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LOCAL SALES TAXES AND SPENDING PATTERNS IN U.S. COUNTY GOVERNMENTS

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Abstract

The fiscal effects of local (option) sales taxes (LOSTs) have remained an open question. This paper assembles a county-level dataset of all the U.S. states from 1970 to 2006, and employs two empirical methods to obtain more convincing and generalizable results. The main goal of this study is to consider the different purposes of LOSTs for county governments and examine the effects of each purpose on local spending patterns.

The empirical results confirm that LOSTs help counties expand their total revenue, own-source revenue, and total expenditure, as well as their operating and capital spending. Further findings reveal that the effects of general-purpose LOSTs (GLOSTs) differ from those of special-purpose LOSTs (SPLOSTs) on the spending patterns in county governments. SPLOSTs expand a county's capital spending and reduce its operating spending, while GLOSTs are more helpful for expanding a county's operating spending. The empirical findings imply that local policy-makers should consider whether it should specify a purpose before they make a decision on LOST adoption.

Keywords: local (option) sales tax, spending pattern, average treatment effects, U.S..

1. Introduction

Historically, local governments in the U.S. have relied heavily on property tax revenues; however, tax revolts began to restrict their taxation in the late 1970s. Since then, local governments have looked to other fiscal instruments as alternative revenue sources. Local (option) sales tax (hereafter, LOST) has become a major replacement fiscal instrument, and the mounting adoptions of LOSTs have motivated research on their effects as the widespread uses of LOSTs have changed the fiscal conditions of local governments. The extant studies, however, are limited in that they have analyzed the effects of LOSTS within a single state or in a few states over short periods. In order to fill a void in this line of inquiry, our study extends the scope to an analysis of a large number of local governments using a nationwide dataset of county governments in all 50 states for 37 years[1].

A thorough review of state statutes regarding LOSTs reveals two types of LOSTs: (1) general-purpose LOSTs (hereafter, GLOSTs) that aim to raise revenue capacity and reduce property tax burdens, and (2) special-purpose LOSTs (hereafter, SPLOSTs) that are earmarked to finance a specific capital project. Unlike GLOSTs, SPLOSTs restrict the government's ability to spend those revenues in any area not previously earmarked. This study focuses on these two different purposes of LOSTs, and hypothesizes that (1) LOSTs have changed the spending behavior of governments by providing an additional revenue source, while (2) an earmark in SPLOSTs have different effects on the behavior from GLOSTs. To test the hypotheses, we constructed a national panel dataset covering the period of 1970-2006 and applied two empirical approaches. Our results confirm that LOSTs expand local revenue capacity, so LOST-levying counties can expand both total expenditures and capital and operational spending. Furthermore, the results reveal that GLOSTs and SPLOSTs have different effects on the spending patterns of counties.

The next section reviews LOSTs and local budget composition in accordance with the extant research and then develops the hypotheses, while the third introduces the empirical model that aims to verify the hypotheses. The fourth section presents the empirical results, and the fifth section concludes.

2. Local (option) sales tax and budget composition

Since the tax revolts of the 1970s, when tax and expenditure limits (TELs) restricted the growth in tax receipts and outlays, local governments have searched for other revenue instruments. In this vein, LOST adoptions began to increase in the 1970s, roughly parallel to, and somewhat following, the spread of TELs. In hindsight, LOSTs emerged with three unique advantages. First, they are an ideal revenue tool that raises revenue capacity to make up revenue losses caused by TELs (Jung, 2001; Sjoquist

1 This study focuses on U.S. counties because they are at the frontline of, and play a dominant role in, the delivery of public services (National Association of Counties, 2012).

et al., 2007). Second, LOSTs contribute to fiscal flexibility and revenue diversification (Rogers, 2004; Edwards, 2006; Carroll, 2009; Sjoquist and Stoycheva, 2012). Third, LOST-payers are more aware of how much they pay in sales than in property and income tax; thus, they may choose to cross a border in order to pay a lower sales tax (Drenkard, 2011). LOSTs became popular among governments because they are a transparent way to collect revenue, and they now represent a significant portion of the revenue portfolio of local governments.

These advantages collectively render LOSTs a vital element in local finance. Craft (2002) found that LOSTs expand local revenues, especially in larger communities, but have also aggravated fiscal disparities. LOSTs reduce property tax burdens while increasing revenue capacity and expenditure; furthermore, SPLOSTs lead to an increase in capital spending for specific purposes (Jung, 2002; Sjoquist, Walker and Wallace, 2005).

After consulting relevant articles on state finance laws, we found that LOSTs are designed to serve two main goals that raise local revenue capacity with the potential benefit of property tax relief, and fund specific capital improvement projects through earmarked restrictions. Once LOSTs are authorized by the state legislatures, local governments have the discretion to adopt them. First, this paper considers whether counties adopted GLOSTs, SPLOSTs, or neither (NA, here) in accordance with state statutes. The GLOST group includes counties that levied sales taxes for general purposes; the SPLOST group includes counties that earmarked specific-purpose LOSTs[2]; the NA group is comprised of counties that did not adopt any LOSTs, including those that were not authorized by their state to adopt LOSTs[3].

Figure 1 shows the numbers of counties that adopted GLOSTs and/or SPLOSTs under their respective state legislation. In 1970, about 15% of counties in our sample adopted GLOSTs and/or SPLOSTs. The percentage doubled within a decade and rose further to 65% by 2006, the last year of our sample[4]. To examine the local budget compositions in the three groups, we obtained each group's property and non-property tax dependence ratios against three measures – total, general and own-source revenues.

According to Table 1, a comparison between property and non-property tax dependences pinpoints changes in the budget compositions, and the overall property tax dependence has decreased in the counties.

