AN ABSTRACT OF THE DISSERTATION OF

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Title: Two Essays on Local Government Finances in the United States

Abstract approved:

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Yong Chen

County governments in the United States play important roles in the tax collection and public service provisions. Thus, a better understanding of the local government finances is closely related to the welfares of residents. In this dissertation, I provide two essays: in the first essay, I examine the fiscal impacts of multiple hurricanes on the county government tax revenues, and in the second essay, I examine the potential correlation between the institutional characteristics of county governments and the spatially varying expenditure determination processes. The two essays contribute to current local government finance literature in the United States.

In the first essay, I investigate the fiscal impact of multiple hurricanes on county government tax revenues and the potential adaptation effect. I compare the changes in tax revenues before and after the multiple hurricane incidences to identify the fiscal impact of multiple hurricanes and the potential adaptation effect. I use the tax revenue data in the year 2002 and 2007. I define the years between 2003 and 2006 as the treatment period and I count the number of hurricanes each county experiences. Then, I divide the counties into two groups: if the number of hurricanes in a county during the treatment period is more than 1, I call it “Treatment”, and otherwise, I call it “Control”. I call the year before the treatment period, 2002, as the pre-treatment year and I call the year after the treatment period, 2007, as the post-treatment year. I preprocess the data using a propensity score matching to construct a well-balanced

sample of Treatment and Control. Once I obtain the well-balanced sample, I compare the changes in the share of property tax, log of property tax, log of sales tax, and log of taxes on others of Treatment and Control before and after the multiple hurricane incidences. I find that the share of property tax in Treatment increases, mainly due to the 45 percent point more decreases in the sales tax of Treatment. However, when I look at the adaptation effect, I see that the share of property tax decreases, partly due to the decrease in the property tax, and partly due to the small decreases in sales tax and taxes on others. In summary, I show that the negative impact of multiple hurricanes on sales tax revenues and the impact is mitigated by the adaptation effects.

In the second essay, I provide one mechanism that suggests a potential correlation between the local institutional characteristics and the spatially varying local expenditure determination processes. Based on the microeconomics theory, I present a cost function that suggests the local government's public service provision expenditure is a function of input price and the level of public service outputs. In the analysis, I use the county governments' public expenditure data in 2017, count level average wage rate, public health measures, and the employment rates as the public service output variables. I firstly employ one of the spatially varying coefficient estimation (SVCM) approaches to estimate the cost function. The estimation results and the results of the following tests support the claim that there exist spatially varying processes in the cost functions of public service provision. Then, I analyze the correlation between the local institutional characteristics, such as the number of elected county officials and the degree of autonomy of county governments, with spatially varying coefficients of the cost function. The regression results suggest that the institutional characteristics are significantly correlated with the spatially varying coefficients of the cost function. In summary, I present evidence that the disparities in the local institutional characteristics could be one potential cause of the spatially varying processes in the local expenditure determination process.

Two Essays on Local Government Finances in the United States

by

Jaeho Jung

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APPROVED:

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Dean of the Graduate School

I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Jaeho Jung, Author

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CONTRIBUTION OF AUTHORS

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Two Essays on the Local Government Finance in the United States

1. General introduction

County governments in the United States play an important role in collecting taxes and providing public services. Understanding about the local government finance has been an important research question for decades because the welfare of residents is closely related to the collection of tax revenues and the expenditure for public service provision. This dissertation focuses on topics related to county governments' revenue and expenditure. This dissertation consists of two essays. The first essay investigates the impact of frequent hurricanes on the county government tax revenues and the potential existence of adaptation. The second essay provides one potential mechanism that could generate spatially varying expenditure determination processes of the county governments.

In the first essay, I have two main objectives. Firstly, I attempt to identify the fiscal impacts of hurricanes. Hurricanes can negatively affect tax revenues in local governments by damaging taxable properties, disrupting local businesses, or labor market. Because tax revenues are used to provide essential public services, the potential fiscal impacts of hurricanes could threaten the welfare of households and impede local economic development. However, compared to the extensive studies on the socio-economic damages of hurricanes, the research about the impact of hurricane on the local government finance is relatively limited. Secondly, I further investigate the potential existence of adaptation effect. Recent policy debates have started highlighting the importance of differential effects of natural disasters and potential adaptation as the hurricane risks increases due to the on-going Climate Change. In general, hurricanes affect limited number of counties. Accordingly, the impacts from hurricane activities and the benefit of adaptive action to future hurricanes risks could vary across counties. However, the existence of potential adaption effects has not been considered in the existing literature. The findings of the first essay will provide new information about the impact of hurricanes and the existence of adaptive effects.

In the second essay, I present one potential mechanism that could generate spatially varying expenditure determination processes. I test the mechanism first employing one of the spatially varying coefficient model (SVCM)s and then analyze potential correlations between spatial variations in the expenditure determination processes and local institutional characteristics. Compared to the existing literature that investigate the expenditure interactions between local governments, there exists few literatures specifically focus on the spatial disparities across the regions. The findings in the second essay add new information that local government expenditure determination processes could be affected by the disparities in local institutional characteristics. The findings also suggest that local contexts that differ across space need to be considered, instead of adopting a universal approach that does not consider local characteristics.

The dissertation has been organized as follows. Chapter 2 presents the essay titled Do Local Economies Adapt to Hurricane Incidences? A Perspective from Local Government Tax Revenue, as a standalone manuscript that includes an introduction, literature review, data, empirical strategy, results and conclusions. Chapter 3 presents the essay titled Potential Relationship between Local Institutional Disparities and Spatially Varying Expenditure Determination Processes which includes an introduction, literature review, model, data, estimation strategy, results and conclusion. An overall conclusion of the dissertation is provided in Chapter 4.

2. Do Local Economies Adapt to Hurricane Incidences? A Perspective from Local Government Tax Revenue

2.1. Introduction

Compared to the extensive studies on the socio-economic damages of hurricanes (Bin and Polasky, 2004; Hallstrom and Smith, 2005; Morgan, 2007; Groen and Polivka, 2008; McIntosh, 2008; Vigdor, 2008; Belasen and Polachek, 2009; Strobl, 2011), the research about the impact of hurricane on the local government finance is relatively limited (Ismayilov and Andrew, 2016; Cui et al., 2019; Miao et al., 2018; Krueger, 2019). Hurricanes can negatively affect tax revenue in local governments by damaging taxable properties, disrupting local businesses, or labor market (Groen and Polivka, 2008; Holtz-Eakin 2005; Ismayilov and Andrew, 2016). Because tax revenues are used to provide essential public services (Bergstrom and Goodman, 1973; Brueckner, 1979), the potential fiscal impacts of hurricanes could threaten the welfare of households and impede economic development.

As the frequency and intensity of hurricanes increase due to the on-going global warming (Webster et al. 2005; Bender et al. 2010), recent policy debates have started highlighting the importance of differential effects of natural disasters and potential adaptation at all levels (Begum et al. 2014; Rohland, 2018). In general, hurricanes affect limited number of counties (Strobl, 2011) and, even within these counties, there exist considerable regional variations in the number of hurricanes each county experiences for a given period of time (Elsner et al. 2000). Accordingly, the impacts from hurricane activities and the benefit of adaptive action to future hurricanes risks could vary across counties. For households, firms, and local governments, whether to take any adaptive action in response to the future disaster exposure is a rational decision based on their perceived benefits and costs (Schenker-Wicki et al., 2010; Tuohy and Johnston, 2014; Platt, 2015; Mechler, 2016). Benefits from adaptation will be higher in counties more likely to have frequent hurricanes. And if the perceived benefit of adaptation exceeds the cost, economic agents will likely adopt an adaptive action.

In this study, I attempt to examine the impacts of different hurricane frequencies on local government tax revenue. By focusing on the differential impact of hurricane frequencies, I further investigate the existence of adaptation. I use county-level government tax revenue data. Using counties with lower probability of hurricanes as benchmarks and applying post-matching regression method, I estimate the impact of frequent hurricanes on tax revenue. I also find evidence of local adaptation. In general, multiple hurricane incidences tend to increase the share of property tax revenue in the total tax revenues from own sources (excluding inter-government transfers). This is associated with significant bigger decreases in the share of sales tax revenues. More importantly, among the counties with multiple hurricane experiences, the increase in the share of property tax revenue is smaller in counties with a high number of past hurricane incidences, where the expected benefit of adaptation is higher. Similarly, the decrease in the share of sales tax is also smaller. Also, the share of other tax revenue is higher in counties with more frequent hurricanes.

Compared to the existing literature, this research is novel for two reasons. Firstly, I focus on the impact of frequent hurricanes on local tax revenues. The existing literature has provided evidence on the socio-economic impact of hurricanes (Bin and Polasky, 2004; Hallstrom and Smith, 2005; Morgan, 2007; Groen and Polivka, 2008; McIntosh, 2008; Vigdor, 2008; Belasen and Polachek, 2009; Strobl, 2011; Ismayilov and Andrew, 2016) and examples of local adaptive actions (Grace et al., 2005; Klein et al., 2007; Landry et al., 2007; McIntosh, 2008; Grasso, 2009; Fussell et al., 2010; Groen and Polivka, 2010; Davlasheridze et al., 2017; Kously, 2017). However, the examination of the hurricane impact on local government tax revenue is relatively scarce (Ismayilov and Andrew, 2016; Cui et al., 2019; Miao et al., 2018). Among these existing studies, no studies have investigated the impact of frequent hurricanes on the structure of local government tax revenue and viewed its change as a measure of local economic adaptation. Secondly, I suggest the possibility of using the frequency measure of hurricanes to capture the potential benefit of adaptation. Because of the probabilistic nature of hurricane occurrence (Kolstad and Moore, 2020), the expected benefit of adaptation is the product of the probability and the perceived benefits. I find statistically significant evidence of adaptation – that is, the marginal effect of multiple hurricane incidences on tax revenue is lower in counties that experience hurricanes more frequently. A similar approach has been employed by Hsiang and Narita (2014) that uses the average intensity of tropical cyclones experienced by a country as a proxy for the potential benefit of adaptation. I show that, in the case of hurricanes that occur repetitively every year, the frequency variable can also serve a similar role.

The impact of hurricanes on local government tax revenue is an important research question because local tax revenues are used to finance many essential public services that are critical to local residents and businesses. The remaining sections of this chapter are organized as follows. Section 2 reviews the existing literature on hurricane impacts and the local government responses. Section 3 summarizes the data. Section 4 describes the estimation strategy. Section 5 presents the results. Section 6 concludes the major findings of this study.

2.2. Literature review

The impact of hurricanes on tax revenues could vary depending on the economic responses following the disaster shock and the structure of revenue sources. (Noy and Nualsri, 2011). Among the major categories of local tax revenues, county governments in the United States have historically relied heavily on the property tax (Bartle et al., 2003; Carroll, 2009; Alm et al., 2011; Lutz et al, 2011; Kim and Warner, 2018) because of its stability (Groves and Kahn, 1952; Ihlanfeldt and Willardsen, 2014). Existing studies suggest that hurricanes may affect the property tax revenue by reducing the number of taxable properties (Hildreth, 2009) or the values of taxable properties (Bin and Polasky, 2004; Hallstrom and Smith, 2005; Morgan, 2007; Payton, 2012; Bin and Landry, 2013; Ortega and Taspinar, 2018; Hamilton, 1975; Krueger et al., 2019). However, these studies do not present concrete evidence of hurricane impacts on property tax revenue.

Only a limited number of studies analyze the fiscal impacts of hurricanes on government tax revenue (Noy and Nualsri, 2011; Ismayilov and Andrew, 2016; Cui et al., 2019; Miao et al., 2018)[1]. Noy and Nualsri (2011) quantify the fiscal impact of natural disasters in developed and developing countries. They show that the developed counties increase government spending while cutting taxes following a large-scale disaster while the developing countries decrease expenditure and increase government revenues. On contrary, Ismayilov and Andrew (2016), Cui et al. (2019), and Miao et al. (2018) use government tax revenue data in the United States to investigate the impact of hurricanes. Ismayilov and Andrew (2016) and Cui et al. (2019) specifically focus on the impact of hurricane Ike in 2008 on sales tax revenues in Texas, and Miao et al (2018) investigate the fiscal impact of natural disasters using the state-level tax revenue data. Ismayilov and Andrew (2016) analyze the impact of hurricane Ike on sales tax revenues in three cities in Texas. They adopt a time series forecasting approach and they find evidence that the impact of hurricane Ike on sales tax revenue is positive in the short-term and negative in the long-term. However, there is no further evidence whether the findings can be generalized into other locations or the county governments. Cui et al. (2019) predict the impact of hurricane Ike on sales tax revenue in Huston Metropolitan Statistical Areas. They collect the data in data in three industries and suggest that Hurricane Resiliency Index (HRI) can be used in sales tax revenue prediction after hurricane strikes at the local level.

