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Discover and Diffuse a New Tax Base:
Spatial Analysis of School Parcel Tax Adoption in California

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Abstract

This paper examines a spatial interdependence of innovation and diffusion of a new tax base in the case of parcel tax adoption across California school districts. The adoption of parcel taxes—typically a lump-sum tax per parcel of real properties—has been geographically uneven. In this paper, we answer whether school parcel tax adoption is a process of policy diffusion from learning by examining spatial patterns of adoption through spatial analysis. We conclude that the home price cap, per pupil current operating spending, together with the parcel tax adoption in the neighboring school districts are the main factors for the adoption and diffusion of this special purpose tax, parcel tax. This research contributes to the literature by accounting for the spatial effects in the diffusion process of parcel taxes.

Keywords: policy diffusion, parcel tax, California, school finance, tax referendum, spatial analysis, proposition 13, property tax.

JEL codes: H71, H75.

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I. Introduction

This paper examines a spatial interdependence of parcel tax adoption across California school districts. A parcel tax is a non-ad valorem tax that is imposed per parcel of real properties. California's Proposition 13 was passed in 1978 to impose a statewide ad valorem property tax at one percent of the purchasing value of real properties. It resulted in severe revenue constraints across school districts, for there is no evidence that Californians demand fewer public services nor the cost of service has declined. To maintain the level of public education, school districts have searched new sources of tax revenues.

The state's constitution allows local governments to raise special taxes for special purposes if approved by a two-thirds of local voters. A parcel tax is a direct outcome of policy innovation in local governments by discovering a new property tax base to fund public schools while not violating the ad varoom property tax cap. Since the first parcel tax election was held in 1983, school districts have increasingly adopted a parcel tax. Since then, parcel tax elections have held in more than 23% of school districts, and 13 percent of school districts have approved at least one parcel tax measure.

However, the geographical spread of the innovation has been uneven. It is the San Francisco Bay Area (the Bay Area hereafter) that proposed and adopted a parcel tax at a much higher rate than the rest of the state. From 1983 to 2017, 70% of school districts that have held at least one parcel tax election were located in the Bay Area. Of those, 70% of school districts that approved a parcel tax measure were located in the Area. Previous studies are puzzled that there is "something special about the Bay Area," and speculate it may be liberal political ideology (Kiewiet and Hill 2015) or other characteristics such as the wealth of the residents in the Area (Lang and Sonstelie 2015). Nonetheless, previous studies do not offer a persuading theoretical reason for the geographic concentration of the parcel tax usage.

In this paper, we answer whether school parcel tax adoption is a process of policy diffusion from learning by examining spatial patterns of adoption. To achieve this goal, we embrace theories of policy diffusion (Shipan and Volden 2012) because we believe that they best explain the geographic concentration of school parcel tax adoption. We hypothesize that spatial interdependence among school districts explains the prevalence of parcel taxes in the Bay Area. For instance, this innovation of revenue raising spreads out faster in the Bay Area because school boards learn from each other and voters easily understand how a parcel tax could affect public school revenues by observing neighboring school districts.

To test the spatial dependence, we will use California school-district level panel data that consists of about 986 school districts from 2008 and 2017. After conducting Lagrange multiplier test of major variables of interest, we attempt to mainly use spatial autoregressive (SAR) models for our analyses to explore and examine the spatial diffusion process. The results demonstrate that the home price cap, per pupil current operating spending, together with the parcel tax adoption in the neighboring school districts are the critical factors affecting the adoption and diffusion of the special purpose tax, parcel tax.

The paper is organized as follows. Section II explains how the geographic concentration of school parcel taxes can be explained within the theory of policy diffusion. Section III describes data and methodology. Results are presented in Section IV. Section V concludes the paper.

II. School Parcel Tax Adoption as a Policy Diffusion

New property tax base, a parcel tax in school districts.

Local governments under strict tax limitations have found ways to raise revenues without violating the restriction. After Serrano vs. Priest and Proposition 13, school districts lost their ability to extract local real estate tax base to fund their public schools. A parcel tax is a policy innovation to work around the current school funding system and the constitutional tax limitation. It is a tax imposed on the real estate per parcel (an administrative unit of real properties). It is a non-ad valorem special tax that requires two-thirds of local votes.

The first school parcel tax proposed in 1983. There are five school districts proposed, and one of them approved a $25 parcel tax for six years. From 1983 to 2017, 695 school districts held at least one parcel election (Ballot Measure Election Results from the California Secretary of State). Between 2008 and 2017, school districts raised almost $4 billion to finance operating expenses. During the 2016-17 school year alone, California school districts raised more than $423 million (California Department of Education).

To raise a parcel tax revenue, school boards must decide whether they propose a parcel tax ballot measure and two-thirds of voters must approve it. Prior research finds that districts with wealthier, educated, and liberal residents are more likely to vote yes on the ballot measure (Brunner 2001; Lang and Sonstelie; Hill and

Kiewiet). Also, A prior study also finds that the cost of election significantly determines the likelihood of proposing an election by school boards and the voter approval depends on the underlying distribution of home prices (Lee 2016).