2 In the states that authorize SPLOSTs, local governments can still adopt SPLOSTs for general purposes. An 'option' for capital projects is regarded as a form of pay-as-you-go in this paper, and restricts how county governments can spend the revenue. If a SPLOST only aims to reduce property tax burden, this paper considers it a general-purpose SPLOST.

3 In some cases, counties in states that authorized SPLOSTs adopted a SPLOST for general purposes like revenue expansion and property tax relief. We place them in the GLOST group. More commonly, counties in such states could adopt both GLOSTs and SPLOSTs. We include those counties in both the GLOST and the SPLOST categories.

4 A county that adopted both GLOST and SPLOST is counted as 2. The counties that once adopted but later terminated LOSTs are included in the NA group.

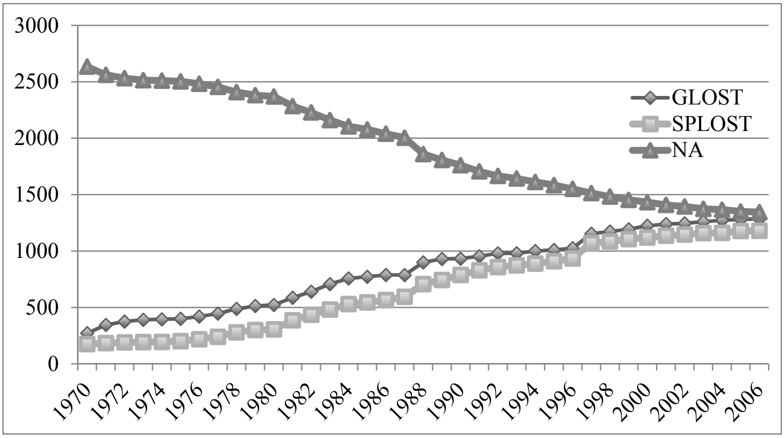

Figure 1: Number of counties adopting Local (Option) Sales Taxes

Contrasting the ratios between the three groups, the property tax dependence of the GLOST group is lower than that of the SPLOST group, while that of the SPLOST group is lower than that of the NA group. These aggregate, average ratios indicate that a county levying GLOSTs and/or SPLOSTs reduced its reliance on property tax, but the reductions are more obvious with the GLOST group. Furthermore, the dependence-reduction effects on LOSTs became more pronounced over time. More specifically, the property tax dependence in the 1970s of the GLOST and the SPLOST groups was 3.04% and 2.87%a lower than that of the NA group, respectively. The differences widened in 2006 to 10% and 8.7%. During this period, the property tax dependences of the GLOST and the SPLOST groups decreased by over 28% and 27%, respectively. As a rough reflection of the reduction of property tax dependence, the ratio of non-property tax revenue increased over the sample period for all three groups of counties by about 5 (GLOST), 3 (SPLOST), and 7 (NA) percentage points. The NA group experienced the highest increase, which suggests that these counties leaned more heavily than those in the other two groups on miscellaneous revenue sources (i.e., fees and charges) since they did not levy sales taxes, even though their non-property tax dependence was still the lowest of all.

During the sample period, counties made efforts to reduce property tax burdens and to diversify their revenue sources. In comparing revenue sources, we found that LOSTs became the second largest own-source revenue because revenues from other sources, such as local income taxes, user fees, and charges were still smaller than property and sales tax revenues. As the second-largest revenue source, we expected that LOSTs would exert influence on local public finance, and that this influence might differ for the two types of LOSTs. Next, we set out to explore the differential effects of GLOSTs and SPLOSTs on local budgets.

Table 1: National average revenue shares of county governments

Ratio (%) of Property Tax Revenue in

	Total Revenue				General Revenue				Own-Source Revenue			
Year	ALL	GLOST	SPLOST	NA	ALL	GLOST	SPLOST	NA	ALL	GLOST	SPLOST	NA
1970	37.81	34.00	36.55	40.16	38.38	34.75	37.49	40.58	63.61	61.62	61.79	64.66
1980	25.47	21.51	27.23	28.42	26.18	22.33	28.20	28.92	45.99	44.54	44.27	47.64
1990	26.98	23.47	27.41	31.27	28.08	24.56	29.03	32.17	41.60	40.26	42.37	45.70
2000	22.56	17.83	20.66	29.13	24.06	19.18	22.83	30.38	34.99	30.98	32.55	41.99
2006	23.97	19.88	22.99	29.63	25.67	21.68	25.56	30.81	36.68	33.36	34.68	43.38

Ratio (%) of Non-Property Tax Revenue in

	Total Revenue				General Revenue				Own-Source Revenue			
Year	ALL	GLOST	SPLOST	NA	ALL	GLOST	SPLOST	NA	ALL	GLOST	SPLOST	NA
1970	5.05	6.58	7.55	4.12	5.13	6.73	7.74	4.17	8.50	11.93	12.76	6.64
1980	8.18	9.91	12.83	6.10	8.40	10.29	13.29	6.21	14.76	20.52	20.86	10.23
1990	9.89	10.35	8.68	7.24	10.29	10.83	9.20	7.45	15.25	17.76	13.43	10.58
2000	10.46	10.23	10.04	7.50	11.15	11.00	11.10	7.82	16.22	17.77	15.83	10.81
2006	11.27	10.20	10.33	9.32	12.07	11.13	11.48	9.69	17.24	17.12	15.58	13.65

Notes: The ratios in each cell are the index of property tax and non-property tax dependences of county governments. The comparisons are between the full sample and three sub-samples of counties. Under '*ALL*' are all county governments. The first subsample, '*GLOST*', is counties that adopt general-purpose LOSTs. The second sub-sample, 'SP*LOST*', is counties that adopt special-purpose LOSTs. The final sub-sample, '*NA,*' is counties that do not adopt LOSTs. Unpaired mean-comparison test (t-test) as group-by-group and year-by-year shows that the revenue shares are statistically different from each other (all p-values < 0.01).