Miao et al., (2018) empirically estimate the impact of natural disasters on U.S. state government finance. In their study, the key independent variable is the size of disaster induced-economic damage. They find that natural disasters significantly decrease property tax revenue. They also show that the sales tax revenue increases right after natural disasters, but this effect declines over time. Lastly, they present opposite impacts of disasters on personal income tax and on corporate income tax over the five-year period.

The existing literature provide important knowledge about the impact of a natural disaster. However, there still exist areas that have not been explored by researchers. Firstly, one of the key features of natural disasters, especially in the case of hurricanes, is the repetitive occurrence. The potential fiscal impacts of frequent hurricanes have received less attention from researchers. Secondly, the potential adaptation effect has not been investigated in the existing literature. In general, past hurricane histories are commonly used in the prediction of future hurricane occurrence (Elsner and Jagger, 2006; Hamilton and Stampone, 2003; Setzer, 2016). According to the economics theory, the expected benefit of any adaptative behavior is the product of the probability and the perceived benefits and the expected benefits would likely be greater than the costs of adaptation in locations where hurricanes are expected to occur more often. My study will provide new information about the fiscal impact of hurricanes using a frequency measure. Further, by using the frequency of hurricanes, I will also investigate the existence of potential adaptation effects.

2.3. Data

In this study, I use U.S. county-level data hurricane, local government tax revenues and socio-economic variables. The definitions of the variables, along with their data source are summarized in Table 2.1., with summary statistics reported in Table 2. These variables are selected based on existing literature on the determinants of local governments' fiscal structures (White and Chou, 1980; Wolman and Hincapie, 2014) and the hurricane impacts (Hsiang and Narita, 2012; Miao et al., 2018). All the prices are adjusted using the price index (100 in 2012). Median household income, median home value, unemployment rate, poverty rate and housing density are used to control for local economic conditions. Farm, Manufacture and Herfindahl-Hirschman Index (HHI) are used to control for the local economic structure. Share of the population with college education, share of nonwhite population, share of male population, share of population over the age of 65 are used to control for local demographic conditions. Metropolitan status is included to control for the potential urban-rural divide. To avoid the simultaneity problem (Vergara, 2010; Reed, 2013; Reed, 2015), I use lagged values of these variables in the regression. Because property taxes in the current year are typically based on the assessed value determined in the preceding year, a two-year lag is used instead of a one-year lag (Anderson, 1993; Lutz, 2008; Payton, 2012; Lutz et al., 2013).

Table 2.1. List of variables and data source

Variable	Definition (Unit)	Source
Government tax		
Property tax	Property tax revenue (thousand dollars).	Census
Sales tax	Sales tax revenue (thousand dollars).	Census
Other taxes	Sum of License tax, Income tax, and Other taxes (thousand dollars).	Census
Share of property tax	Share of property tax in total tax revenue (%).	Calculated
Hurricane records		
Hurricanes records	Number of hurricanes.	SHELDUS
Past hurricane history	Number of hurricanes before the study period,	SHELDUS
Economic, social variables		
Income	Real median household income (thousand dollars).	Census
Home value	Median home value (thousand dollars).	Census
Farm	Share of workers in agriculture (%).	BLS
Manufacture	Share of workers in manufacture (%).	BLS
HHI	Herfindahl index (0 to 1).	calculated
Unemployment	Unemployment rate (%).	BLS
Poverty	Poverty rate (%).	Census
Housing density	Housing density (house / squared miles).	Census
College	Share of college degree and above (%).	Census
Nonewhite	Share of nonwhite Americans (%).	Census
Male	Share of male (%).	Census
Aged	Share of population above 65 (%).	Census
Metro	1 if metro county, 0 otherwise.	USDA

Note: SHELDUS, Spatial Hazard Events and Losses Database for the United States. BLS, Bureau of Labor Statistics. USDA, United State Department of Agriculture.

Table 2.2. Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Government tax				
Property tax	42,104.7	145,336.2	43.7	2,886,214.0
Sales tax	13,888.0	56,759.1	0.0	1,048,250.0
Other taxes	2,565.5	11,679.4	0.0	208,879.5
Share of property tax	0.714	0.212	0.106	1.000
Hurricane records				
Hurricane records	1.580	1.099	1	6
Past hurricane experience	1.064	1.589	0	8
Treatment (D)	0.440	0.497	0	1
Social economic variables				
Median household income	46,664.8	12,897.9	22,107.0	108,027.5
Median home value	106,477.2	49,845.3	32,281.8	473,243.0
Farm	0.061	0.058	0.000	0.482
Manufacture	0.152	0.097	0.000	0.549
HHI	0.401	0.090	0.242	0.786
Unemployment	0.046	0.017	0.014	0.174
Poverty rate	0.161	0.070	0.026	0.509
Housing density	75.290	220.270	0.144	3,854.205
College	0.160	0.080	0.054	0.602
Nonwhitepop	0.244	0.178	0.005	0.869
Male	0.493	0.021	0.426	0.656
Pop65	0.140	0.038	0.039	0.347
Metro	0.329	0.470	0	1

According to the US Bureau of Census (2006), government tax revenue can be classified into five major categories: property taxes, sales and gross receipts taxes (referred to as sales tax hereafter), license taxes, income taxes, and other taxes. To mitigate the problem of missing observations, I maintain categories of property tax and sales taxes. The license taxes, income taxes and other taxes[1] are summed together and referred to as the Other taxes in the following discussion. Because this research focus is on the hurricane impact on local tax revenue structure, I convert the tax revenues into the corresponding ratios to the total tax revenue. For instance, the ratio between the property tax revenue and the total tax revenue is calculated and will be referred to as the share of property tax hereafter.

While the US county-level data are available for the years 1992, 1997, 2002, 2007, and 2012[2], I focus only on the period of 2002-2007. For the other periods, propensity score matching fails to generate a balanced sample (see Appendix).

SHELDUS includes information about the date of an event, county affected, and economic loss. N_i denotes the number of hurricanes a county i experienced between 2002 and 2007. The hurricanes county i experiences in the year with government revenue data are excluded. For instance, hurricanes in 2002 and 2007 are not included in N_i. This is because of the way the amount of a property tax revenue is determined. Not like sales tax and other taxes, the total amount of property tax each county government can collect in a given fiscal year is predetermined based on the property assessment value reported a year ago. Because of this time lag, the hurricanes in 2007 will affect the property tax revenue of 2008.

With a focus on local government tax revenues, I use the number of hurricanes in the most recent election periods (from 1989 to 2000) before the year 2002 as a measure of past hurricane experience, because election pressure may provide politicians with incentives to respond to disasters (Abney and Hill, 1966; Arceneaux and Stein, 2006; Healy and Malhotra, 2009; Gasper and Reeves, 2011), especially in counties with high hurricane frequencies. The number of hurricanes a county i experienced over the most recent three presidential election[3] is denoted as H_i. This variable captures a county's past hurricane experience (Table 2.3.).

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[1] The Other taxes include Death and Gift Taxes, Documentary and Stock Transfer Taxes, Severance Taxes, and Taxes NEC.

[2] Because the frequency and intensity of natural disasters exhibit structural changes in 1990s (Landsea et al., 1996; Webser et al., 2005), I focus on the hurricanes since 1990.

[3] I test the hurricane records during two presidential election period (eight years).

Table 2.3. Past hurricane history and the number of counties

H	Number of counties
0	177
1	120
2	37
3	29
4	54
5	31
6	16
7	2
8	3
Total	469

The social, economic and demographic characteristics of counties are denoted as X. Real median household income and real median home values are calculated using the consumer price index (BLS).

2.4. Empirical strategy

The main objective of this study is to examine the fiscal impact of frequent hurricane incidences on county government tax revenue and its structure. Hurricane occurrence is random and is plausibly exogenous to other variables (Dell et al., 2014; Kolstad and Moore, 2020). I use the exposures to frequent hurricane incidences to estimate the effect of multiple hurricanes on tax revenue. I consider the potential existence of adaptation based on the spatial variations in hurricane frequencies and the differences in the perceived benefits of adaptation. For example, if the cost of adaptation exceeds the benefit, it is rational not to adapt. However, if the perceived benefit exceeds the perceived cost of adaptation, adaptation is a rational choice. When exposed to the hurricane risks, the perceived benefit of adaptation is proportional to the expected frequency of the hurricanes. Other things equal, households, businesses and local governments in counties with more frequent hurricanes are more likely to take adaptive actions. The frequency of hurricanes in the recent past is used as a proxy for the perceived frequency in future hurricanes.

The estimation strategy is based on the idea of the Difference-in-Difference (DID) estimation approach. The DID compares the two groups of counties that are similar in their observable characteristics and only differ in their exposure to exogenous shocks, in this case, the frequent hurricanes. However, simply comparing counties with and without multiple hurricanes could produce biased results. This is because of the geographical concentration of hurricanes (Strobl, 2011) that can potentially trigger relocations of household/firms and affect location choice of household/firm. If this sorting behavior exists, the counties experiencing frequent hurricanes could be systematically different from those with no or infrequent hurricanes (Berlemann and Steinhardt, 2017). When the treated counties and the control counties are systematically different, an ordinary regression technique such as OLS alone may not identify treatment effects (Ho et al., 2007; Locke et al., 2017). To control for this potential selection bias, I first pre-process the data to construct the comparable samples of counties that are only different in their exposures to frequent hurricanes. Once I construct the comparable counties, I apply a post-matching panel regression, which is commonly used in policy evaluation studies (Arriagada et al., 2012; Stuart et al., 2014; Jones and Lewis, 2015; Chen et al., 2016; Ferraro and Miranda, 2017).

2.4.1. Propensity Score Matching

I first pre-process the data to constructs a control group that is similar to those exposed to frequent hurricanes based on a selected set of covariates from the pre-treatment observations. The normalized differences, a scale-invariant measure of the size of the difference (Imbens and Rubin, 2015), before and after the matching are reported in Table 2.5. The rule of thumb is that a normalized difference exceeding 0.25 suggests a systematic difference between the control and treatment group. Compared to the counties with no and infrequent hurricanes, counties with frequent hurricanes tend to have a lower share of property tax, lower household income, lower median home value, higher unemployment rate, poverty rate, and a higher ratio of nonwhite population, as shown in Table 2.5.

The year 2002 is considered as the pre-treatment year (denoted as $T = 0$) and the year 2007 is considered as the post-treatment year (denoted as $T = 1$). According to the value of N_i, I create a Treatment variable (D). If a county experiences only one hurricane between pre- and post-treatment year, I call it as Control and $D = 0$. If a county experiences two or more hurricanes, I call it as Treated and $D = 1$ (Table 2.4). Since I only focus on counties that experience at least one hurricane between the years 2002 and 2007, the number of counties that are considered in the analysis is 469. Among these counties, 193 counties are coastal counties[4].

Table 2.4. Hurricane records (N) and the number of counties

Dummy variable D	N	Number of counties
$D = 0$ (Control)	1	223
$D = 1$ (Treated)	2	141
	3	34
	4	30
	5	24
	6	17
Total		469

In the matching, I regress the treatment dummy variable D_i, which equals one if a county experienced more than one hurricanes and zero otherwise, on the dependent variable (y_i), the share of property tax, and a set of county-specific pre-treatment social and economic variables (X_i) and the past hurricane experiences (H_i).

$$D_i = \alpha_0 + \alpha_1 share\ of\ property\ tax + \alpha_2 X_i + \alpha_3 H_i + \mu_i, \qquad (1)$$

[4] A county is considered as the coastal watershed county when one of the following criteria is met: “(1) at a minimum, 15 percent of the county’s total land area is located within a coastal watershed or (2) a portion of or an entire county accounts for at least 15 percent of a coastal USGS 8-digit cataloging unit.” (NOAA, 2017)

A one-to-one matching with replacement is used. The caliper size is set to be one quarter of the standard deviation of the estimated propensity score (Guo and Fraser, 2010; Chen et al., 2016).