All previous studies mention "something about the Bay Area." Sonstelie (PPIC 2013) states that the Bay Area has been the center of "the parcel tax movement" and its geographic concentration is attributed to liberal attitudes towards taxation and spending (p.5). In the similar vein, Kiewiet and Hill (2015) maintain that wealthy and liberal school districts that are able to and willing to pay parcel taxes seem to be "within a comfortable driving distance of the Golden Gate Bridge (p.11)." More importantly, Lang and Sonstelie (2015) conclude that the Bay Area districts are significantly more likely to levy a parcel tax than are other districts. They think that it is because of the districts' higher income than in the rest of the state. They also mention that observed characteristics in their study explains only a third of the difference between Bay Area districts and other districts in the likelihood of parcel tax adoption.

In our data from 1983 to 2017 election data, approximately 70% of the 695 school parcel elections were held in the Bay Area. Figure 1 shows the number of school parcel tax elections by year in Panel A. The number of elections held in the Bay Area is indicated in dark blue. The geographic concentration, however, appeared in the early 1990s. The majority of the first five school districts that held a parcel tax election in 1983 was not in the Bay Area. Only the San Mateo Union High School District was located in the Bay Area, and its proposal failed after all. In the subsequent years, there is no clear indication that the Bay Area is more likely to consider a parcel tax until the early 1990s. Since then, parcel tax elections are concentrated in the Bay Area. As a result, as shown in Panel B, most school districts that raised revenue through parcel taxes in 2016 were located in the Bay Area.

[Figure 1 about here]

In previous literature, “something about the Bay Area” has been speculated as wealth, income, liberal political preference. In other words, these internal factors lead to parcel tax adoption that happens to be in the Bay Area. In this logic, only the internal factors of districts determine the likelihood of parcel tax adoption; the parcel tax adoption has independently emerged in the Bay Area.

Nevertheless, school districts’ use of parcel tax might be a result of policy diffusion where policy choices are interdependent. (Braun and Gilardi 2006). According to policy diffusion literature, diffusion occurs when one government’s decision about whether to adopt policy innovation is influenced by previous choices by other governments (Graham et al. 2008). Policy diffusion literature emphasizes that both internally heterogeneous preferences and external interdependence/interaction among governments determine policy adoption (Berry and Berry 2007). In the local context, previous studies show a clear spatial pattern of policy adoption such as municipal living wage policy adoption (Martin 2001), Florida’s development impact fee (Jeong 2006), California school districts’ charter school adoption (Rincke 2007), municipal antismoking policy adoption (Shipan and Volden 2008), Oklahoma’s municipal local option sales tax adoption (Burge and Piper 2012), Florida counties’ unreserved general fund balances (Guo and Wang 2017), tax incremental financing in Missouri counties (Mitchell et al 2017), and N ew York property tax reassessment (Eom et al 2017).

In the context of school parcel tax election, the internal, endogenous demand model is limited in that it does not explain why school districts propose a parcel tax election which requires a substantial election cost and a high threshold to pass. The theory of policy diffusion can explain this supply side of the story. In fact, although previous studies fail to account for the interdependence of policy adoption across school districts, they suspect and acknowledge that "something about the Bay Area" might reflect "mimicking" where a district sees a parcel tax as more acceptable when and if neighboring districts have passed on (Sonstelie 2003, p.5). Land and Sonstelie (2015) state that their model excludes variables that may explain part of the difference between Bay Area districts and other districts. As an example, they mention a fiscal innovation and diffusion throughout the state.

Further, Lee (2016) finds that when the proposal and voting decisions are separated into two different decision-making stages, "the Bay Area indicator is statistically significant only in the first stage of proposing an election, whereas it is insignificant in the second stage of voting." In other words, a parcel tax is much more likely to be considered in the Bay Area as a viable revenue source, while voters in the Bay Area are equally likely to approve a parcel tax compared to voters in the rest of the state. This finding implies that the concentration of parcel tax usage in the Bay Area should be attributed to policy learning and diffusion among the school boards in the Bay Area, not to the preference of the Bay Area voters. Thus, prior studies call for systematic scrutiny on the spatial interdependence of parcel tax adoption.

The policy diffusion literature provides potential mechanisms to explain why parcel tax usage spread and how this diffusion comes about. Graham et al. (2012) review policy diffusion studies and find 104 different terms that describe diffusion. They identify four main processes of mechanisms of policy diffusion: learning, competition, coercion, and socialization.[1] Maggetti and Gilardi (2014), however, argue that coercion is not diffusion. We agree. Also, in the context of parcel taxes, coercion is inapplicable since local adoption is entirely voluntary. Our discussion focuses on the three mechanisms: learning, emulation, and competition.

Policy learning is a policy diffusion process where government officials are influenced by the consequences of policy success in other governments (Berry and Baybeck 2005; Berry et al. 2007; Mooney 2001; Maggetti and Gilardi 2014).[2] Policy adoption is more likely if the policy has been *successful* elsewhere. In essence, the learning mechanism emphasizes that policymakers are outcome-oriented and that they rely on knowledge and experiences from other governments. Volden, Ting, and Carpenter (2008) maintain that if we ignore the learning process, then we assume that they learn from their own experience only, which is unrealistic in practice.[3]

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[1] Some scholars agree on the categorization (Shipan and Volden 2008). Braun and Gilrardi (2006, see Table 1, p.313) offer six: learning, competitive and cooperative interdependence, coercion, common norms, taken-for-grantedness, and symbolic imitation.

[2] Local officials' ideology plays a role here. They are unwilling to learn if they are ideologically predisposed to oppose it. But if they learn the policy is effective and successful, they overcome the predisposition to oppose. (Butler et al. no year info)

[3] Learning is different from following common norms. In the common norm mechanism, governments adopt a policy because it is the appropriate behavior in a given context with a given identity. Learning is also different from symbolic imitation where government officials adopt a policy that they think is proper and adequate (e.g., Children's Health Insurance Program).

