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Another look at tax policy and state economic growth: The long-run and short-run of it

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HIGHLIGHTS

- I use a spatial Durbin model to estimate the short and long run effects of taxes on state economic growth.
- Data for 48 contiguous US States.
- Taxes have negative short and long run direct, spillover, and total effects on state economic growth.

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ABSTRACT

I use a spatial Durbin model to estimate the effects of taxes on state economic growth. Results indicate that taxes have negative short-run and long-run own-state and spatial spillover effects on state growth.

1. Introduction

The literature on the effects of taxes on state economic growth is vast. Early studies on the relationship between these variables typically employ ordinary least squares estimation on a cross-section of states (e.g. Crain and Lee, 1999). Subsequent studies use fixed effects, random effects, or the Generalized Method of Moments on state-level panel data (Bania et al., 2007; Reed, 2008), while recent studies apply a panel error-correction methodology that allows for the estimation of the short-run and long-run growth effects of taxes. Ojede and Yamarik (2012) use a pooled mean group estimator to estimate the short-run and long-run effects of taxes on state growth, providing evidence that property and sales taxes have negative long-run effects on growth, while income taxes have no impact.

This note takes another look at the short and long-run effects of tax policy and state economic growth. I estimate a model that is different from Ojede and Yamarik (2012) in two significant ways. First, Ojede and Yamarik estimate a panel data model that contains a mix of I(0) and I(1) variables. Results from a panel unit root test show that some of their variables are stationary whereas others are nonstationary. Second, changes in tax policy will not only affect the state that changes its policy, but nearby states, as well. The total effect of taxes will depend on the magnitudes of the direct (own-state) and spatial spillover (cross-state) effects. Therefore, there is need to specify an appropriate model that not only captures the short and long-run effects of taxes on state economic growth, but the corresponding own-state and spatial spillover effects too.

Fortunately, spatial econometric models allow for the decomposition of the effects of taxes on state growth into direct and spatial spillover effects. Furthermore, advances in spatial econometric modeling (see e.g. Lee and Yu, 2010; Baltagi et al., 2011 and Baltagi et al., 2012) have made it possible to specify dynamic spatial panel data models which allow for the decomposition of the direct and

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Table 1
Summary statistics of the data.

Variable	Mean	Standard deviation	Minimum	Maximum
Log of private income net of transfers	11.2171	1.0915	8.6586	13.9919
Growth in private income net of transfers	0.0231	0.0308	−0.1799	0.2504
Log of private nonfarm employment	0.0058	1.0623	−2.6550	2.5399
Private non-farm employment growth	0.0241	0.0274	−0.1114	0.1406
Gross private investment share	0.0600	0.0254	−0.0518	0.3045
State and local expenditures net of transfers	9.5865	1.0662	6.9447	12.4859
Intergovernmental revenue	0.0370	0.0125	0.0094	0.1134
State and local general revenue	0.1781	0.0309	0.3925	0.1030
State and local budget deficit	−0.0045	0.0099	−0.0851	0.0269
Total tax burden	0.1009	0.0131	0.0709	0.1924

Notes: See Ojede and Yamarik (2012) for detailed descriptions data and sources.

Table 2
Hadri Lagrange multiplier stationarity test.

Variable	Level	First Diff.	Variable	Level	First Diff.
Log of private income	78.6987 (0.000)	−2.4070 (0.992)	Intergovernmental aid	30.2560 (0.000)	−0.3943 (0.653)
Log of private employment	78.1043 (0.000)	1.3485 (0.089)	State and local budget deficit	15.3324 (0.000)	−4.8861 (1.000)
Gross private investment share	10.4728 (0.000)	−5.4462 (1.000)	Total tax burden	21.0920 (0.000)	−3.2336 (0.999)
State and local expenditures	78.5226 (0.000)	−1.7562 (0.961)	State and local general revenue	51.5062 (0.000)	−1.6896 (0.9544)

Notes: Numbers in parentheses are *p*-values.

Table 3
Tests for spatial dependence.

Test	Statistic	*p*-value	Test	Statistic	*p*-value
Lagrange Multiplier (LM) error	965.6905	0.000	Likelihood Ratio (LR) error	94.7586	0.000
Robust LM error	1076.0375	0.000	Wald error	91.2813	0.000
LM lag	255.9073	0.000	LR lag	92.2144	0.000
Robust LM lag	366.2544	0.000	Wald lag	91.6400	0.000

spillover effects into short and long-run effects. To our knowledge, this paper is the first to use a dynamic spatial econometric model to estimate the short-run and long-run own-state and spillover effects of taxes on state growth.

2. Data

The variables and their sources are discussed in Ojede and Yamarik (2012). Unlike Ojede and Yamarik (2012) who use data for the 48 contiguous US states from 1967 to 2008, our dataset is annual from 1965 to 2005. I adopt the measure of tax progression used by Ojede and Yamarik (2012) by dividing taxes by personal income. I capture the trade-off between state taxes and spending by following the budget approach of Ojede and Yamarik (2012):

$$def_{it} = exp_{it} - tax_{it} - aid_{it} \quad (1)$$

where def_{it}, exp_{it}, tax_{it}, and aid_{it} are the year t state budget deficit (or surplus), total expenditures net of welfare, total tax revenue, and intergovernmental revenue, respectively. Table 1 provides summary statistics.

2.1. Panel unit root test

Several procedures exist for testing the presence of unit roots in panel data. Baltagi (2013, Chapter 12) provides a discussion of the testing literature on nonstationary panels. I use the Hadri (2000) Lagrange multiplier (LM) test. The null hypothesis of the test is that all panels are stationary. Table 2 shows that all the variables are nonstationary in levels, but stationary after first differencing. Estimating a model containing variables with a mix of stationary and nonstationary variables, as in Ojede and Yamarik (2012), could lead to spurious results on the effects of taxes on state growth. The model presented below only contains stationary variables.

2.2. Tests for spatial dependence

Ojede and Yamarik (2012) estimate the short-run and long-run effects of taxes on state economic without accounting for spatial dependence between states. Failure to account for spatial processes, if present, results in biased, inconsistent and/or inefficient estimates (LeSage and Pace, 2009). It is therefore necessary to test the nature of the spatial dependence. Baltagi (2011) presents a review of the testing literature on spatial dependence. I follow the specific-to-general approach of Florax et al. (2003) and the general-to-specific approach of LeSage and Pace (2009). Florax et al. (2003) propose estimating the nonspatial panel model, and then using LM tests to determine the nature (lag or error) of spatial dependence. Elhorst (2012a) proposes LM tests that are robust to the inclusion of spatial/time effects. If the (robust) LM tests for both spatial lag and error are significant, the spatial Durbin model (SDM) is the appropriate specification. LeSage and Pace (2009), however, suggest an estimating procedure that begins with the SDM. The SDM nests the lag and error models, so restrictions can be placed on its parameters, and then Likelihood Ratio or Wald tests are used to determine if the SDM can be reduced to the lag or error specifications. The results of these tests, when a row-stochastic spatial contiguity weights matrix is used (Table 3) show that the (robust) LM test statistics are significant, indicating that the SDM is appropriate. Furthermore, the Wald and LR tests reject the spatial error and lag models in favor of the SDM.