This matching process significantly reduces the differences of covariates in the pre-treatment year between the control and treated counties. As shown in Table 5, the post-matching sample is much more balanced with all the normalized differences below the 0.25 threshold.

Table 2.5. Summary statistics before and after matching

	Unmatched			Matched		
Variable	Treated	Control	Normalized difference	Treated	Control	Normalized difference
Share of property tax	0.70	0.73	-0.16	0.70	0.70	-0.03
Past distribution	2.95	2.01	**0.33**	2.95	3.04	-0.01
Median household income	42,684	47,925	**-0.45**	42,684	42,592	0.01
Median home value	93,117	112,054	**-0.44**	93,117	90,890	0.06
Farm	0.06	0.06	0.04	0.06	0.06	-0.12
Manufacture	0.14	0.14	0.02	0.14	0.15	-0.06
HHI	0.40	0.40	0.01	0.40	0.40	0.05
Unemployment	0.05	0.04	**0.57**	0.05	0.05	0.09
Housing density	53.77	59.9	-0.06	53.77	55.89	-0.01
Poverty rate	0.19	0.15	**0.60**	0.19	0.18	0.08
Col_edu	0.15	0.15	-0.06	0.15	0.15	0.04
Pnonwhite	0.32	0.27	**0.33**	0.32	0.29	0.16
Pmale	0.49	0.49	-0.20	0.49	0.49	0.04
Pa65o	0.14	0.14	0.04	0.14	0.14	0.01
Metro	0.31	0.34	-0.06	0.31	0.36	-0.05

2.4.2. Post-Matching Regression

I specify the empirical model as follows,

$$y_{i,t} = \alpha_0 + \alpha_1 D_i + \alpha_2 T + \alpha_3 D_i T + \alpha_4 D_i T H_i + \alpha_5 H_i + \alpha_6 H_i T + \alpha_7 X_{i,t-k} + \varepsilon_{i,t} \qquad (2)$$

where $y_{i,t}$ is the share of property tax in total tax revenue and tax revenues such as property tax, sales tax, and Other taxes. The subscript i and t are the county and time indices, respectively. $T = 0$ stands for the pre-treatment year (2002). $T = 1$ stands for the post-treatment year (2007). The dummy variable D_i indicates whether, in the current period, county i experienced only one hurricane ($D_i = 0$) or multiple ›incidences ($D_i = 1$) between the pre- and post-treatment year. In general, any weather event including hurricane occurrence varies randomly over a given time scales (Hsiang, 2016; Kolstad and Moore, 2020) and I also utilize this random nature of hurricanes to identify the impact of hurricanes on tax revenues. The impact of multiple hurricane incidences on $y_{i,t}$ is captured by the interaction variable $D_i T$.

The number of hurricanes a county experienced over the most recent three presidential election is denoted as H_i[5]. This variable is used as a proxy for the perceived future risk of hurricanes[6]. In my study, the higher the value of H_i, the higher the perceived likelihood of experiencing frequent hurricanes and so is the expected benefit from adaptation. When adaptation occurs, it mitigates the hurricane impacts. I interact H_i with D_i and this interaction term captures the effect of the impact of adaptation on the fiscal impact of hurricanes. The estimated impacts for adaptation should be opposite to the direct hurricane impacts.

The difference form of the equation (2) helps to control for un-observed time-invariant county characteristics (equation 3). In order to control for time-varying county characteristics, a set of county-specific social and economic variables ($\Delta X_{i,t-k}$) in the regression. The post-matching regression is specified as follows:

$$y_{i,1} - y_{i,0} = \Delta y_i = \beta_0 + \beta_1 D_i + \beta_2 D_i H_i + \beta_3 H_i + \beta_4 \Delta X_{i,t-k} + \Delta \varepsilon_{i,t}, \qquad (3)$$

---

[5] The key conclusions are robust to alternative definitions of H_i. Instead of defining H_i as the number of hurricanes during the recent three presidential election periods, I also explored two presidential election periods. The conclusions in the paper do not change.

[6] Similar approach has been used by Hsiang and Narita (2012) that use the past cyclone intensity variable as a proxy for the perceived future risks of cyclone.

where Δy is the changes in the dependent variables, capturing changes in the difference sources of local government tax revenues. In the estimation, standard errors are clustered at the state level because the tax revenue structure of county governments is mainly determined by the state government (Shadbegian, 1999; Jewett, 2010).

In the equation (3), the effect of being exposed to frequent hurricanes using counties with lower probability of hurricanes as benchmarks is β_1, and the adaptation effect based on the future risk perception is captures by β_2. The marginal effect of frequent hurricane incidences can be written as,

$$\{E[\Delta y_{i,t} \mid D_i = 1] - E[\Delta y_{i,t} | D_{i,p} = 0]\} = \beta_1 + \beta_2 \times H_i \tag{4}$$

In equation (4), the adaptation effect is the product of β_2 and H_i. H_i is the proxy for the probability of having hurricanes in the future and the bigger value of H_i implies the more chance of being hit by hurricanes. Among the counties with frequent hurricane incidences during the current period, the perceived benefits of adaptive actions would be greater than the costs of adaptation in counties where H_i is greater. If past hurricane incidences have triggered adaptation, the sign of the coefficient β_2 is the opposite to the sign of β_1 and the frequent hurricane impact will be mitigated[7].

To validate that the difference between the treatment and control group is induced by the treatment, it is important to verify two additional assumptions. The use of binary treatment variable allows me to interpret the panel regression approach that I employ after the matching process using the difference-in-difference estimation (Chen et al. 2016). One is the common trend assumption and the other is the common support assumption (Angrist and Pischke, 2009; Imben and Wooldridge, 2009). To verify the common trend assumption, I plot the average pre-treatment trends of the

[7] Note that this is different from the lagged effect of past hurricane incidences. To support this claim, I generate the variable h_i that counts the number of hurricanes right before the year 2002 and run the same estimation. The logic here is that if there exists a lagged effect of past hurricanes on the effect of multiple hurricane incidences in current period, the lagged effect right before the year 2002 is the biggest and the coefficient of the interaction variable should be significant. However, I could not find a statistically significant lagged effect (See Appendix IV).

dependent variable for both the control and treatment groups (Figure 2.1.). The common support assumption requires sufficient overlap in the characteristics of the control and treatment counties (Imben and Wooldridge, 2009). Overlap assumption can be examined graphically (Harder et al., 2010) and is confirmed in Figure 2.2.

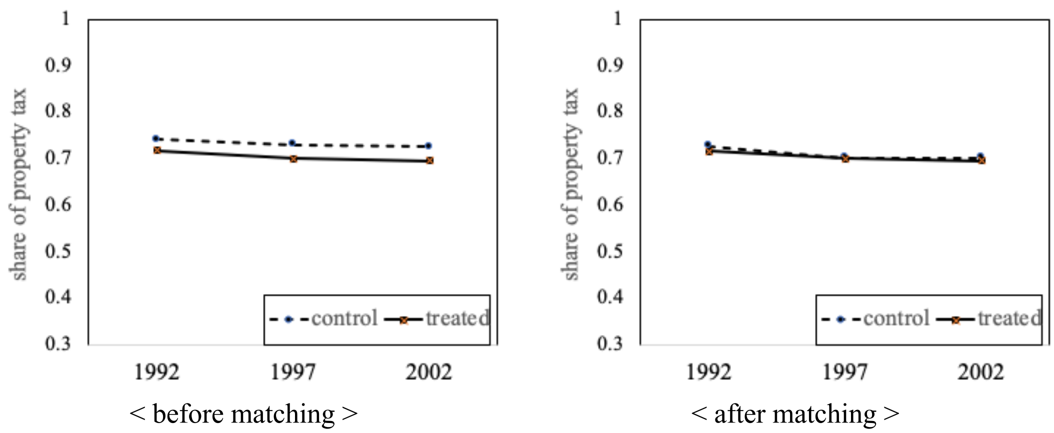

Figure 2.1. Common trends before and after matching

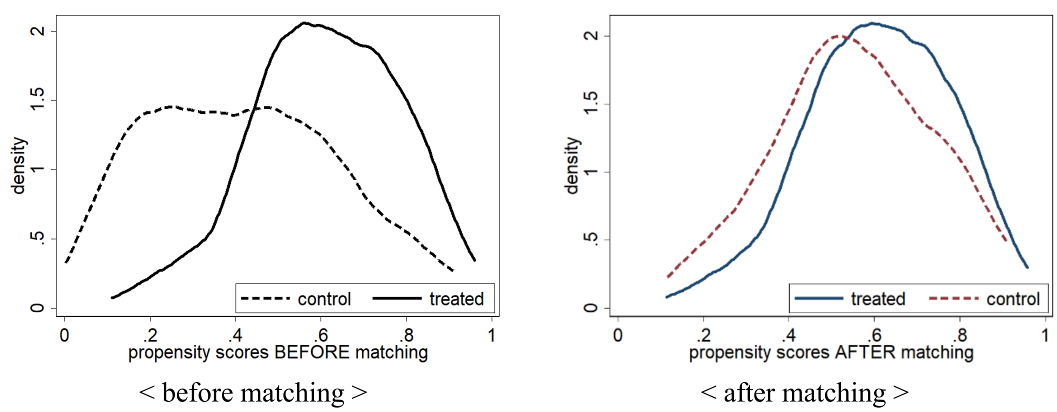

Figure 2.2. Common support before and after matching

2.5. Estimation Results

2.5.1. Results

The main object of this study is to examine the impact of frequent hurricane incidences on county government tax revenue and its structure. Because the adaptation in response to the hurricane will likely to occur in counties where future hurricane risk is high, or where hurricane frequently strikes, I also can identify the potential effect of adaptation if it exists.

Key estimation results are summarized in Table 6. Compared to the counties with infrequent hurricanes, the changes in the share of property tax in counties with frequent hurricanes is around 3.7 percent point higher (Model 1). In other words, the decreases in the share of property tax revenue in frequent hurricane counties is 3.7 percent point higher compared to the decreases in counties with infrequent hurricanes. This could potentially be driven by either a smaller decrease in property damage or a bigger decrease in the total tax revenue due to the bigger decreases in tax revenues other than the property tax. A smaller decrease in property damage in counties with more frequent hurricanes is counterintuitive. This possibility is ruled out by the regression result of Model 2 reported in Table 2.6. The changes in the property tax revenues in counties experiencing frequent hurricanes in the current period is not statistically different from those in counties with infrequent hurricanes. The hypothesis of a bigger decrease in the total tax revenue is supported by a 44.9 percent point higher decrease in sales tax among the counties with frequent hurricanes (Model 3). The change in the revenue from other taxes is not different between counties with frequent and infrequent hurricanes (Model 4). In summary, the estimates of β_1 in Model 2 to Model 4 suggest that frequent hurricane incidence does not have a differential effect in terms of the property tax or other taxes while it decreases the sales tax revenue more in counties with frequent hurricanes compared to the decreases in the sales tax revenue in counties with low hurricane probability. Because of the relatively more decreases in sales tax revenue, the changes in the share of property tax in frequent hurricane counties is higher. The mean of sales tax revenue of counties is 13,888 thousand dollars (Table 2.2.) and the result in Model 3 implies that the sales tax revenue would decreases by 6,250 thousand dollars in the treated counties due to the multiple hurricane incidence.