Policy emulation (or policy imitation, mimicking) is copying policies that are considered to be appropriate. In emulation, objective outcomes of policy effectiveness are not essential or unrelated to policy adoption (Maggetti-Gilardi 2014). In this sense, adoption is only symbolic. Socialization is also a part of the reason for emulation. Empirically the emulation mechanism has been hypothesized that governments are more likely to adopt an innovative policy when a sizeable neighboring jurisdiction previously adopted it.

Lastly, in competition, governments follow the policies of competitors. The competition follows the policies of competitors. Besley and Case (1995) formalize yardstick competition that voters in one jurisdiction observe surrounding localities when making decisions. The model then implies spatial clustering of policy choices. The competition mechanism has been examined in the context of tax and revenue competition. Mitchell, Stewart, and Hamman (2017) ask why local governments adopt tax incremental financing districts (TIFs) despite their erratic performance. They find that economic competition drives Missouri counties to adopt TIFs in fear of losing revenue to neighboring retail development. This TIF case is well explained in the framework of policy diffusion in conjunction with the Tiebout competition.

We believe that the school parcel tax adoption can be best explained within the policy diffusion framework, especially the geographic concentration of parcel tax adoption in the Bay Area. We also believe that the mechanism of policy diffusion is mainly policy learning. One of the school board members in the [4] stated, "The School District's policies *seem* to diffuse in tax policy more than innovate. Statue, or

[4]San Francisco Bay Area

rather *case law*, doesn't allow much innovation." He mentioned that new information is disseminated and shared through Local Education Agencies such as the California School Boards Association and, Association of California School Administrators, and the California Association of School Business Officials. For instance, lawyers in the California School Boards Association's Legal Defense and Education Alliance offers seminars and workshops for statewide conferences. He, however, emphasized that school board members meet and talk much more regularly with *regional* colleagues than with similar groups across the state.[5]

The difference between policy learning and policy emulation (mimicking, imitation) is whether policymakers think the policy of interest is effective in achieving goals or it is something appropriate to adopt regardless of its outcome. We believe that parcel tax adoption diffuses through policy learning for two reasons. First, the effectiveness of parcel tax adoption is obvious: additional funding for operating expenses. Parcel taxes usually finance specific operating expenses such as high-quality teacher retention, science, and art education. Second, parcel tax elections are costly. School districts must pay for the administrative costs of an election including the cost of printing and distributing the text of the measure and the payment to the Registrar of Voters for election administration. These costs range from $200,000 to $360,000 (Lee 2016). A parcel tax election can be politically costly as well. The superintendent of the Menlo Park School District stepped down

[5] He also mentioned the role of political advisor firms. According to the New York Times, school boards receive promotion pamphlets from political consulting firms. We believe that it is difficult to isolate their role in the parcel tax diffusion process, but it is something that future research will need to pursue.

from the leadership after failing two parcel tax elections consecutively in 2016. Hence, a parcel tax election is not something school boards to adopt symbolically since it incurs significant financial and political costs while requiring a supermajority of votes to pass.

Although the competition mechanism among local school districts weakened after Serrano v. Priest and Proposition 13, it can be considered as a diffusion mechanism of a parcel tax. Geographically close, neighboring districts compete to attract locally mobile parents for more enrollment and to hire and retain high-quality teachers who are locally mobile. This can be explained by the yardstick competition where voters respond to parcel tax adoption in neighboring districts and learn that it enhances the quality of public education in the districts. Knowing that voters make such comparisons, school boards account for neighboring districts' parcel tax adoption when they make their own decisions. This spillover effect from adjacent jurisdictions implies that there will be spatial clustering of parcel tax adoption.

We believe that the neighboring effect is as much important as the internal demand factors for parcel tax adoption. As Lang and Sonstelie (2015) report, income and other endogenous factors explain only a third of the difference in the likelihood of parcel tax adoption between Bay Area districts and districts for the rest of the state. We think that their conjecture is worth exploring because a large majority of public school students do not benefit from parcel taxes for various reasons. Neighboring districts' policy choice is potentially another factor that creates disparities in educational funding that the *Serrano v. Priest* prohibited almost half a century ago.

III. Data and Method

As indicated in the above literature review, policy learning is a policy diffusion process where government officials are influenced by the consequences of policy success in other, especially neighboring governments (Berry and Baybeck 2005; Berry et al. 2007; Mooney 2001; Maggetti and Gilardi 2014). Thus, policy adoption is more likely if such a policy has been successful elsewhere. At the same time, not only government officials are aware the of policies in the nearby districts, but citizens are also naturally aware of the situation in their neighbors while making their decisions in an election. Therefore, when we explore and examine the determinants of parcel tax adoption, we should not only consider the factors within their school districts but should also include the influence of learning effect from their neighboring school districts. We hence believe and hypothesize the adoption of a parcel tax in one school district is hence more likely if the nearby school districts have adopted in addition to the idiosyncratic features within this school district. This study intends, for the first time, to test this hypothesis incorporating the necessary spatial dimension together with the conventional explanatory variables.