2.1. Hypotheses

Local governments have few fiscal instruments for generating revenue under their discretionary control. Local finance is more vulnerable to changes in politics, economy, socio-demographics, and fiscal institutions and constraints. Demands for public services tend to escalate in recession years when local own-source revenues shrink, state aid dwindles, and states push down outlay responsibilities to relieve their fiscal burdens. LOSTs become a key fiscal instrument to raise local revenue in order to finance earmarked program outlays. In keeping with the extant research cited in the previous section, this study hypothesizes that LOSTs are adopted in response to revenue losses caused by fiscal institutions and economic pressure, and that LOSTs lead to an increase in local own-source revenue capacity, which in turn raises expenditures. Our first hypothesis states that:

H1a: Own-source revenue will increase in a county that levies LOSTs.

H1b: Program outlays will increase in a county that levies LOSTs.

We consider GLOSTs and SPLOSTs separately with regard to their purposes in the sense that each jurisdiction uses LOST revenue differently (Hsiung, 2001; Jung, 2002; Blackwell *et al.*, 2006). Our second hypothesis is that the two LOST types differentially influence fiscal behavior because their enabling and operational mechanisms vary. Local governments adopt GLOSTs in order to expand their own-source revenue, while a SPLOST is designated to fund specific capital projects and an earmark designated in a SPLOST determines where the LOST revenue should be spent. Local governments can neither spend the earmarked revenue on other purposes, nor transfer the revenue to other budget items. Hence, an earmark may not contribute to the expansion of a local government's overall revenue and expenditure as much as a GLOST does because the intended outcomes of SPLOSTs and their interrelationships may cause complications (e.g., voter reluctance in the approval process).

In addition, our review of the data revealed that GLOSTs have typically lasted longer than SPLOSTs and SPLOSTs were terminated more frequently due to the approval period. The termination is also dependent on the target amount to fund any capital project. GLOSTs enjoyed a longer implementation period that helped local governments consistently increase their revenue following periods of expenditure expansion. To further specify the difference between GLOST and SPLOST, we hypothesize that:

H2a: The amount of revenue will expand in a county that levies more GLOSTs than SPLOSTs.

H2b: The amount of expenditure will expand in a county that levies more GLOSTs than SPLOSTs.

Our third hypothesis explores local spending patterns. In keeping with the second set of hypotheses, earmarks of SPLOSTs suggest that SPLOSTs contribute more to capital spending than to operational and personnel spending. GLOST revenue collected without any specific spending purposes can be distributed to personnel and non-capital budget items. Furthermore, a county tends to expand its revenue through GLOSTs, which are not expected to have significant effects on expenditure types. Consequently, non-stringency in GLOS revenue is not internally or externally controlled, and a county spends the revenue at its own discretion. As such:

H3: SPLOSTs mainly serve to increase local capital spending, while GLOSTs have no significant effects on capital spending.

3. Empirical models and data

3.1. Average treatment effects (ATE)

A widely used approach to examine the effects of newly adopted policies is to estimate the average treatment effects (ATEs). The ATEs simply compare the average outcomes between the treated group and the non-treated group, and only one outcome estimates the ATEs in the random sample during the period (Abadie and Imbens, 2011); hence, the missing data problem results in estimation bias. Some scholars have identified biases in the simple estimators of ATEs and the inefficiency of ATEs in directly comparing the treated and the non-treated group (Rubin, 1974; Rosenbaum and Rubin, 1983).

Due to endogeneity of the ATEs in a time-variant dataset, a proposed remedy is the average treatment effects on the treated group (ATETs) that remove variations from systematic differences between the treated and the non-treated group and improve the efficiency of ATE estimators. Biases resulting from missing data can be removed by combining weights and adjusting regression (Robins and Rotnitzky, 1995; Robins, Rotnitzky and Zhao, 1995). A matching method was developed using asymptotic standards for propensity-score estimators from the kernel-based regression (Heckman, Ichimura and Todd, 1998). Conditional biases in matching estimators result in the semiparametric inefficiency of ATEs. Therefore, a matching estimator can correct biases (Abadie and Imbens, 2002) through the weights in matching nonparametric estimates for propensity scores (Hirano, Imbens and Ridder, 2003). Recent developments of ATETs (Abadie and Imbens, 2011) support the use of a matching estimator that replaces a large-size sample with a fixed number of matches through propensity scores, and a bias in treatment effects can be corrected through matching estimators adjusted with linear regression.

The studies on LOSTs have not been subject to these biases due to their single-state data; however, this study covers the counties in all 50 states. The counties in 14 states are not allowed by their state legislatures to adopt LOSTs, so the treatment of LOST adoption is not randomized. The large sample violates the random-sampling criterion, which erodes efficiency in measuring treatment effects, ultimately raising bias issues. The ATET approach corrects biases by propensity-score matching with the nearest neighbors and matches the treated with the non-treated group by creating a counterfactual that isolates the effects. In ATEs, the treatment effects of a county *i* are $E(Yi(1))$-$E(Yi(0))$. However, ATETs consider the treatment effects of potential outcomes that depend on whether the observation is treated (T_i). Based on the outcomes (Y_i), their ATETs (τ_{ATET}) are defined as:

$$\tau_{ATET} = E\left[Y_i(1) - Y_i(0) \mid T_i = 1\right] \quad (1)$$

where, $Y_i = Y_i(T_i) = \begin{cases} Y_i(0) & \text{if } T_i = 0: \text{a county without LOST} \\ Y_i(1) & \text{if } T_i = 1: \text{a county with LOST} \end{cases}$