In equation (4), the estimate of $D_i H_i$ captures the adaptation effect. If H_i is 0 in county i, then it means that the number of expected hurricanes is 0 and the expected benefit of adaptive action this there is also zero. If $H_i > 0$, then the adaptive effect is increasing with H_i. For example, if $H_i = 1$, the estimate of the interaction term suggests that, conditional on experiencing multiple hurricanes in the current period, the share of property tax increases 1.6 percentage points less among counties experienced more hurricanes in the current years. Or, in other words, around 43 percent of the estimated impact of multiple hurricanes is mitigated away. This change in the share of property tax revenue is the results of adaptive effects on the property tax, sales tax, and other taxes. The amount of property tax decreases more in counties with frequent hurricane incidences in the past. The sales tax revenue decreases 18.1 percentage points less in counties experienced more hurricanes in the preceding years, which is around 40% of the estimated impact of multiple hurricanes, that is, the estimated value of β_1 in Model 3 (around 2,500 thousand dollars). Moreover, counties experienced more hurricanes in the preceding years, the share of other tax revenues increased by 25.2 percent. The property tax revenue is significantly lower if the county experiences multiple hurricanes in the recent past and is hit by multiple hurricanes again in the current period (see estimated β_2 in Model 2).

Table 2.6. Estimation result using matched sample

Variable	Dependent variable			
	Model 1 *share of property tax*	Model 2 *Log(property tax)*	Model 3 *Log(sales taxes)*	Model 4 *Log(other taxes)*
D_i	0.037** (0.019)	0.087 (0.055)	-0.449** (0.169)	-0.728 (0.497)
D_iH_i	-0.016*** (0.004)	-0.031** (0.013)	0.181** (0.085)	0.252* (0.139)
H_i	0.007 (0.004)	0.044*** (0.007)	-0.089 (0.099)	-0.131 (0.082)
County Fixed Effect	Yes	Yes	Yes	Yes
Robust Standard error (State level)	Yes	Yes	Yes	Yes
Observation	828	828	828	828

Notes: significance levels are $***p < 0.01$, $**p < 0.05$, and $*\ p < 0.1$.

2.5.2. Robustness analyses

To test whether the estimation results are robust, I run several tests. First, I try alternative definitions of past hurricane experience. Instead of defining it as the number of hurricanes experienced in the past three presidential election periods, I define it as the number of hurricanes in the recent two presidential election periods. The results are similar (see Table 2.7). For example, in Table 8, the share of property tax is 3 percent point higher8 in counties with frequent hurricanes (Model 5). This is because of the bigger decreases in the total tax revenue driven by 53.9 percent higher decreases in the sales tax revenue (Model 7). The change in the other tax revenue is not different between the counties with frequent hurricanes and infrequent hurricanes. The estimate of β_2 suggests that the share of property tax increases 0.8 percentage points less in counties that experienced more hurricanes in the preceding years, which is around 26 percent of the estimated impact of multiple hurricanes (β_1 in Model 5). The share of sales tax decreases by 12.1 percentage points less, which is around 22.4 percent of the estimated impact of multiple hurricanes in counties experienced more hurricanes in the preceding years (Model 7).

Table 2.7. Robustness test using eight-year past hurricane experiences

	Dependent variable			
	Model 5	Model 6	Model 7	Model 8
	share of property tax	*Log(property tax)*	*Log(sales taxes)*	*Log(other taxes)*
D_i	0.030 (0.020)	0.100 (0.066)	-0.539*** (0.177)	-0.420 (0.323)
D_iH_i	-0.008 (0.005)	-0.026** (0.011)	0.121* (0.065)	0.093 (0.054)
H_i	0.001 (0.005)	0.031** (0.009)	-0.071 (0.080)	-0.030 (0.035)
County Fixed Effect	Yes	Yes	Yes	Yes
Robust Standard error (State level)	Yes	Yes	Yes	Yes
Sample size	848	848	848	848

[8] The p-value of this coefficient is 0.152.

Notes: significance levels are $***p < 0.01$, $**p < 0.05$, and $*\ p < 0.1$.

Secondly, I define Control group as the counties with low-frequency counties and the counties with no hurricane between the years 2002 and 2007 and repeat the same process. Including counties without hurricane experience during the years between 2002 and 2007 into the analysis does not change the conclusion of the paper. Instead of separating the counties into low frequency and high-frequency counties, I classify the counties into high-frequency counties as Treated and the rest of the counties with low frequency and with no hurricanes as Control. After the matching, I could get a balanced sample from the year 2002 and 2007, and the year 2007 and 2012. However, from the period between 2007 and 2012, matching generates only 37 matched samples and including those matched samples does not affect the conclusions of the paper.

Table 2.8. Estimation result using matched sample (no and low counties as Control)

	Dependent variable			
	Model 1	Model 2	Model 3	Model 4
	share of property tax	*Log(property tax)*	*Log(sales taxes)*	*Log(other taxes)*
D_i	0.059*** (0.014)	0.088* (0.044)	-0.568** (0.184)	-0.544** (0.235)
D_iH_i	-0.022*** (0.005)	-0.042** (0.019)	0.202** (0.061)	0.168** (0.056)
H_i				
County Fixed Effect	Yes	Yes	Yes	Yes
Robust Standard error (State level)	Yes	Yes	Yes	Yes
Sample size	960	960	960	960

Notes: significance levels are $***p < 0.01$, $**p < 0.05$, and $*\ p < 0.1$.

2.6. Conclusion

Although there exists a high volume of literature that analyzes the socio-economic impact of hurricanes, the relationship between the hurricanes and the local government finance has received less attention. Further, the existence of adaptation in response to hurricanes from the perspective of local government tax revenue is rarely studied. This study aims to fill the gap between public finance literature and the regional science literature by specifically focus on the frequent hurricane exposures and the potential adaptation effects in local economies. I use county-level tax revenue data and county-level hurricane records in the analysis. I pre-process the data to construct two different counties that are similar in their social and economic characteristics. One group of counties are exposed to frequent hurricane strikes while the other is not over the study period. I apply post-matching regression with fixed effect to identify the effect of frequent hurricane incidence on the county government tax revenues and to identify the potential existence of the adaptation effect. I find that, with the multiple hurricane incidence, the share of property tax revenue increases mainly due to the significant decreases in sales tax revenue. However, compared in counties with less frequent hurricane strikes, the sales tax revenue decreases less, suggesting that the adaptation occurs.

The empirical results provide policy implications. Firstly, the potential fiscal impacts of disaster could be mitigated by diversifying tax sources. Historically, county governments have been heavily dependent on the property tax revenue for its stability. However, hurricanes often damage taxable properties, and this could increase the uncertainties in tax revenues. As the local economy adapts to hurricanes in a way to increase the sales tax revenues, changing revenue portfolio could be one way to mitigate the fiscal impacts of hurricanes. Secondly, local communities that experience recent changes in climate conditions may learn from disaster-prone local governments. Ongoing climate change ever increases the climate-related risks, and, in fact, many nations already experience unprecedented disasters such as perfect storms. By actively respond to changes in climate and increasing future risks can not only mitigate the economic losses, but it also helps governments to provide essential public services continuously. Learning from others' experiences could allow local governments to efficiently adapt to future risks.

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2.8. Appendix I.

According to National Oceanic and Atmospheric Administration (NOAA)'s hurricane track information, 30 hurricanes have landed or passed the coastlines of the U.S. continents over the period from 1960 to 2012 (Figure 2.3.).

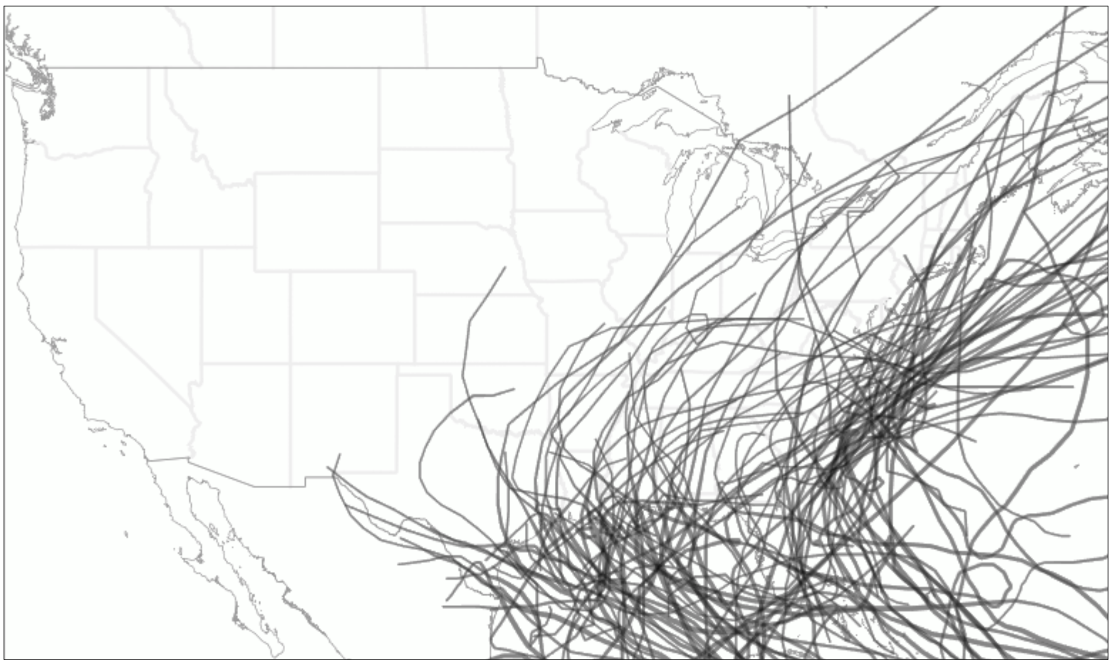

Figure 2.3. Hurricane paths that lands on U.S. continents (from 1960 to 2012)

1,243 counties in 20 states have at least one hurricane record over the period from 1960 to 2012, according to the hurricane records in the SHELDUS data (version 12). Among these counties, Charleston County in South Dakota records 67 times of hurricanes, followed by 47 times of hurricanes of Jefferson County in Louisiana (Figure 2.4.). 156 counties (12.6%) out of 1,243 counties have one hurricane records.

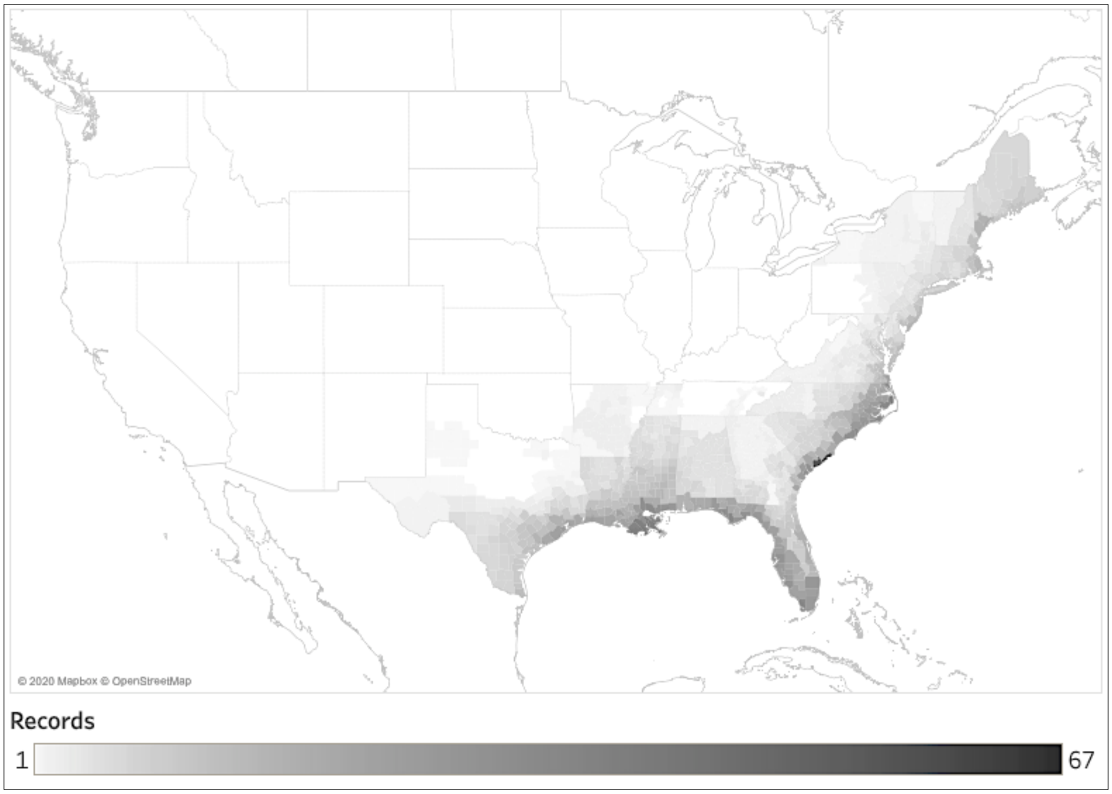

Figure 2.4. Number of hurricane records by counties (from 1960 to 2012)

2.9. Appendix II.

I apply a Binary-Logit model that regresses the binary variable D on county specific social and economic characteristics using one-to-one match with replacement within a caliper size equal to one fourth of the standard deviation of the propensity score. Matching using subperiod 1, 2, and 4 do not provide balanced-matched sample (Table 2.9. to Table 2.11.).

