(2.00)
Δlnn	-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 2 in the appendix.
* p<0.10, **p<0.05, *** p<0.01

Table 4: 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

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

Table 5: 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	0.006	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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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	