Depending on propensity-score matching estimators with the nearest neighbors, a non-treated outcome $Y_i(0)$ is matched to the mean values of a treated outcome $Y_i(1)$ that has a similar value to the non-treated outcome before it is exposed to the treatment. The nearest-neighbor matching process randomly sorts the propensity scores of each observation (Caliendo and Kopeinig, 2008). GLOST and SPLOST counties are matched with counties found in states that permit LOST policy. The ATETs recognize the similar value of treated observations prior to a treatment by considering the other covariates; therefore, the group-matching process in the ATETs can correct the ATET biases resulting from a large group of non-treated observations that are randomly distributed (Abadie *et al.*, 2004; Grilli and Rampichini, 2011). Therefore, the matching process can correct biases when the treatment effects from experiments are measured in purely randomized samples of the non-treated group.

We selected covariates that condition similar pre- and post-treatment values for ATETs; those variables capture unbiased treatment effects and develop the propensity-score matching process for our empirical analysis. ATET estimators are obtained by matching the non-treated with continuous covariates that correspond with matching discrepancies. The correspondences depend on the nearest-neighbor one-to-one matching without replacement in order to keep variances low, and the estimator corrects large-sample bias using regression with non-binary covariates (Abadie and Imbens, 2006). Adjustment by a linear function of covariates should be applied in the matching process because the matching is not always consistent, especially when we match two or more continuous covariates (Abadie and Imbens, 2011). We chose covariates for a linear function based on the aforementioned literature on local finance and taxation. Although the equations recognize the effects between pre- and post-treatments, the ATETs of propensity scores do not actually consider time effects. Moreover, the current ATETs of matching propensity-scores cannot include two different treatment variables simultaneously. Since LOSTs in this study are divided into GLOST, SPLOST and NA, we obtained separate matching estimates of propensity scores for LOST and NA, and for GLOST and SPLOST.

3.2. Regression models

Per legal provisions of states that authorize LOSTs, counties are able to make a change in GLOSTs and/or SPLOSTs that they have already implemented. SPLOSTs particularly face pre-set terminations of options that are approved for a fixed period. Hence, we build regression models that consider the behaviors of counties over time and compare regression results with ATETs. These considerations allow us to isolate the effects of specific actions and treatments. Using the NA counties as the base, our first regression model is defined as:

$$Y_{it} = \alpha + \beta Y_{it-1} + \rho GLOST_{it} + \delta SPLOST_{it} + \tau BOTH_{it} + \theta X_{it} + \mu_i + \varphi_t + \varepsilon_{it} \quad (2)$$

where the dependent variables (Y_{it}) are total revenue, own-source revenue, total expenditure, capital spending, and operational spending that an individual county *i* collected or spent in a fiscal year *t*[5]. The two key variables, $GLOST_{it}$ and $SPLOST_{it}$, are binary forms that indicate whether a county levied GLOSTs and SPLOSTs, respectively. Additionally, we add another binary variable, $BOTH_{it}$, identifying counties that adopted both GLOSTs and SPLOSTs because both LOST types generate different budgetary effects. X_{it} is a vector of control variables identical to those used in the ATET model. Lastly, both the ATET model and the two regression models include the one-year lagged dependent variable that controls for the incremental behavior in government budget.

The regression model includes all counties in our sample, placing the NA group as a base. Our third hypothesis compares the effects of GLOSTs and SPLOSTs on local budget patterns; thus, it is required to compare GLOST and SPLOST counties after dropping the NA group. In this sense, the base is the counties that adopted SPLOSTs, and we also considered another regression model that excludes the variable ($SPLOST_{it}$).

3.3. Data and variables

Our sample is composed of 3,046 counties and covers the period of 1970 to 2006[6]. The key variables ($GLOST_{it}$, $SPLOST_{it}$ and $BOTH_{it}$) are the treatments of GLOSTs, SPLOSTs and both, and we collected the key variables from the archives of all the U.S. state and county governments. The covariates in ATETs, as with control variables in the regression models, consider local dynamics of politics, economics, socio-demographics, and fiscal conditions and institutions in counties in Table 2.

First, the covariates and control variables consider sales tax rate because with a higher sales tax, a county would generate more revenues to alleviate increased expenditures. To rule out the effects of the sales tax rate on our five dependent variables, we controlled the two empirical models with the LOST rate in each county[7]. Further, we obtained a spatially lagged variable of the combined sales tax rates; then, we added

5 The dependent variables are transformed to natural logarithm form to resolve any skewness in their distribution. The budget items of some county governments were reported as zero. The transformation to natural logarithm form will lose the county governments that reported zero in their budget information. Thus, a very small number (1.0×10^{-9}) was added before the transformation.

6 This study only focuses on county governments due to the unavailability of data from sub-county governments. The unavailability of fiscal information on counties further restricts the sample period for the empirical analysis in this study to the final year of 2006 because the dependent variables retrieved from the U.S. Bureau of Census have not been provided since that time. Hence, there remains a limitation for future research.

7 State sales tax rate is not considered because the revenue from state sales tax does not affect a county's fiscal conditions.