Table 2.9. Summary statistics of pre-treatment variables before and after matching (1992-1997)

LOW-HIGH	Unmatched			Matched		
Variable	Treated	Control	Normalized difference	Treated	Control	Normalized difference
Share of property tax	0.75	0.74	0.05	0.75	0.77	-0.11
Past distribution	2.59	2.28	0.17	2.59	2.15	0.23
Median household income	41046	40318	0.09	41046	40745	0.04
Median home value	106467	92823	**0.39**	106467	97650	**0.25**
Farm	0.05	0.06	-0.02	0.05	0.06	-0.12
Manufacture	0.12	0.22	**-0.97**	0.12	0.13	-0.18
HHI	0.42	0.35	**0.79**	0.42	0.4	**0.26**
Unemployment	0.07	0.07	-0.06	0.07	0.07	0.01
Housing density	71.64	44.36	**0.27**	71.64	58.47	0.13
Poverty rate	0.17	0.19	**-0.34**	0.37	0.31	0.14
Col_edu	0.13	0.13	0.08	0.13	0.12	0.14
Pnonwhite	0.20	0.29	**-0.61**	0.2	0.25	**-0.31**
Pmale	0.50	0.48	**0.50**	0.5	0.51	**-0.58**
Pa65o	0.17	0.13	**0.74**	0.17	0.15	**0.38**
Metro	0.37	0.34	0.07	0.17	0.18	-0.12

Table 2.10. Summary statistics of pre-treatment variables before and after matching (1997-2002)

LOW-HIGH	Unmatched			Matched		
Variable	Treated	Control	Normalized difference	Treated	Control	Normalized difference
Share of property tax	0.74	0.68	**0.40**	0.74	0.75	-0.03
Past distribution	2.86	1.91	**0.46**	2.91	2.33	**0.28**
Median household income	43354	43828	-0.04	43373	41614	0.16
Median home value	108663	116969	-0.15	106250	105785	0.01
Farm	0.05	0.05	0.02	0.06	0.06	-0.12
Manufacture	0.12	0.16	**-0.38**	0.13	0.11	0.17
HHI	0.43	0.40	**0.32**	0.41	0.4	0.03
Unemployment	0.06	0.06	-0.14	0.06	0.06	0.05
Housing density	78.64	84.59	-0.03	65.27	49.38	0.07
Poverty rate	0.16	0.18	**-0.31**	0.45	0.33	0.24
Col_edu	0.14	0.14	-0.02	0.14	0.14	0.02
Pnonwhite	0.24	0.26	-0.16	0.26	0.28	-0.11
Pmale	0.49	0.49	0.03	0.49	0.49	-0.19
Pa65o	0.16	0.13	**0.53**	0.14	0.15	-0.17
Metro	0.50	0.40	0.21	0.17	0.18	-0.15

Table 2.11. Summary statistics of pre-treatment variables before and after matching (2007-2012)

LOW-HIGH	Unmatched			Matched		
Variable	Treated	Control	Normalized difference	Treated	Control	Normalized difference
Share of property tax	0.64	0.58	**0.29**	0.64	0.62	0.09
Past distribution	2.00	1.13	**0.40**	1.88	2.52	**-0.30**
Median household income	42575	45798	**-0.29**	42229	44089	-0.17
Median home value	94405	98421	-0.10	92333	99888	-0.19
Farm	0.03	0.05	**-0.47**	0.04	0.03	0.09
Manufacture	0.13	0.11	0.15	0.13	0.13	-0.05
HHI	0.42	0.42	-0.06	0.41	0.42	-0.02
Unemployment	0.05	0.06	**-0.40**	0.05	0.05	**0.32**
Housing density	43.03	63.13	-0.20	42.42	43.12	-0.01
Poverty rate	0.19	0.17	**0.35**	0.57	0.57	0.00
Col_edu	0.15	0.15	0.04	0.15	0.16	-0.17
Pnonwhite	0.31	0.26	**0.28**	0.32	0.27	0.24
Pmale	0.49	0.49	**-0.33**	0.49	0.49	-0.06
Pa65o	0.13	0.14	**-0.26**	0.13	0.13	-0.04
Metro	0.60	0.41	**0.39**	0.19	0.17	**0.37**

2.10. Appendix III.

I summarize all of the coefficient of estimation results in Table 2.12.

Table 2.12. Estimation result using matched sample

	Dependent variable			
	Model 1	Model 2	Model 3	Model 4
	share of property tax	*Log(property tax)*	*Log(sales taxes)*	*Log(other taxes)*
$\beta_{cons.}$	0.690** (0.285)	9.999*** (0.583)	8.824** (2.935)	10.211*** (1.662)
β	0.037** (0.019)	0.087 (0.055)	-0.449** (0.169)	-0.728 (0.497)
β_2	-0.016*** (0.004)	-0.031** (0.013)	0.181** (0.085)	0.252* (0.139)
β_3	0.007 (0.004)	0.044*** (0.007)	-0.089 (0.099)	-0.131 (0.082)
$\beta_{4,Unemployment}$	0.556* (0.291)	-2.983** (0.944)	-2.886 (5.319)	-0.220 (5.099)
$\beta_{4,HHI}$	-0.059 (0.543)	-1.276 (1.025)	-2.971 (3.645)	-2.400 (2.652)
$\beta_{4,Farm}$	0.524 (0.467)	1.009 (1.340)	-18.804 (19.196)	-10.540 (8.665)
$\beta_{4,Manufacture}$	-0.152 (0.475)	-0.815 (0.984)	2.212 (4.789)	0.928 (3.518)
$\beta_{4,Metro}$	-0.013 (0.009)	0.046 (0.046)	-0.072 (0.118)	0.014 (0.084)
County Fixed Effect	Yes	Yes	Yes	Yes
Robust Standard error (State level)	Yes	Yes	Yes	Yes
Sample size	856	856	856	856

Notes: significance levels are $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}\ p < 0.1$.

2.11. Appendix IV.

I report the summary statistics, the common trend, common support before and after matching, and the all the coefficients of each robustness analysis; that uses the number of past hurricane experiences for the two presidential election period (Table 2.13., Figure 2.5., Figure 2.6., and Table 2.14.), and that separate the counties into high frequency counties and the rest of the counties (Table 2.15., Figure 2.7., Figure 2.8., and Table 2.16).

In the robustness analysis that uses the number of past hurricanes over the two presidential periods, I obtained a well-balanced control and treatment counties over the period 3 (2002-2007).

Table 2.13. Summary statistics before and after matching

	Unmatched			Matched		
Variable	Treated	Control	Normalized difference	Treated	Control	Normalized difference
Share of property tax	0.70	0.73	-0.16	0.70	0.70	-0.03
Past distribution	2.95	2.01	**0.33**	2.95	3.04	-0.01
Median household income	42,684	47,925	**-0.45**	42,684	42,592	0.01
Median home value	93,117	112,054	**-0.44**	93,117	90,890	0.06
Farm	0.06	0.06	0.04	0.06	0.06	-0.12
Manufacture	0.14	0.14	0.02	0.14	0.15	-0.06
HHI	0.40	0.40	0.01	0.40	0.40	0.05
Unemployment	0.05	0.04	**0.57**	0.05	0.05	0.09
Housing density	53.77	59.9	-0.06	53.77	55.89	-0.01
Poverty rate	0.19	0.15	**0.60**	0.19	0.18	0.08
Col_edu	0.15	0.15	-0.06	0.15	0.15	0.04
Pnonwhite	0.32	0.27	**0.33**	0.32	0.29	0.16
Pmale	0.49	0.49	-0.20	0.49	0.49	0.04
Pa65o	0.14	0.14	0.04	0.14	0.14	0.01
Metro	0.31	0.34	-0.06	0.31	0.36	-0.05

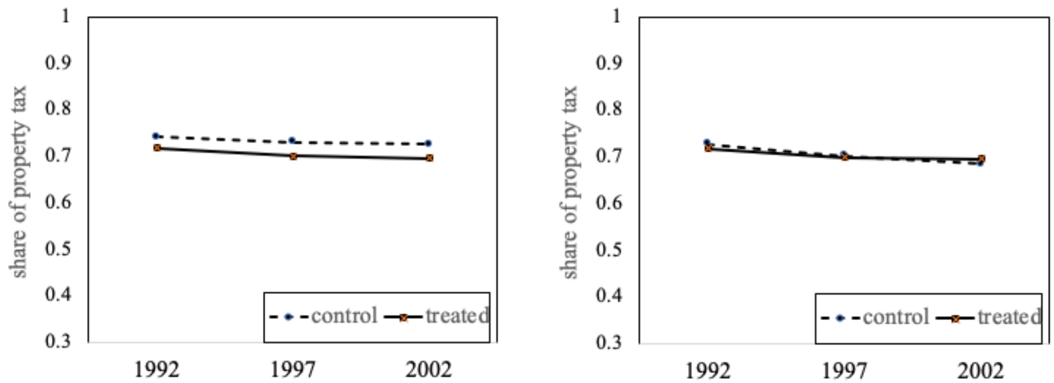

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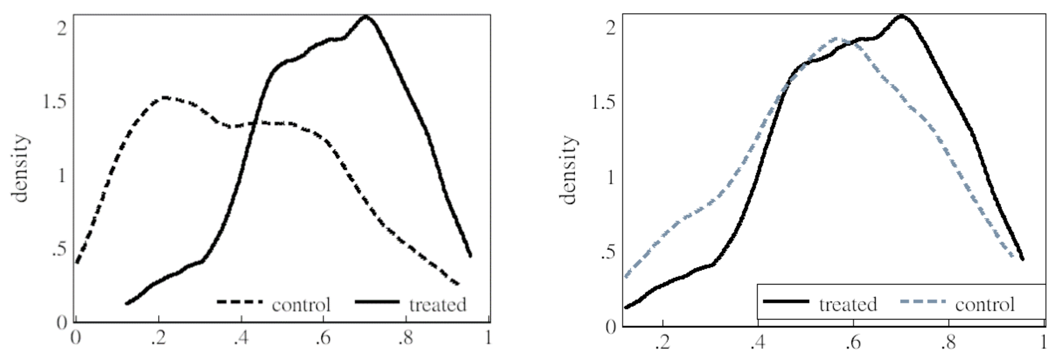
Figure 2.5. Common trends before and after matching



< before matching > < after matching >

Figure 2.6. Common support before and after matching

Table 2.14. Robustness test using hurricane records during two presidential periods

	Dependent variable			
	Model 1	Model 2	Model 3	Model 4
	share of property tax	*Log(property tax)*	*Log(sales taxes)*	*Log(other taxes)*
β_0	0.899*** (0.259)	10.055*** (0.502)	6.843* (3.704)	6.499*** (1.684)
β_1	0.030 (0.020)	0.100 (0.066)	-0.539*** (0.177)	-0.420 (0.323)
β_2	-0.008 (0.005)	-0.026** (0.011)	0.121* (0.065)	0.093 (0.054)
β_3	0.001 (0.005)	0.031*** (0.009)	-0.071 (0.080)	-0.030 (0.035)
$\beta_{4,Unemployment}$	0.337 (0.746)	-2.274** (0.773)	-7.403 (10.591)	-7.508 (5.815)
$\beta_{4,HHI}$	-0.407 (0.570)	-1.543 (0.905)	0.369 (5.373)	4.005 (3.549)
$\beta_{4,Farm}$	0.255 (0.366)	0.569 (1.193)	-20.188 (20.998)	0.973 (3.357)
$\beta_{4,Manufacture}$	-0.269 (0.365)	-0.086 (0.715)	7.523 (7.108)	5.780 (3.215)
$\beta_{4,Metro}$	-0.001 (0.014)	0.045 (0.045)	-0.099 (0.205)	0.043 (0.052)
County Fixed Effect	Yes	Yes	Yes	Yes
Robust Standard error (State level)	Yes	Yes	Yes	Yes
Sample size	848	848	848	848

Notes: significance levels are $***p < 0.01$, $**p < 0.05$, and $*\ p < 0.1$.