Table 1 and Figure 2 are the Local Moran's I statistics of three different parcel tax-related variables, including the parcel tax election, parcel tax existence and parcel collected value in the year 2014 tax using two different weight matrices, Rook contiguity and K(3) nearest neighbors. After conducting the 999 permutations, the results are still all significant, which indicates the existence of spatial autocorrelation and spatial analysis is hence the necessary for conducting spatial analysis (Anselin, 2005).

[Table 1 about here]

To conduct the spatial analysis, we have a cross-sectional data of 758 California K12 school districts of all three kinds, elementary, high and unified districts. All observations are selected only if the average daily attendances in 2014 are more than 200. Within the sample, 103 districts out of the 758 districts have collected parcel tax revenue. The reason for using the cross-sectional data is the nature of parcel tax elections and adoption. Once a parcel tax is approved, the effect can last for several years. The focal point of this study is to identify the diffusion and the learning effect across school districts rather than changes within a district, which makes the cross-sectional data appropriate for spatial analysis.

The non-spatial component of the data was initially collected from the Annual Finance Data (California Department of Education), American Community Survey (U.S. Census Bureau), and local ballot measure information from Ed-Data (www.ed-data.k12.ca.us). The shapefiles of three districts are acquired from the US Census Bureau. After merging the data using the code of districts, we eventually get only 758 districts other than the original 986 districts.

To test the spatial diffusion effect of parcel tax adoption and diffusion. Two dependent variables are selected in the model. The two dependent variables of interest are binary variables, which respectively indicate the existence of parcel tax transaction in 2014 and the existence of parcel tax election between 2008 and 2014.

Home value gap. The first explanatory variable is the distribution of home value within a school district. A lump-sum parcel tax imposes different tax rates due to different property values. Thus, a broader distribution of home values would decrease the likelihood of proposing and approving a parcel tax because of the unfairness. The variable is construed based on the self-reported property value in the U.S. Census Bureau. The ratio is calculated using the average property value of the lower quartile divided by the average value of the upper quartile within a given district.

Population size. We include the total population size because of its association with campaign and administrative costs and broader distribution of preferences towards public school system (Balsdon et al. 2003). Furthermore, school quality may depend on the economies of scale.

Proposed tax amount. A higher amount of proposed tax could naturally decrease the approving rate hence it is very likely to be associated with the parcel tax adoption and diffusion.

Renters. The portions of renters within the population can also potentialbe associated with the preferences for the parcel tax since literature suggests renters have a higher expectation of local public goods and services than property owners (Bergstrom and Goodman 1973; Oates 2005; Brunner et al. 2015).

Income bracket of the decisive voter. Demand for schooling will increase with the income level of voters, hence the higher probability of adopting parcel tax. This positive association is also justified in the previous studies (Lang and Sonstelie 2015; Kiewiet and Hill 2015). Meanwhile, since parcel tax requires a two-thirds supermajority to be approved, the desirable variable adopted here is not the median income but the 33rd percentile. More specifically, this variable is constructed using the cumulative density with categories as less than $25,000, $25,000 to $50,000, $50,000 to $75,000, and $75,000 and more.

Per pupil current operating spending. Current operating expenditures per pupil might be associated with the likelihood of parcel tax election. Low expenditure might at least provide incentives for the parcel election in a given school district.

Cost of providing schooling. Cost of providing schooling is associated with the salaries and benefits of school employees, which can reflect the local condition as noted in Lang and Sonstelie (2015).

Cost of an election. By law, school districts are responsible for the administrative cost. Therefore, whether parcel tax can be combined with other elections is also important in this context. The election cost is constructed using the Herfindahl Index to estimate the election cost. Higher values represent higher levels of incongruence, which will lead to higher costs of an election.

Political ideology. More liberal means more spending (Kiewiet and Hill 2015; Lang and Sonstelie 2015) it is constructed using the percentage of votes for Barack Obama in the 2012 presidential election as a proxy.

Educational level of the population. A higher percentage of college graduates are more likely to realize the importance of education and hence more likely to vote or adopt the parcel tax.

Population age 65 and older. Senior population tent to demand less public schooling (Poterba 1997). Therefore, we include the percentage of senior citizens.

Bay Area Indicator. In the previous studies, the higher prevalence of parcel tax has been identified in the Bay Area. For instance, Lang and Sonstile (2015) divide the data into Bay Area districts and non-Bay area districts, so we hence also include this indicator, which includes Alameda, Contra Costa, Marin, San Francisco, San Mateo, and Santa Clara Counties. Table 2 presents the descriptive statistics of variables included in the model.

[Table 2 about here]

The model adopted in this project is the Spatial autoregressive (SAR) model based on the hypothesized diffusion effects from the learning mechanism across different school districts within the State of California. "Spatial dependence reflects a situation where values observed at one location or region, depend on the value of neighboring observations at nearby locations." (LeSage and Pace 2009, p. 2). There are generally two common spatial econometric models, spatial lag/spatial autoregressive (SAR) model and spatial error model (SEM). The SAR considers the spatial dependence of a dependent variable whereas SEM considers the spatial dependence in the error term.

Regarding the model selection, we follow Anselin (2005) and Elhorst (2010a) that suggest the two-step approach. We first ran a conventional nonspatial model and then apply the Lagrange Multiplier (LM) test to select between the SAR and SEM model. If one of the models are deemed appropriate, the model selection will follow the LM test. If both of the SAR and SEM are considered appropriate, we will consider other spatial models, such as the spatial Durbin model. (Anselin, 2005; Guo & Wang, 2017).