Table 2: Descriptive statistics of variables

Variable*	N	Mean	S.D.	Min	Max	Description & Data Source**	
				Dependent Variables			
TR	79,144	6.159	0.940	-20.723	9.952	Per capita total revenue (logged)	BC
OSR	79,144	5.665	0.968	-20.723	9.938	Per capita own-source revenue (logged)	BC
TE	79,145	6.128	0.993	-20.723	10.168	Per capita total expenditure (logged)	BC
CE	79,145	2.306	5.587	-20.723	9.229	Per capita capital expenditure (logged)	BC
OE	79,145	5.850	1.254	-20.723	10.168	Per capita operating expenditure (logged)	BC
				Explanatory Variables			
LOST(D)	112,517	0.335	0.472	0	1	=1 when a county adopts either GLST or LOST; 0, otherwise	SDR
GLOST(D)	109,281	0.280	0.449	0	1	=1 when a county adopts GLST; 0, otherwise	SDR
SPLOST(D)	109,281	0.228	0.419	0	1	=1 when a county adopts LOST; 0, otherwise	SDR
BOTH(D)	112,554	0.158	0.365	0	1	=1 when a county adopts both GLST and LOST; 0, otherwise	SDR
LOST Rate(%)	109,281	0.541	0.997	0.000	8.000	LOST rate	SDR
TAXGAP	109,096	0.020	0.703	-5.143	9.000	Difference of sales tax rates between a county and its neighbors	
PTR	79,145	4.807	1.553	-20.723	9.847	Log of per capita property tax revenues	BC
IGR	79,145	4.849	1.948	-20.723	9.766	Log of per capita intergovernmental revenue	BC
TELPTR(D)	112,517	0.404	0.491	0	1	=1 when a county is limited by property tax revenue TELs; 0 otherwise	DS
TELGR(D)	112,517	0.040	0.195	0	1	=1 when a county is limited by general revenue TEL; 0 otherwise	DS
GOV(D)	112,443	0.454	0.498	0	1	=1 when state governor is Republican; 0 otherwise	CQ
REP(%)	112,052	51.253	13.168	1.620	93.803	Ratio of local voters to Republican candidate	CQ
PCI	111,300	19,899.96	5,525.67	4,886.13	106,684.60	Per capita income in year -2000 real dollars (logged)	BEA
MALE(%)	112,370	49.303	1.725	42.527	88.694	Ratio of male population	BC
WHITE(%)	112,370	89.387	15.188	4.621	100.000	Ratio of white population	BC
BLACK(%)	112,370	8.238	14.040	0.000	86.898	Ratio of African-American population	BC
YOUNG(%)	112,370	28.124	18.575	0.561	74.523	Ratio of population under 20 years old	BC

Variable*	N	Mean	S.D.	Min	Max	Description & Data Source**	
OLD(%)	112,370	8.295	5.025	0.064	35.424	Ratio of population over 65 years old	BC
POP	112,370	10.266	1.404	4.344	16.792	Size of population (logged)	BC
POPD	112,323	231.599	1,860	0.051	115,145	Population density	BC
METRO(D)	112,517	0.305	0.460	0	1	=1 when a county is metropolitan area; 0 otherwise	BC
MICRO(D)	112,517	0.481	0.500	0	1	=1 when a county is micropolitan area; 0 otherwise	BC

Notes: * All monetary variables are in 2000-year dollars; (D) indicates dummy variable; (%) indicates percentage. ** BC = U.S. Census Bureau; DS = state department of revenue; CQ = CQ Press Voting and Elections Collections; and BEA = U.S. Bureau of Economic Analysis.

the variable indicating the differences in sales tax rates between a county and its neighbors to control for the neighboring effects of tax competition. Since the variation in state sales tax rates was greater than in local sales tax rates, counties along a state border had a greater difference from their neighbors in another state, especially the neighbors within the four states that had not levied sales taxes. Thus, the spatially lagged variable that accounts for the differences in sales tax rates considers the combined sales tax rates.

Because grants and property taxes are still the main revenue sources for local governments, they are included as controls. In addition, we included the political characteristics of elected representatives and voters in a county because taxation is a political process (Holcombe, 1998). LOSTs can be implemented with state legislative authorization; thus, we considered the governor's political party, which enabled us to control for inter-state differences. Furthermore, voter approval enables LOST adoptions, so we included election results to reflect the political climate of each county (CQ Press, 2017)[8].

Local economy considers income level, which influences sales activities (U.S. Bureau of Economic Analysis, 2017). The urbanization level of a county divided into metropolitan and micropolitan areas considers the economies of scale in a county (U.S. Census Bureau, 2011). Since local socio-demographic characteristics determine the tax base and the scope of public service demands, we considered the characteristics of population size, population density and composition by gender, race and age (U.S. Census Bureau, 2014). TELs restrict state and local governments from expanding their revenue and expenditures, and have a major impact on the growth of local budgets. We considered the two TELs of property tax revenue and general revenue that mostly constrain local budgets (Mullins and Wallin, 2004; Deller and Stallman, 2007). Finally, two sets of dummy variables indicating each state and each year are included to rule out the differences across states over the time period.

8 Voters for the Republican Party, based on electoral districts, is measured by the results of four elections – President, federal Senators, US House Members, and Governor. For non-election years, we use the previous year's election results (Adams *et al.*, 2004).

4. Results

Prior to running regression models, we conducted tests to address estimation issues[9]. Our data revealed serial autocorrelation and heteroskedasticity in the error terms. To handle these issues, we obtained the Newey-West estimators for heteroscedasticity and autocorrelation-consistent (HAC) standard errors (Newey and West, 1987)[10]. The different empirical models can discern differences in the dependent variables and explain them. Table 3 reports the ATET results[11] and Table 4 reports Newey-West HAC estimations that examine the effects of GLOSTs, SPLOSTs, and both on county budgets in our full sample. Table 5 reports the effects of GLOSTs and both among the subsamples of counties without the NA group. We discuss our findings by comparing effects on revenues and expenditures over the three tables[12].