Instead of separating the counties into low frequency and high frequency counties, I categorize the counties into high frequency counties and the rest of the counties with low frequency and with no hurricanes. After the matching, I could get a balance sample from the year 2002 and 2007, and the year 2007 and 2012. However, for the period between 2007 and 2012, matching generates only 37 matched samples. Including those matched samples does not affect the conclusions of the paper.

Table 2.15. Summary statistics before and after matching

	Unmatched			Matched		
Variable	Treated	Control	Normalized difference	Treated	Control	Normalized difference
Share of property tax	0.70	0.69	0.03	0.69	0.70	-0.05
Past distribution	2.00	0.82	0.67	2.07	1.98	0.04
Median household income	42,684	48,895	-0.53	43,312	42,285	0.11
Median home value	93,117	113,885	-0.46	94,844	91,516	0.09
Farm	0.06	0.05	0.06	0.05	0.05	-0.05
Manufacture	0.14	0.15	-0.12	0.14	0.15	-0.08
HHI	0.4	0.4	-0.05	0.4	0.39	0.08
Unemployment	0.05	0.04	0.65	0.05	0.05	0.14
Housing density	53.77	85.13	-0.18	54.95	48.7	0.07
Poverty rate	0.19	0.14	0.69	0.19	0.19	-0.08
Col_edu	0.15	0.17	-0.24	0.15	0.15	0.05
Pnonwhite	0.32	0.21	0.64	0.31	0.34	-0.17
Pmale	0.49	0.49	-0.16	0.49	0.49	0.05
Pa65o	0.14	0.14	0.07	0.14	0.14	0.01
Metro	0.31	0.37	-0.12	0.37	0.36	0.01

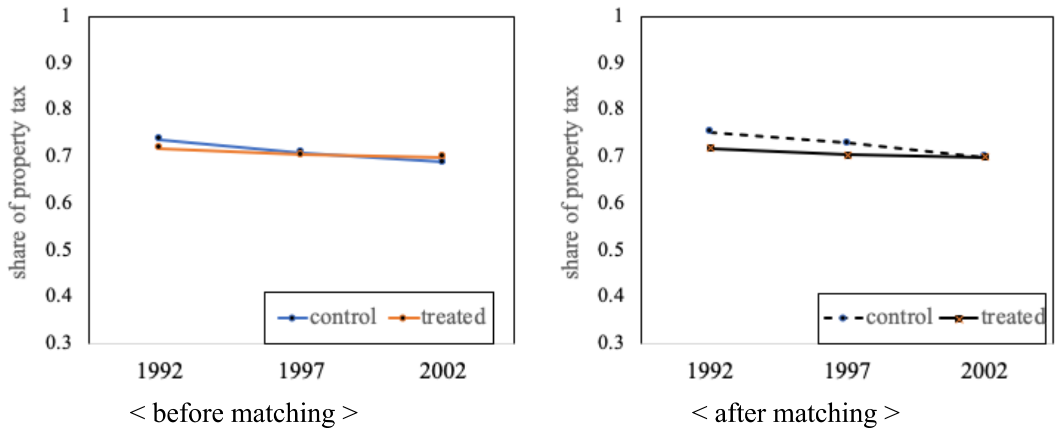


Figure 2.7. Common trends before and after matching

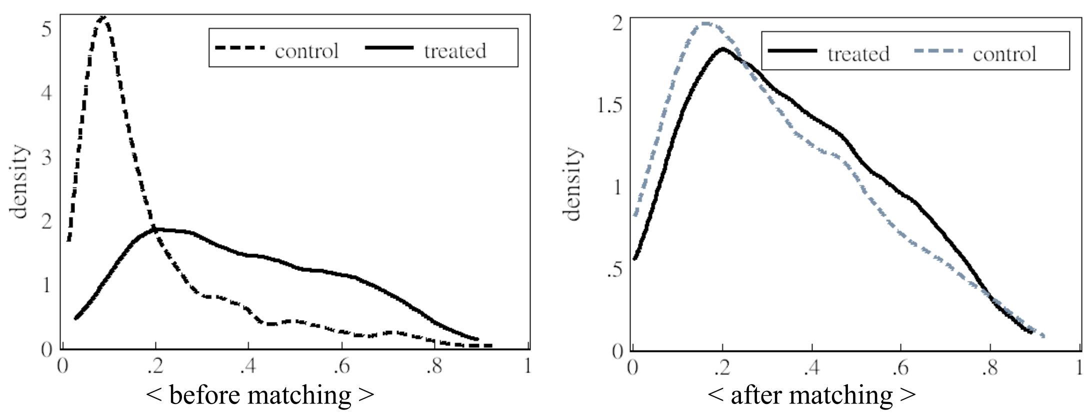


Figure 2.8. Common support before and after matching

Table 2.16. Estimation result using matched sample (no and low counties as Control)

	Dependent variable			
	Model 1	Model 2	Model 3	Model 4
	share of property tax	*Log(property tax)*	*Log(sales taxes)*	*Log(other taxes)*
β_0	0.611 (0.513)	13.577 (1.351)	3.066 (9.248)	8.201 (5.181)
β_1	0.059*** (0.014)	0.088* (0.044)	-0.568** (0.184)	-0.544** (0.235)
β_2	-0.022*** (0.005)	-0.042** (0.019)	0.202** (0.061)	0.168** (0.056)
β_3	0.012** (0.005)	0.049 (0.018)	-0.117 (0.062)	-0.070 (0.031)
$\beta_{4,Unemployment}$	0.019 (0.236)	-2.812*** (0.637)	5.468 (7.250)	-3.684 (3.382)
$\beta_{4,HHI}$	0.074 (0.442)	-1.001 (1.118)	-6.369* (3.701)	-2.278 (2.918)
$\beta_{4,Farm}$	0.328 (0.390)	1.169 (1.848)	-14.859 (13.946)	-3.599 (2.769)
$\beta_{4,Manufacture}$	0.151 (0.297)	0.079 (0.639)	0.339 (2.892)	1.238 (3.119)
$\beta_{4,Metro}$	0.009 (0.013)	0.069** (0.030)	-0.095 (0.219)	-0.003 (0.080)
$\beta_{4,Income}$	-0.000 (0.000)	-0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)
$\beta_{4,Home\ value}$	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
$\beta_{4,Housing\ density}$	0.002*** (0.000)	-0.000 (0.002)	0.009 (0.029)	-0.023 (0.013)
$\beta_{4,Poverty}$	-0.283 (0.328)	-1.777** (0.759)	6.669 (7.621)	3.194 (4.123)
$\beta_{4,College}$	-0.585 (0.309)	-0.749 (1.227)	14.221** (6.746)	10.226 (6.266)
$\beta_{4,Nonewhite}$	0.414 (0.253)	-0.551 (0.339)	-20.612*** (5.447)	-4.159** (1.936)
$\beta_{4,Male}$	-0.410 (0.991)	-5.803** (1.701)	24.369 (15.177)	4.497 (8.810)
$\beta_{4,Aged}$	1.315 (0.994)	2.419 (2.489)	-9.641 (8.451)	3.228 (8.611)
County Fixed Effect	Yes	Yes	Yes	Yes

Robust Standard error (State level)	Yes	Yes	Yes	Yes
Sample size	960	960	960	960

Notes: significance levels are $***p < 0.01$, $**p < 0.05$, and $*\ p < 0.1$.

3. Potential Relationship between Local Institutional Disparities and Spatially Varying Expenditure Determination Processes

3.1. Introduction

Understanding the determinants of local expenditures has been an important topic in regional science literature because of the continuous increases in the demand for public services (Bradford et al. 1969; Ladd, 1992) and because of limited budgets available (Afonso and Fernandes, 2008; Mulamba and Tregenna, 2020).

With the increasing accessibility of the spatial data, regional scientists pay close attention to the spatially varying nature of local expenditure determination processes. For example, there exists a large volume of literature that theoretically or empirically investigate the spatial dependencies of local expenditure determinations such as expenditure competition or expenditure spillover effects (Case et al. 1993; Revelli, 2006; Solé-Ollé, 2006; Foucault et al. 2008; Minkoff, 2009). They show that the regional interaction is one of the potential sources that generates spatially varying expenditure determination processes.

On the contrary, the spatial variations that could arise from intrinsic differences in local context has received fewer attention. One exception is the study by Mulamba and Tregenna (2020). They suggest that South Africa's high degree of disparities in the local contexts, such as revenue streams or levels of skills and capacity, could be potential sources that generate spatially varying processes in local expenditure determination. They employ one of the spatially varying coefficient models (SVCMs) and they show that the relationships between the expenditure determinants and the local expenditure vary across regions. However, the potential mechanism that generates such variation has not been analyzed.

In this study, I extend the study of Mulamba and Tregenna (2020), firstly by providing one potential mechanism that could generate a spatially varying process in local expenditure determination and, secondly by testing the mechanism empirically. I suggest the possibility that local institutional disparities could be closely correlated with the spatial variation in local expenditure determination processes. There exist a volume of the regional science literature that shows institutional characteristics play important roles in local decision-making processes (Arceneaux, 2006; Bunch, 2014; Feiock et al., 2010; Feiock et al., 2012; Richardson, 2011; Warner and Hebdon, 2011; Wolman et al, 2008). On the contrary, I present an alternative perspective that the disparities in the institutional characteristics could be one potential source of the spatial variation in expenditure determination processes.

In this mechanism, a local expenditure for multiple public service provisions is a function of input prices and public service output levels. The coefficients of input prices and output levels could vary across space, given disparities of local institutional characteristics. This model specification first allows me to investigate the existence of spatially varying processes in local expenditure determinations, and it allows me to test the potential correlation between the spatially varying processes and disparities of local institutional characteristics. I estimate spatially varying coefficients of the input price and the output levels by employing one of the nonparametric estimation strategies, the Bivariate Penalized Splines on Triangles (BPSTs) that imposes fewer restrictions on the functional form compared to the Geographically Weighted Regressions (GWR). I employ a linear regression to investigate the potential correlation between the spatially varying coefficients and the disparities in local institutional characteristics.

Compared to the existing literature, this research is novel for three reasons. Firstly, I provide one potential mechanism that local institutional disparities could generate spatial variations in the local governments' expenditure determination. The mechanism is based on the microeconomics theory and the mechanism is testable. Secondly, I empirically test the mechanism and I first show that the coefficients do vary across space, then I show that the variations in coefficients are significantly correlated with the disparities of local institutional characteristics. The empirical results also support the Mulamba and Treggena (2020)'s conjecture that spatial variations in the coefficients of expenditure determinants could exist because local governments operate in diverse local contexts. Lastly, BPSTs introduced by statisticians (Mu et al., 2018), is new to regional science literature. Compared to the GWR that have been commonly used for spatial variation analysis in regional science literature, the BPSTs does not depend on the distance metric between any pair of two locations, and the computation of BPSTs is fast compared to the GWR when dealing with the large size spatial data (Mu et al., 2018).

The study is organized as follows. In the following section, I summarize existing literature on local government finances. The theoretical model will be presented in section 3. In section 4, I summarize the variables that are used in the analysis. In section 5, I explain estimation strategies and the results will be discussed in section 6. Section 6 concludes the findings.

3.2. Literature

It is important to note that local government finance data has locational aspects, and because of these aspects, two issues arise that violate the assumptions of OLS regression: one is the spatial dependency between observations and the other is the spatial variations in the data generating process. The first issue contradicts to the OLS assumption that the observations are independent, and the second issue contradicts to the OLS assumption that the model remains constant across space, or study areas (Anselin, 1999; LeSage, 1999).