The weight selection is also very critical within the spatial analysis. There are different kinds of ways to construct a weighting matrix, such as contiguity, distance-based and K-nearest neighbors. Based upon the nature of our data with some missing variables, we hence select the approach of K-nearest neighbors and pick the value of 3, which will guarantee each district to have three neighbors that don't necessarily share a geographical boundary. This is one of the typical ways of conducting spatial analysis in the field of public finance due to the nature of data (Guo &Wang, 2017). The geographic proximity, especially the Rook contiguity is normally considered as the default spatial weighting matrix (Anselin, 2005) and this type of selection using Queen contiguity will be adopted in the robustness check to further justify the model selection as well as the learning effect through the diffusion process.

[Table 3 about here]

According to the above LM test diagnostics for spatial dependence, Lagrange Multiplier (SARMA) using both of the two weight matrices further justify the spatial dependence within the variables. The SAR is considered as the only appropriate model regardless of the choice of weight matrices. We will hence adopt SAR[6] for the model to explore and examine the spatial diffusion of a parcel tax.

$$Y=\rho WY+X_s'\beta+e$$

In this reduced form, where Y is the dependent variable, X represents the matrices of independent variables and dependent variables, β is the vector of regression parameters to be estimated from the data, ρ is the autoregressive coefficient, which tells us how strong the resemblance is, on average, between Yi and its neighbors. The matrix W is the spatial weight matrix, describing the spatial network structure of the observations.

IV. Empirical Results

After using the LM test further justify the spatial dependence within the data set, SAR is considered as the only appropriate model. The following table 4 presents the current estimation using SAR models, which include the spatial lag of dependent variables.

[Table 4 about here]

Within both of the tests, we can preliminarily conclude that the home income gap, per pupil current operating spending together with the weight matrix are all statistically significant. Meanwhile, within the control variables, the education level of citizens and the Bay area indictor are also statistically significant. More specifically, from the spatial dimension, this indicates that a given school district is more likely to hold parcel tax election or has adopted parcel tax if the neighboring

[6] See Anselin (2005), page 199.

districts have held parcel tax election or have adopted parcel tax. From a non-spatial dimension, home price gap and per pupil current operating spending both consistently demonstrate statistical significances. This demonstrates the bigger the home price gap, the less likely to have a parcel tax election or less likely to find the existence of parcel tax transaction. In addition, the high per pupil current operating spending shows the expensive areas are more likely to have or have tendencies to use this innovative tax to raise revenue. Furthermore, in both of our models, similar to previous studies, the education level and the Bay indicators all consistently demonstrate the positive association with the existence of parcel tax election and parcel tax transaction.

[Table 5 about here]

Due to the common and easy disagreement over the choice of spatial matrices, we hence also apply and compare the Rook and Queen contiguity and presented the results in the above in the following table 5. The results, especially the spatial autocorrelation of the existence of parcel tax still hold consistently together with most of the chosen independent variables, which justify the issue is parcel tax election and adoption can be more likely be explained through a normative account through spatial diffusion as well as from an economic/instrumental perspective other than from a perspective of political ideology in our model. Furthermore, just like in previous studies (Lang and Sonstelie 2015; Kiewiet and Hill 2015), the Bay area indeed consistently exhibits statistical significance. Since the control of political ideology is not significant in both of the models, we might be able to rule out the political liberal ideology but more focus on the high family income.

V. Conclusion

This paper explores and justifies the spatial interdependence of parcel tax election and adoption across California school districts. We have applied spatial autoregressive regression and identified that the possibility of adopting parcel tax is higher if there are also parcel tax adoption in the neighboring school districts. Meanwhile, the variables of home price gap together with the per pupil current operating spending are also significantly correlated with the adoption of parcel tax after controlling for demographic, political as well as other idiosyncratic features used in previous studies, within the school districts. The mechanism is through learning other than competing effects across school districts within the state of California.

For the next stage, according to our current model, the parcel tax adoption is going to continue to diffuse and we are also going to collect the data along the way. Once the collection of panel data is reached as well as the disagreement of spatial panel data analysis within R package has been resolved or further developed, we can start to conduct the spatial panel analysis of these two dependent variables once again. We attempt to use the spatial panel analysis as well as hazard ratio model in the next stage to further explore and examine the factors affecting the spatial diffusion of the parcel tax longitudinally.

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Table 1.
Moran's I and Z-Values of Parcel Tax Variables

Variables	Moran's I		Z-Value (999 Permutations)	
	K-3	Rook Contiguity	K-3	Rook Contiguity
Parcel Election	.497	.493	16.143	22.711
Parcel Tax Adoption	.523	.525	17.406	23.489
Parcel Tax Value	.249	.366	9.707	19.138

Table 2.
Summary Statistics

Variables	Mean	S.D.	Min.	Max.
Parcel Tax Election	.17	.38	0	1
Parcel Tax Adoption	.14	.34	0	1
Home price gap (log)	.72	.3	0	2.44
33rd percentile income	2.21	.7	1	4
Current expenditure per pupil (log)	9.1	.19	8.67	10.1
Cost index	.22	.17	-.21	.51
Average Daily Attendance (log)	7.89	1.43	5.3	13.17
Average Daily Attendance ((log, square)	64.27	22.88	28.13	173.57
Renters (log)	3.59	.38	1.8	4.49
Bay Indicator	.18	.38	0	1
% of Obama gained (log)	3.98	.24	3.33	4.42
% population 65+(log)	2.53	.42	.47	3.54
% population with a BA degree(log)	2.62	.65	-.36	3.86
City-School District Incongruence (log)	-1.21	1.09	-6.22	-.03
# of past elections	.49	1.52	0	11
Tax price (log)	-1.25	.81	-4.21	2.91
Heterogeneity (log)	-.81	.4	-3.13	-.26
Median income (log)	10.98	.38	9.92	12.43
Basic aid (log)	8.9	.19	8.66	10.19
Population (log)	10.02	1.49	4.78	15.35