Table 3: Average treatment effects of LOSTs on the treated group

Treatment	LOST			GLOST		
DV	Effects	S.E.	N[(a)]	Effects	S.E.	N[(b)]
Total Revenue	0.150***	(0.006)	63,839	0.214***	(0.023)	21,685
Own-Source Revenue	0.015**	(0.007)	63,839	0.253***	(0.023)	21,685
Total Expenditure	0.095***	(0.009)	63,841	0.096***	(0.024)	21,687
Capital Spending	0.040	(0.083)	63,841	-0.243*	(0.145)	21,687
Operating Spending	0.038***	(0.011)	63,841	0.114***	(0.026)	21,687

Notes: All the dependent variables are the logged value normalized by population. The left panel (a) includes all counties; the right panel (b) includes only counties that have adopted LOSTs. Robust standard errors in parentheses. Significance levels are: *** p<0.01, ** p<0.05, * p<0.1.

9 First, the Breusch-Pagan/Cook-Weisberg test revealed significant heteroskedasticity (Prob > Chi-Square=0.000 for all the dependent variables) using the ordinary least squares (OLS) estimator. The Huber-White-sandwich estimator of the variance was conducted to ensure the robustness of the remaining specification test statistics (Cameron and Trivedi, 2010), and it is used to produce heteroscedasticity-robust standard errors for all estimations.

10 The Newey-West HAC estimator corrects the bias by ordering maximum lags in the autocorrelation structure. Following Newey and West (1987), we conducted regression analysis with two-year through four-year lags, and we did not find big differences across them. Thus, we include only two-year lags in our regression model. In addition, we also tested robust OLS estimators with county- and year-fixed effects following the central limit theorem, and the results demonstrated little difference.

11 Table 3 reports the ATETs adjusted by linear regression of covariates. We also checked the not adjusted ATETs. There are no systematic differences between them, so the results are not reported but available upon request.

12 We obtained the ATETs and Newey-West HAC estimates without the lagged dependent variables. The results excluding the lagged dependent variables are similar to the results presented in Table 3-5. The magnitudes of the key explanatory variables are shown to be greater than the results, except for the two revenue variables in Table 3-5 with the smaller p-values. The results that exclude the lagged dependent variable can be provided upon request.

Table 4: Regression results of the effects of GLOSTS and SPLOSTS (NA as base)

DV	Total Revenue		Own-Source Revenue		Total Expenditure		Capital Spending		Operating Spending	
VARIABLES	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
Lagged DV	0.648***	(0.064)	0.697***	(0.053)	0.606***	(0.059)	0.467***	(0.010)	0.414***	(0.036)
GLOST	0.028***	(0.009)	0.022**	(0.009)	0.023**	(0.009)	0.166*	(0.098)	0.062***	(0.011)
SPLOST	0.021**	(0.010)	0.028**	(0.011)	0.014	(0.013)	0.300***	(0.092)	-0.035**	(0.016)
BOTH	-0.019**	(0.008)	-0.023**	(0.011)	0.012	(0.015)	0.515***	(0.132)	0.054***	(0.017)
LOST Rate	0.030***	(0.007)	0.033***	(0.007)	0.032***	(0.006)	0.103***	(0.038)	0.034***	(0.006)
TAXGAP	-0.006**	(0.003)	-0.008**	(0.003)	-0.005**	(0.003)	-0.079***	(0.028)	-0.001**	(0.004)
PTR	0.061***	(0.014)	0.086***	(0.020)	0.051***	(0.015)	0.067**	(0.030)	0.138***	(0.023)
IGR	0.071***	(0.013)	0.023*	(0.014)	0.063***	(0.013)	0.247***	(0.031)	0.139***	(0.020)
TEL-PTR	-0.005	(0.006)	-0.012*	(0.006)	0.004	(0.008)	-0.221***	(0.061)	0.008	(0.010)
TEL-GR	-0.033**	(0.014)	-0.016	(0.016)	-0.046***	(0.016)	0.133	(0.128)	-0.020	(0.020)
GOV	-0.010***	(0.004)	-0.009**	(0.004)	-0.010***	(0.004)	-0.179***	(0.035)	-0.009*	(0.005)
REP	0.000**	(0.000)	0.001***	(0.000)	0.001***	(0.000)	0.009***	(0.002)	0.001**	(0.000)
PCI	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)
MALE	0.001	(0.002)	0.001	(0.003)	0.001	(0.002)	0.019	(0.015)	-0.002	(0.003)
WHITE	-0.001	(0.001)	-0.001*	(0.001)	-0.000	(0.001)	0.006	(0.005)	-0.001	(0.001)
BLAK	0.000	(0.001)	-0.001	(0.001)	0.001	(0.001)	0.003	(0.005)	-0.000	(0.001)
YOUNG	0.001	(0.001)	0.000	(0.001)	0.002	(0.001)	-0.002	(0.009)	0.002	(0.001)
OLD	-0.001	(0.001)	-0.002**	(0.001)	-0.000	(0.001)	-0.036***	(0.010)	0.000	(0.001)
POP	-0.042***	(0.009)	-0.034***	(0.007)	-0.049***	(0.008)	0.129***	(0.028)	-0.071***	(0.007)
POPD	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)	-0.000	(0.000)	0.000***	(0.000)
METRO	-0.060***	(0.019)	-0.042***	(0.015)	-0.074***	(0.020)	0.103	(0.099)	-0.086***	(0.019)
MICRO	-0.051***	(0.016)	-0.038***	(0.013)	-0.066***	(0.017)	0.053	(0.074)	-0.070***	(0.015)