The developments in computation techniques allow researchers to address such issues. For example, a large volume of literature has investigated spatial dependencies of local government expenditures in European countries or in the United States. These studies assume that the observable characteristics or unobservable error terms are correlated between local governments. Using spatial econometrics techniques, they analyze two different types of spatial dependency: spillover effects (Case et al., 2003; De Siano and D'uva, 2017; Greene, 1977; López et al., 2017; Solé-Ollé, 2006), and fiscal competitions such as yardstick competition (Allers and Elhorst, 2005; Agrawal, 2015; Bivand and Szymanski, 1997; Bordignon et al., 2003; Carlsen et al., 2005; Hall and Ross, 2010; Hauptmeier et al., 2012; Keen and Marchand, 1997; Musgrave, 1997; Revelli, 2006; Revelli and Tovmo, 2007; Wildasin, 1988).

However, compared to the abundance of spatial dependency analysis, researches that investigate spatially varying processes in expenditure determinations that could arise from disparities in local contexts are scarce. One exception is the study by Mulamba and Treggena (2020). They present empirical evidence that the relationships between municipal governments' operation expenditures and its expenditure determinants vary across space in South Africa. They suggest that this variation could come from when local governments operate in diverse local contexts. However, compared to their extensive efforts in presenting the evidence of spatially varying expenditure determination processes, this potential mechanism has not been tested.

There are two aspects that require additional discussions in Mulamba and Tregenna (2020). Firstly, I note their brief discussion that local governments operate in diverse local contexts and its potential for spatially varying expenditure determination processes. They emphasize that there exist wide disparities in various aspects across locations within South Africa, and it is highly probable that the relationships between local expenditures and its determinants could vary. One following question that has not been addressed in their study is that if the disparities in the local context are potential sources of spatially varying expenditure determination processes, can it be empirically tested? Secondly, they compare the GWR estimation results that are obtained from using two different distance metrics and from two different kernel weighting functions. In the use of GWR estimation, researchers need to construct a weight matrix by choosing the distance metric between pairs of two locations, the kernel-weighting function, and the kernel-weighting function's bandwidth. However, there exist no clear guidelines regarding the selection criteria for each choice (Mulamba and Tregenna, 2020), and additional model comparison techniques are required to choose between competing specifications (Gibbons and Overman, 2012; LeSage and Pace, 2010). An alternative SVCM approach that does not depend on such choices would be necessary in the analysis of spatially varying expenditure determination processes.

A number of regional science literature investigate potential effects of institutional characteristics on local governments' decision-making process (Langbein et al. 1996; Besley and Case; 2003; Bradbury and Stephenson, 2003; MacDonald, 2008; Choi, et al. 2010; Bunch 2014). For example, Choi, et al. (2010) argue that the counties adopting a Home Rule[9] in Florida spend more of their expenditures on developmental and redistributive projects than allocational functions compared to the counties adopting Dillon Rule. Coate and Knight (2011) show that the amount of public spending of city governments under the mayor-council form (a mayor and city council are elected by voters) is lower compared to the city governments' spending under the council-manager form (council appoints a manager) in the United States. Although the two studies investigate different local institutional characteristics and their potential effects on local expenditure, the two studies commonly imply that the differences in institutional characteristics could affect local governments expenditure determination processes differently.

Understanding a potential source of spatially varying expenditure determination processes is important to better provide policy advice targeting local expenditure, instead of providing a "one-size-fits-all" (Mulamba and Tregenna, 2020) approach. In this study, I provide one potential mechanism that could support the existence of spatially varying expenditure determination processes. The mechanism will be tested by using one of the SVCM estimation approaches and by analyzing the potential correlations between the spatially varying processes I obtain and local institutional characteristics.

3.3. Model

I provide a potential mechanism that could support the potential existence of spatially varying local expenditure determination processes. This mechanism is based on the cost function analysis in the microeconomics theory. According to the microeconomics theory, a production of goods or services incurs costs and the costs is a function of input prices and output levels. Let the log of a local government's total expenditure for public service provisions, $\ln c$, is a function of input price vector, w, and a vector of public service outputs levels, y (equation 1).

[9] I explain the definitions of Home Rule and Dillon Rule in Section 4 where I present variables that I use in the analysis.

$$\ln c = f(w, y) + \epsilon \tag{1}$$

A local government located at point $\boldsymbol{u}_i$, where $\boldsymbol{u}_i = (u_{i1}, u_{i2})^T$ is the coordinate of ith point ($i = 1, \dots, n$ that ranges over space), operates given its own local context, $s(\boldsymbol{u}_i)$. $s(\boldsymbol{u}_i)$ is a vector of local context variables that differ across $\boldsymbol{u}_i$s. It could contain any characteristic such as residents' willingness to pay for a certain public service or institutional characteristics such as the degree of autonomy and the number of elected officials. In this study, I focus on the institutional characteristics as $s(\boldsymbol{u}_i)$. Suppose that the disparities in $s(\boldsymbol{u}_i)$ could give rise to spatially varying expenditure determination processes for public service provisions. Then, equation (1) would be written as a function of w and y for a given $s(\boldsymbol{u}_i)$.

$$\ln c = f(w, y; s(\boldsymbol{u}_i)) + \epsilon \tag{2}$$

I consider the total operation expenditure[10] as c. Based on the definition of operation expenditure, I consider a county-level average wage rate as the unique input price. And I assume that each local government produces K different public services (y_k, where $k = 1, \dots, K$). By employing the first-order Taylor series expansion approximation at the mean value of w and each of y_ks, the equation (2) can be expressed as follows,

$$\ln c(w, y; s(\boldsymbol{u}_i)) = \ln c(\bar{w}, \bar{y}; s(\boldsymbol{u}_i)) + \frac{c_w(\bar{w}, \bar{y}; s(\boldsymbol{u}_i))}{c(\bar{w}, \bar{y}; s(\boldsymbol{u}_i))}(w - \bar{w}) + \sum_k \frac{c_{y_k}(\bar{w}, \bar{y}; s(\boldsymbol{u}_i))}{c(\bar{w}, \bar{y}; s(\boldsymbol{u}_i))}(y_k - \bar{y}_k) \tag{3}$$

Recall that s is a vector of local institutional characteristics that differ across $\boldsymbol{u}_i$. If there exists spatially varying expenditure determination processes that are correlated with the disparities in $s(\boldsymbol{u}_i)$, then the coefficients $\ln c(\bar{w}, \bar{y}; s(\boldsymbol{u}_i))$, $\frac{c_w(\bar{w}, \bar{y}; s(\boldsymbol{u}_i))}{c(\bar{w}, \bar{y}; s(\boldsymbol{u}_i))}$, and

[10] According to Classification Manual by Census (2006), operation expenditure is the expenditure for compensation of own officers and employees and for supplies, materials, and contractual services except for any amounts for capital outlay. Based on this definition, I consider labor in public sector is the unique input for the public service provisions.

$\frac{c_{y_k}(\bar{w},\bar{y};s(\boldsymbol{u}_i))}{c(\bar{w},\bar{y};s(\boldsymbol{u}_i))}$ could be written as functions of $s(\boldsymbol{u}_i)$s such that $\beta_{cons}(s(\boldsymbol{u}_i))$, $\beta_w(s(\boldsymbol{u}_i))$, and $\beta_{y_k}(s(\boldsymbol{u}_i))$, respectively. I rewrite the equation (3) using the βs as follows,

$$\ln c(w,y;s(\boldsymbol{u}_i)) = \beta_{cons}(s(\boldsymbol{u}_i)) + \beta_w(s(\boldsymbol{u}_i))(w-\bar{w}) + \sum_k \beta_{y_k}(s(\boldsymbol{u}_i))(y_k-\bar{y}_k) \quad (4)$$

Note that if the true spatial variation generating processes for each βs is known and all the relevant variables of $s(\boldsymbol{u}_i)$ are available, then I could explicitly express the equation (4) as a function of s, w and y_ks. However, in reality, it is nearly impossible to know the true model that generates spatially varying expenditure determination processes. Also, obtaining all the relevant variables that generate such variations might not be possible. Any misspecification of the relationships between each of βs and $s(\boldsymbol{u}_i)$ will produce biased estimates[11]. To avoid such risks, I only include w and y_ks in the cost function estimation and I will first apply one of the SVCM approaches in the cost function estimation to investigate potential existence of spatially varying expenditure determination processes. Then, I will further investigate the potential correlation between s with spatially varying βs after I confirm that βs do vary across space. I will run a linear regression using each of βs as the dependent variable and s as the independent variable (equation 5).

$$\beta = \omega_0 + \sum_{m=1}^{M} \omega_m s_m s(\boldsymbol{u}_i) + \eta,\ \beta \in \{\beta_{cons}(s), \beta_w(s), \beta_k(s)\}. \quad (5)$$

3.4. Data

I use the variables in Table 3.1. in the analysis and the summary statistics of variables are presented in Table 3.2.

Table 3.1. List of variables

Variables	Definition	Source

[11] See Appendix I for more discussion.

Cost	Current operation expenditure by county government (dollar)	Census
Wage	Average county wage (dollar)	Census
Employment	Employment rate in percentage (%)	BLS
Health	Weighted sum of standardized measure of Health Behaviors and Clinical Cares	County Health Rankings & Roadmaps
Population[12]	Population (number)	Census
Elected	Number of elected county officials (number)	NACO[13]
Rule	1 for Home Rule or Hutchinson Rule, 0 otherwise (Dillon Rule)	NACO
Amenity	Natural Amenity Scales	USDA

Table 3.2. Summary statistics of variables

Variables	Mean	Std. Dev.	Min.	Max.
Expenditure	62,807,440	339,948,311	1,000	13,691,327,000
Wage	39666.6	8484.6	22770.0	126707.0
Health	1.80	0.48	-1.60	3.96
Employment	0.95	0.02	0.81	0.98
Population	93,012.3	267,283.3	112	5,238,216
Elected	12.73	6.28	3	62
Rule	0.31	0.46	0	1
Amenity	0.03	2.32	-6.40	11.17

I specifically focus on the expenditures by the county government of the United States[14]. It is because the public services produced by county governments are

[12] I include the number of populations in counties (Population) in the cost function estimation as a robustness analysis.
[13] National Association of Counties (www.naco.org)
[14] The expenditure data of Alaska, Hawaii are excluded in the analysis. Also, the counties in the New England States (Maine, Vermont, New Hampshire, Massachusetts, Connecticut, and Rhode Island) are excluded. This is because the county government system is not active in the New England States (https://www.sec.state.ma.us/cis/cislevelsofgov/ciscounty.htm).

directly tailored to local needs (King and Cotterill, 2007) and a better understanding of the relationships between the local public service expenditures and its determinants could ultimately improve the welfares of residents and boost local economic growth. I denote the current operation expenditures of the county government as *Expenditure* and the log of *Expenditure* is the dependent variable in equation (4).

The variable *Wage* is the county-level average wages and it is obtained from the Bureau of Labor Statistics (BLS) [15]. For the public service output variables, y_ks, in equation (4), I consider *Health* and *Employment*. The variable *Health* is a weighted sum of standardized measures of Health Behaviors and Clinical Cares obtained from "County Health Rankings & Roadmaps"[16]. These two categories reflect the physical and mental well-being of residents at the county-level, respectively. Thus, this variable can be considered as a proxy for the level of public health services that county governments provide to residents and it also provides some ideas on whether health-related public services of county governments are working (Hood et al., 2016). The variable *Employment* is a proxy for the public services that aim to boost local economic growth. I calculate this variable using the county-level unemployment rate obtained from the Bureau of Labor Statistics (BLS).