Table 3
Diagnostics for Spatial Dependence

Weight Matrices	K (3) Nearest Neighbors			Rook Contiguity		
TEST	MI/DF	VALUE	PROB	MI/DF	VALUE	PROB
Moran's I (error)	.09	3.18	.00	.08	4.18	.00
Lagrange Multiplier (lag)	1.00	18.64	.00	1.00	32.01	.00
Robust LM (lag)	1.00	11.19	.00	1.00	18.90	.00
Lagrange Multiplier (error)	1.00	8.66	.00	1.00	14.50	.00
Robust LM (error)	1.00	1.21	.27	1.00	1.40	.24
Lagrange Multiplier (SARMA)	2.00	19.85	.00	2.00	33.40	.00

TABLE 4.
Main Results

VARIABLES	Parcel Tax Adoption	Z-Value	Parcel Tax Election	Z-Value
W_ Parcel Tax Adoption	.459*** (.045)	10.288	.394 *** (.049)	8.032
Home price gap (log)	-.115*** (.035)	-3.311	.015 *** (.022)	.665
Tax price (log)	.007 (.015)	.434	.007*** (.015)	3.420
Expenditure per pupil (log)	.164*** (.056)	2.925	.203* (.059)	1.798
%Renters (log)	.030 (.028)	1.080	-.016 (.010)	-1.634
%Obamavote (log)	.061 (.052)	1.166	.007 (.009)	.859
%BAdegree(log)	.065*** (.019)	3.374	.104*** (.058)	1.779
%65+(log)	-.032 (.030)	-1.065	.069** (.028)	2.506
Bay Indicator	.180*** (.033)	5.493	-.051 (.034)	5.493
CONSTANT	-1.796*** (.500)	-3.589	.188*** (.040)	-1.494
			-2.397 (.569)	-4.213
Observations	*754*		*702*	
R-squared	*.491*		*.440*	

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

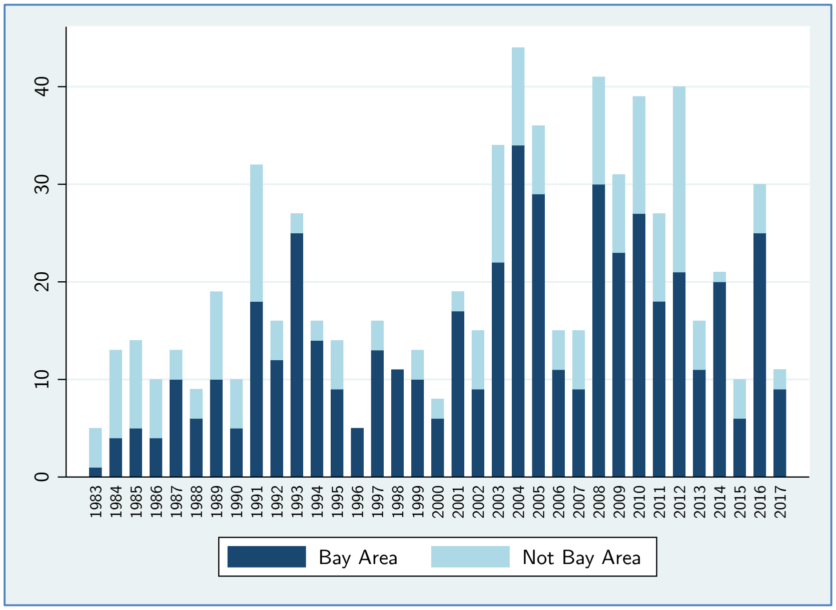
TABLE 5
Robustness Checks

	Parcel Tax Adoption		Parcel Tax Election	
	Rook	Queen	Rook	Queen
W_ Parcel Tax Adoption	.459***	.458***	.394 ***	.390 ***
	(.045)	(.045)	(.049)	(.049)
Home price gap (log)	-.115***	-.115***	.015 ***	.015 ***
	(.035)	(.035)	(.022)	(.022)
Tax price (log)	.007	.007	.007***	.007***
	(.015)	(.015)	(.015)	(.015)
Expenditure per pupil (log)	.164***	.165***	.203*	.204*
	(.056)	(.056)	(.059)	(.059)
%Renters (log)	.030	.030	-.016	-.017
	(.028)	(.028)	(.010)	(.010)
%Obamavote (log)	.061	.060	.007	.007
	(.052)	(.052)	(.009)	(.008)
%BAdegree(log)	.065***	.065***	.104***	.104***
	(.019)	(.019)	(.058)	(.058)
%65+(log)	-.032	-.033	.069**	.069**
	(.030)	(.031)	(.028)	(.028)
Bay Indicator	.180***	.180***	-.051	-.051
	(.033)	(.033)	(.034)	(.034)
CONSTANT	-1.796***	-1.802***	.188***	.189***
	(.500)	(.500)	(.040)	(.040)
			-2.397	-2.415
			(.569)	(.570)
Observations	*754*	*754*	*702*	*702*
R-squared	*.491*	*.490*	*.440*	*.438*