Constant	2.318***	(0.485)	1.759	(0.000)	2.640***	(0.431)	-3.678***	(1.186)	3.666	(0.000)
N	63,839		63,839		63,841		63,841		63,841	
Counties	2,926		2,926		2,926		2,926		2,926	
R-squared	0.481		0.479		0.370		0.156		0.405	

Note: Fixed effects, included in running the regressions, are not reported in the table. Newey-West Robust standard errors in parentheses. Significance levels are: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Regression results of the effects of GLOSTs (SPLOSTs as base)

DV	Total Revenue		Own-Source Revenue		Total Expenditure		Capital Spending		Operating Spending	
VARIABLES	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
Lagged DV	0.671***	(0.125)	0.762***	(0.095)	0.531***	(0.116)	0.462***	(0.020)	0.422***	(0.101)
GLOST	0.003	(0.007)	0.005	(0.004)	0.047*	(0.024)	-0.080*	(0.045)	0.041*	(0.023)
BOTH	-0.013*	(0.007)	-0.002**	(0.001)	0.052**	(0.021)	0.107*	(0.063)	-0.044**	(0.018)
LOST Rate	0.028**	(0.011)	0.026**	(0.012)	0.040***	(0.011)	0.112**	(0.053)	0.043***	(0.010)
TAXGAP	-0.006**	(0.003)	-0.005**	(0.003)	-0.008*	(0.004)	-0.080**	(0.034)	-0.008*	(0.005)
PTR	0.071**	(0.031)	0.095***	(0.036)	0.064**	(0.030)	0.124**	(0.063)	0.065**	(0.029)
IGR	0.183**	(0.078)	0.104	(0.065)	0.185**	(0.079)	0.204**	(0.087)	0.200**	(0.078)
TEL-PTR	-0.009	(0.025)	0.008	(0.027)	0.009	(0.030)	0.074	(0.159)	0.000	(0.033)
TEL-GR	-0.053*	(0.031)	-0.026	(0.031)	-0.091***	(0.034)	0.255	(0.205)	-0.026	(0.030)
GOV	0.010**	(0.005)	0.011**	(0.006)	0.003	(0.007)	-0.130***	(0.049)	0.000	(0.007)
REP	0.001	(0.000)	0.001	(0.000)	0.001**	(0.000)	0.009***	(0.003)	0.001**	(0.000)
PCI	0.000**	(0.000)	0.000**	(0.000)	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)
MALE	0.003	(0.002)	0.004*	(0.002)	0.003	(0.002)	0.020	(0.020)	0.002	(0.003)
WHITE	0.001*	(0.001)	0.001	(0.001)	0.001**	(0.001)	0.003	(0.005)	0.002***	(0.001)
BLAK	0.002*	(0.001)	0.002*	(0.001)	0.003***	(0.001)	0.004	(0.006)	0.003***	(0.001)
YOUNG	0.001	(0.001)	0.000	(0.001)	0.004**	(0.002)	0.012	(0.010)	0.003**	(0.001)

DV VARIABLES	Total Revenue		Own-Source Revenue		Total Expenditure		Capital Spending		Operating Spending	
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
OLD	-0.002*	(0.001)	-0.003*	(0.001)	-0.001	(0.001)	-0.005	(0.011)	-0.001	(0.002)
POP	-0.009	(0.010)	-0.003	(0.008)	-0.024**	(0.012)	0.134***	(0.036)	-0.057***	(0.016)
POPD	0.000	(0.000)	0.000	(0.000)	0.000**	(0.000)	-0.000	(0.000)	0.000***	(0.000)
METRO	0.018	(0.022)	0.040	(0.026)	-0.011	(0.032)	-0.009	(0.139)	-0.034	(0.033)
MICRO	0.026	(0.019)	0.042*	(0.023)	0.003	(0.028)	-0.091	(0.110)	-0.023	(0.029)
Constant	0.369	(0.000)	-0.295	(0.000)	1.230	(0.000)	-4.451	(0.000)	2.231**	(0.885)
N	21,685		21,685		21,687		21,687		21,687	
Counties	1,416		1,416		1,416		1,416		1,416	
R-squared	0.574		0.560		0.395		0.088		0.315	

Note: Fixed effects, included in running the regressions, are not reported in the table. Newey-West Robust standard errors in parentheses. Significance levels are: *** p<0.01, ** p<0.05, * p<0.1.

4.1. Effects on total and own-source revenue (OSR)

We used two dependent variables relevant to a county's revenue capacity: total revenue and own-source revenue (OSR). Table 3 provides consistent evidence that LOSTs increase total revenue and GLOSTs increase total revenue more than SPLOSTs do, in support of H1a. More specifically, the total revenues of counties that levied LOSTs increased by 15.0% versus counties without LOSTs (left-panel, Table 3) and GLOST counties collected 21.4% more than SPLOST counties (right-panel, Table 3). Similar findings are observed in a county's OSR; however, OSR increased less than total revenue did when we compared the counties that levied any type of LOST with those without LOST.

In addition to the ATETs, the Newey-West regression results provide insights into the separate effects of GLOST, SPLOST, and GLOST-SPLOST in tandem with BOTH. In Table 4, GLOSTs are shown to increase total revenue by more than 2.8% and OSR by 2.2% only. SPLOSTs have positive effects on total revenue and OSR; however, the effects of SPLOSTs are greater on total revenue (2.1%) and smaller on own-source revenue (2.8%) compared with GLOST. In addition, counties that levied both LOSTs collected 1.9% and 2.3% less in both total revenue and OSR. These results support H2a and partially support H1a. Table 5, which compares GLOST with SPLOST counties, shows no systematic differences between the two types. This negative effect of levying both types of LOST opens a new question that demands future research. From these findings, we can draw an overall conclusion that LOSTs help a county raise its revenue capacity, while a county with both GLOSTs and SPLOSTs (labeled BOTH) is faced with a potential loss of revenue.

4.2. Effects on total expenditures and spending behavior

In keeping with the increase in revenue capacity, LOSTs expand a county's total expenditures. As with the two revenue measures, counties with LOSTs spent more by about 9.5% versus counties without LOSTs (left-panel, Table 3), and GLOST counties spent about 9.6% more than SPLOST counties (right-panel, Table 3). The regression results in Table 4 reveal evidence that counties increased their expenditures by about 2.3% when they levied a GLOST. With the sub-sample where the SPLOST group is the default in Table 5, GLOST caused an increase of 4.7% in total expenditures; further, the effects of BOTH are also positive on expenditures (increasing expenditures by 5.2%) relative to SPLOST-only counties.

For capital spending, the ATETs (Table 3) show that LOST was not likely to expand this outlay, while GLOST counties reduced capital spending by about 24.3% when compared with counties that levied SPLOSTs. These data support H3 based on the earmarked purposes. However, the regression approaches in Table 4 and 5 provide a complicated result. Table 4 shows that a GLOST county spent about 16.6% more on capital spending than a county without LOST, while a SPLOST county spent about 30.0% more. A county that adopted both GLOSTs and SPLOSTs, on the other hand, expanded its capital spending by almost 51.5%. These results are confirmed by those in Table 5: the capital spending of counties with GLOSTs was about 8.0% less than counties with SPLOSTs, while 10.7% more was spent on capital purposes in counties that levied both LOSTs. Although LOSTs helped counties expand their capital spending more than non-LOST counties, the negative sign in the ATETs of GLOSTs (right-panel, Table 3) implies that counties with SPLOSTs expand their capital spending more due to the referendum earmarks. The findings in Tables 3 through 5 provide the overall conclusion that the type of LOST (general vs. special) with or without an earmarked purpose influences the spending behavior of a county, as anticipated in H3. The above findings confirm the proposition that earmarked options in SPLOSTs prohibit counties from spending their collected revenues on other general purposes.

Turning attention to operational spending, counties that levied LOSTs could afford to spend an average of 3.8% more for operational purposes (left-panel, Table 3). Furthermore, GLOST counties were shown to spend almost 11.4% more than SPLOST counties (right-panel, Table 3). In comparison, regression results provide similar insights. On average, a county with a GLOST was likely to expand its operational spending by 6.2% more than a county without any LOST, while operational spending decreased by about 3.5% in counties with SPLOSTs. Furthermore, counties in the category BOTH expanded their operational spending by 5.4%, as shown in Table 4 because BOTH counties also collected sales tax revenues for general purposes. When we compare the GLOST and SPLOST groups, GLOST counties spent 4.1% more than SPLOST counties on general operations; however, BOTH counties decreased their operational spending by 4.4%. Thus, the ATETs and regression results partially support H2b.

5. Conclusion

Since the 1970s, LOST has become more relevant to public finance due to its increasing share in local budgets. As local governments have adopted their own sales taxes, fiscal conditions in local governments have changed with the potentially regressive features of sales tax in their revenue system and the elasticity of sales tax revenue. Furthermore, it is necessary to expand the scope of research to uncover heterogenous diversity across states and localities. Multi-state analysis might raise a problem unless legal and institutional structures within the states are not fully controlled for.

To solve the problem, we have empirically examined the fiscal effects of LOSTs in county governments by employing two different empirical approaches to yield convincing and generalizable results. We found that LOSTs enable county governments to increase their total revenues and own-source revenues, as well as to expand total expenditures and operational spending. According to the two empirical approaches, a county with LOSTs is able to expand its fiscal capacity, while its capital spending might decline in keeping with the extant literature; however, a more significant contribution of this study is that, to our knowledge, it is the first one to explore the different effects of LOST types on local budgets. We consider the effects of general-purpose LOSTs and special-purpose LOSTs separately. The empirical findings strongly support the argument that GLOSTs increase total revenue, own-source revenue, and operational spending more than SPLOSTs do. SPLOSTs increase capital spending, in contrast to GLOSTs, because SPLOST revenues are earmarked by voter approval. GLOSTs are maintained for longer periods than SPLOSTs, so GLOSTs are a more sustainable way to expand county revenues. In addition, the three budget components (total revenue, own-source revenue and total expenditure) decrease in counties that adopt both GLOSTs and SPLOSTs. The decreases result from the fact that the combined sales tax rate is higher, and the tax bases are driven to their lower sales-taxing neighbors.

However, this study has some limitations. Although this study makes efforts to consider the fiscal effects of LOSTs through a national dataset in a period of 37 years up to 2006, this study fails to consider more recent years. Another limitation is that this study cannot consider the LOSTs that municipality-level governments have levied due to limited data availability. Lastly, European and Asian countries also have sales taxes as a form of value-added tax (VAT); however, this study cannot be internationally applied because local governments in VAT countries do not have much discretionary power to tax compared with local governments in the U.S. These limitations leave a niche for future research.

In spite of the limitations, this study has provided consistent evidence that LOSTs increase local revenue capacity. Another contribution of this study is to show that general and earmarked purposes of LOSTs have different influences on local budgets and their components. An adoption of a new tax can raise an issue of tax evasion. To avoid public resistance against an increase in tax burdens, this study provides a motivation for local policy-makers to consider the fiscal purposes of new sales taxes, such as increasing revenue capacity and/or expanding any specific spending area (e.g., capital investment). When a local government adopts LOST and increase LOST rate through the referendum process, it can ease resistance on the part of voters by demonstrating a convincing purpose for the adoption.

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