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

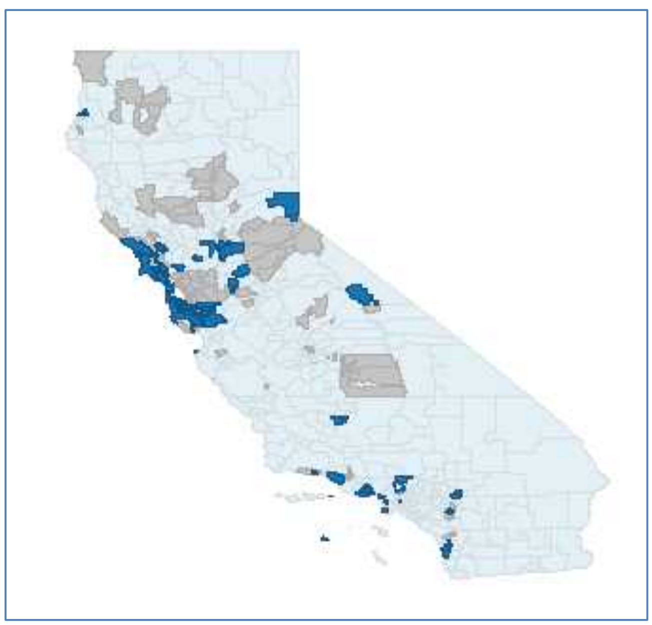
Figure 1.
Geographic Distribution of Parcel Tax Election and Adoption

Panel A.



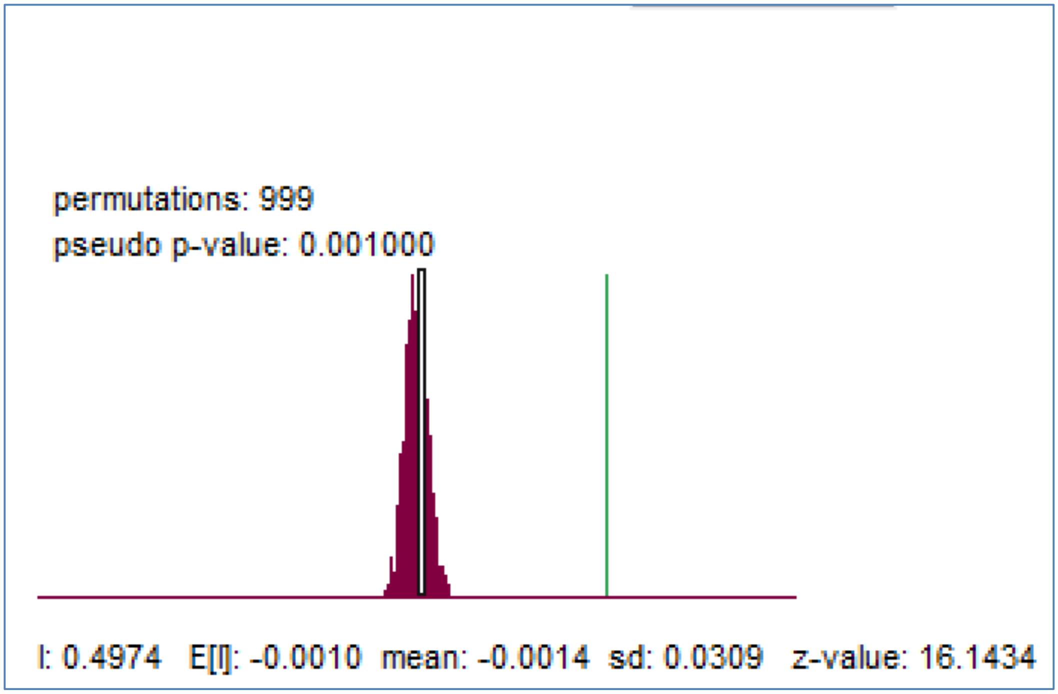
Number of parcel tax elections by year.
Bay Area districts are in the dark blue, and other districts are in light blue.

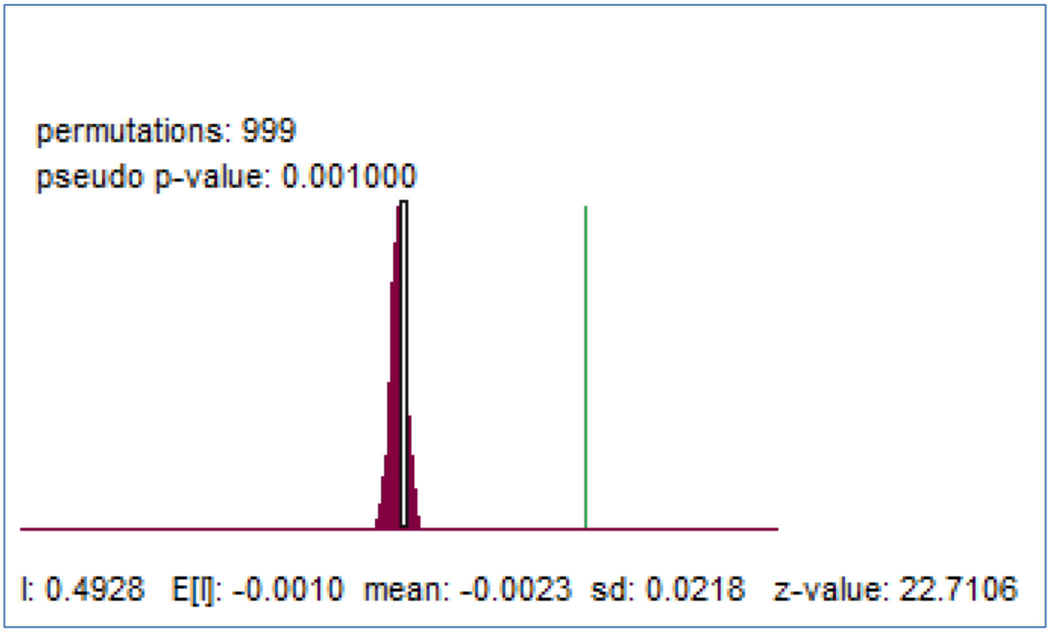
Panel B.



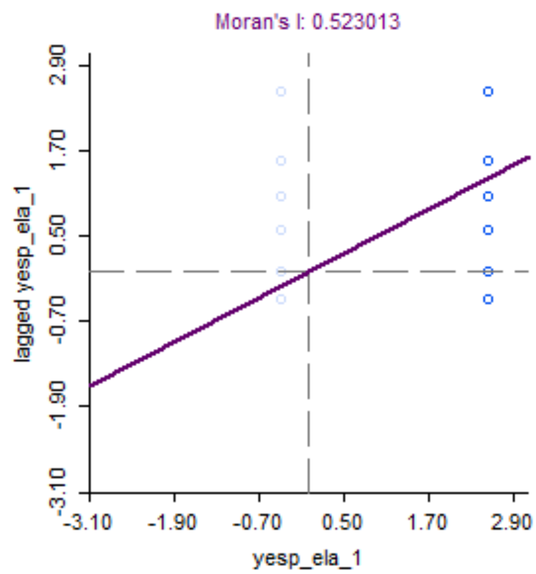
Dark blue areas are school districts that raised parcel tax revenue in 2016. Light blue areas indicate school districts with no parcel tax revenue in 2016.
Grey areas have no data.

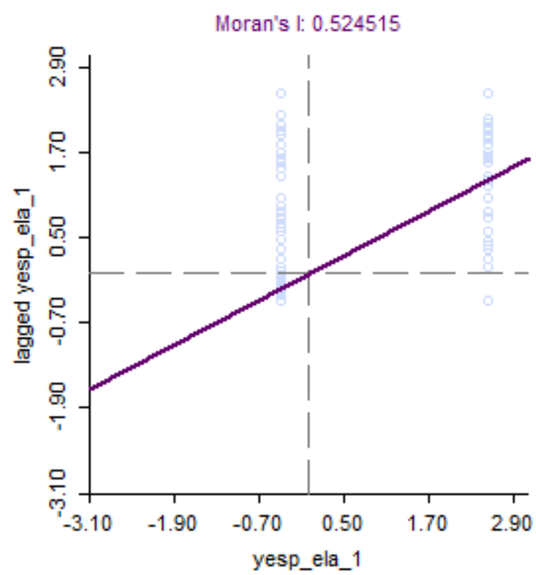
Figure 2.
Sample Permutation Results of Parcel Tax with K3 and Rook Matrices



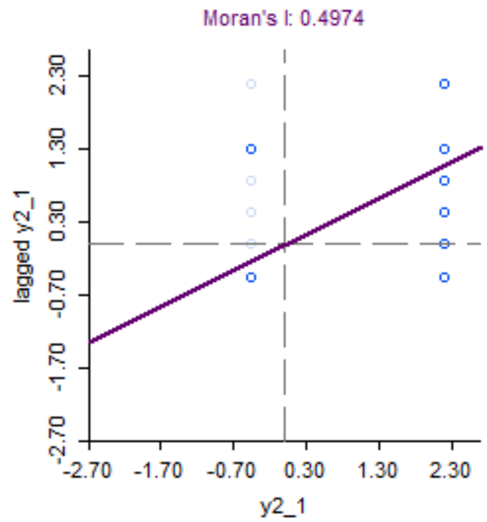


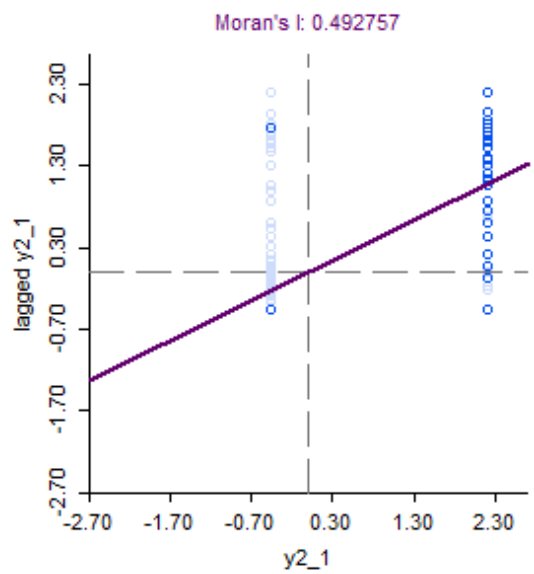
Appendix.
A. Parcel Tax Adoption K3 vs Rook.





B. Parcel Tax Election K3 vs Rook.





C. Parcel Tax Volume K3 vs Rook