For county-specific characteristics, s, I focus on the two institutional variables, *Elected*, and *Rules.* The two variables are chosen based on the public policy literature (Lewis and Taylor, 1994; Wang, 2000; Lansford, 2006; Bundy and Jensen, 2015). The variable *Elected* is the number of elected county officials. It has been known that the elected officials actively engage in local politics not only to meet the public demands but also to maximize their interests by deciding how to spend the government budgets (Feiock, et al., 2010; Garrett and Jensen, 2011). The variable *Rule* is a dummy value that has value 0 for counties adopting Dillon's Rule and the value is 1 for counties adopting Home Rule or Hutchinson Rule. Dillon's Rule is based on the two court decisions issued by Judge John F. Dillon of Iowa In 1868. The

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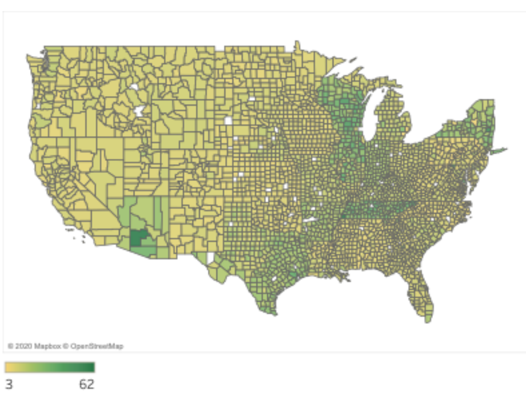
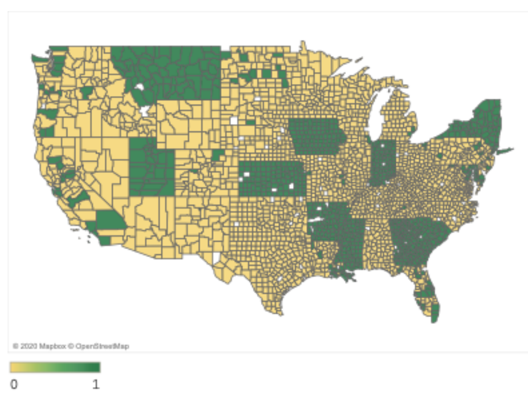
[15] BLS also provides wage rates in the public administration sector. However, around 600 counties' public administration sector wage information is not open to the public. I use the public sector wage rate in the robustness analysis.

[16] For more detailed information about the variables used in the variable *Health* calculation, please see the Appendix II.

decisions affirm that the substate governments only engage activities that the state governments sanctioned. However, the role of county governments evolved over time to meet the increasing demands for local public services by residents and some state governments granted local government authorities such as adopting new laws and initiating new regulations to address local concern (Briffault, 2004). This new practice is called as Home Rule[17]. Similarly, in Utah state, the Supreme Court states that Dillon's rule would no longer be considered binding in court and it grants county governments the power to adopt ordinances for the county objectives (Brown, 2018). The idea is similar to Home Rule, but it is called as Hutchinson Rule. In summary, county governments adopting Home Rule or Hutchinson Rule have more autonomy than county governments adopting Dillon's Rule in terms of levying fees and taxes to provide these additional services (Bunch, 2014). The variable *Amenity* is an aggregate measure of the physical characteristics such as climate, topography, and water areas. The higher value implies that the area is preferred by people. The spatial distribution of each *s* is presented in Figure 3.1. In the case of *Elected* variable, I can see that the values are high, in general, in Arizona, Texas, Arkansas, Tennessee, Wisconsin, Illinois, and New York. In the case of *Rule* variable, all the counties are adopting Home Rule in the states such as Montana, Kansas, Iowa, Indiana, Arkansas, Louisiana, New York and South Carolina, and Utah (Hutchinson Rule). And in the states including Washington, Oregon, California, North Dakota, and Florida, some of the counties are adopting Home rule while others are not.



< *Elected* >



< *Rule* >

[17] For more information about Dillon Rule and Home Rule, please refer to the following link (https://web.archive.org/web/20160804131854/http:/www.nlc.org/build-skills-and-networks/resources/cities-101/city-powers/local-government-authority).

Figure 3.1. Spatial distribution of county specific institutional characteristics

3.5. Estimation Strategy

The main objective of this study is to present one potential mechanism that the local institutional characteristics could be one of the potential sources that generate spatially varying expenditure determination processes. Based on the cost function that I specified, I firstly investigate whether there exist spatial variations in the cost function of public service provisions. If there exist spatially varying expenditure determination processes, the coefficients in equation (4) will differ across the counties. Once I confirm the existence of spatially varying coefficients, then I will further analyze the correlations between the spatially varying coefficients and the county-specific institutional characteristics.

The empirical analysis consists of two processes. Firstly, I employ one of the Spatially Varying Coefficient Model (SVCM) instead of a global model such as Ordinary Least Squares (OLS). Secondly, I employ OLS in the correlation analysis, using the spatially varying coefficients as the dependent variable and using the institutional characteristics as the independent variables.

3.5.1. 1st Stage: Existence of Spatially Varying Coefficients

The empirical approach I employ is the Bivariate Penalized Splines on Triangles (BPSTs) that is introduced by statisticians (Mu et al., 2018). A global model such as OLS assumes that there exist no variations in the model across the study area and thus it cannot be used in the investigation for the spatially varying data generating process (Mu et al., 2018). On the contrary, spatially varying coefficient models (SVCM) such as Geographically Weighted Regression (GWR) or BTSPs allow the coefficients of independent variables to vary across the study area. In the use of GWR estimation, researchers need to construct a weight matrix by choosing the distance metric between pairs of two locations and the kernel-weighting function. However, there is no clear guidelines regarding the selection criteria for each choice (Mulamba and Tregenna, 2020), and additional model comparison techniques are required to choose between competing specifications (Gibbons and Overman, 2012; LeSage and Pace, 2010). Compared to the GWR, the BPSTs does not require such choices. Also, the BPSTs imposes fewer restrictions on the functional form and the computation is fast for the large size spatial data (Mu et al., 2018).

The log of operation expenditure is a function of input price, w, and the public service output levels, y_k (equation 6). The coefficients of each independent variable, βs, where $\beta \in \{\beta_{cons}(s), \beta_w(s), \beta_k(s)$, would vary across the study area if there exist spatially varying expenditure determination processes for a given institutional characteristics, $s(\boldsymbol{u}_i)$ ($\boldsymbol{u}_i = (u_{i1}, u_{i2})^T$ is the coordinate of ith county and $i = 1, \ldots, n$).

$$\ln c_i\,(w, y; s) = \beta_{cons}\big(s(\boldsymbol{u}_i)\big) + \beta_w\big(s(\boldsymbol{u}_i)\big) \cdot w + \sum_k \beta_k\big(s(\boldsymbol{u}_i)\big) \cdot y_k \tag{6}$$

To estimate βs in equation (6), I employ the BPSTs. The BPSTs is an extension of Bivariate Splines over Triangulations (BST) presented by Lai and Schumaker (2007) and Lai and Wang (2013). Both approaches firstly decompose the study area into triangles (Triangulation). $\Delta = \{\tau_1, \ldots, \tau_L\}$ is the set of triangles that are generated over the study area $\Omega = \cup_{l=1}^{L} \tau_l$. Then, piecewise polynomial functions over triangulated space are estimated (Lai and Wang, 2013). Given a set of triangles in Δ, let $t|_{\tau_l}$ be the polynomial piece of spline t restricted in triangle τ_l. $t|_{\tau_i}$ could be any rth continuously differentiable functions for given Δ over Ω with degree d (or, $t|_{\tau_i}$ is the element of a spline space of degree d and smoothness r over Δ that is denoted as $T_d^r(\Delta)$). Let X_i be a vector of one, w_i, and y_ks at location $\boldsymbol{u}_i$ ($X_{io},\ o = one, w, y_k$s). Then, both of the BST and the BPSTs minimize the sum of squared residuals (equation 7, equation 8),

BST:
$$\min_{t_k \in T_d^R(\Delta)} \sum_{i=1}^{n} \left\{ ln\, c_i\,(w, y; s) - \sum_o X_{io} t_o(\boldsymbol{u}_i) \right\}^2 \tag{7}$$

BPSTs: $$\min_{t_k \in T_d^R(\Delta)} \sum_{i=1}^{n} \left\{ ln\, c_i\,(w, y; s) - \sum_{o} X_{io} t_o(\boldsymbol{u_i}) \right\}^2 + \sum_{o} \lambda_o \varepsilon(t_o) \tag{8}$$

Note that compared with BST, BPSTs has one additional term $\sum_o \lambda_o \varepsilon(t_o)$. This is similar to the thin-plate spline penalty (Green and Silverman, 1994) in that λ_o serves as the amount of pressure to smoothly plot the dependent variable continuously across the bivariate surface in three-dimensions (Lia and Wang, 2013; Wood, 2003). The inclusion of a separate penalty parameter for each X_o in the estimation allows different smoothness for different coefficient functions (Mu et al., 2017). A large value of λ_o smooths a fitted function with potential risks of larger fitting errors, while a small value produces a rough fitted function with potentially smaller fitting errors (Wang et al., 2016). The values of λ_o is chosen using the generalized cross-validation (GCV). According to Mu et al., (2018), under the common assumptions in the nonparametric regression estimations[18], the spline estimator $\hat{\beta}_o(\cdot)$ is consistent.

There is one issue in the cost function approach. In general, county governments provide multiple public services such as police protection, local fire management, road construction, and management. However, there is no common agreement on how to measure these services (Heineke and Darrough, 1977). To address potential bias from omitting these output variables, I exclude the operation expenses on the public services that I do not have proper output measures from the total operation expenditures. For example, I subtract the operation expenditures on Police Protection, Local Fire Management, Judicial and Legal, Libraries, Parking Facilities from the total operation expenditures[19].

In the estimation, space is split into 232 triangles. And the parameters, d and r, are selected based on Mu et al. (2018) as presented in Table 3.3.

Table 3.3. List of parameters

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[18] For more details, please see Mu et al. (2018).

[19] Detailed information regarding the expenditure categories can be found from the Classification Manual (https://www2.census.gov/govs/pubs/classification/2006_classification_manual.pdf).

Parameter	Definition	Value
L	Number of triangles	232[20]
d	Degree of piecewise polynomials	3
r	Smoothness parameter over triangles	1

Once I obtain BPSTs estimates and OLS estimates, the natural question is whether the coefficients of the cost function do vary across space and whether any of SVCM approaches is necessary or not. To answer to this question, I first run a "***global test***" presented by Mu et all. (2018). The H_0 of this test is:

$$H_0: \beta_o(s(u_i)) = \alpha_o, \tag{9}$$

$$H_1: \beta_o(s(u_i)) \neq \alpha_o, \text{ for at least one } o. \tag{10}$$

In equation (9) and (10), α_o is the OLS estimates for o (where $o = 0, w, y_k$s). If the test result rejects the null hypothesis (9), then I can say that at least one of the coefficients of the expenditure function is spatially varying. This test compares the residual sum of squares (RSS) of BPSTs estimation and OLS estimation. The RSSs from OLS and BPSTs are expressed as RSS_{OLS} and RSS_{BPSTs}, respectively. The test statistics T_n is obtained as follows,

$$T_n = (RSS_{OLS} - RSS_{BPSTs})/RSS_{BPSTs} = RSS_{OLS}/RSS_{BPSTs} - 1 \tag{11}$$

Calculating the bootstrap test statistics T_n sufficient times, say B times $(T_{n1}, \dots, T_{nB})$, will provide a consistent estimator of the null hypothesis (Mu et al., 2018). By comparing T_{nB}s and the actual T_n(or, T_{obs}) that I originally obtained from the equation (11), I can calculate the p value as follows: $\hat{p} = \sum_{b=1}^{B} I\ (T_{nB} > T_{obs})/B$

[20] For the robustness check, I split the space into smaller number of triangles and repeat the same estimation process.

where $I(\cdot)$ is the indicator function. I reject the null hypothesis H_0 when when $\hat{p}$ is greater than the upper α quantile of $(T_{n1}, \dots, T_{nB})$.

Once I confirm the existence of spatially varying cost function, the following question is which variable of the cost function has the spatially varying relationship with the local government expenditure. To answer this question, I run the "***individual test***" presented by Mu et al. (2018). This test investigates which independent variable's estimate varies across space. The null hypothesis of the individual stationary test is that the coefficients of each independent variable do not vary across space.

$$H_{0o}: \beta_k(s(u_i)) = \beta_o, \tag{12}$$

$$H_{1o}: \beta_o(s(u_i)) \neq \beta_o, \text{ for } o \in \{0, w, y_k s\} \tag{13}$$

Let $\hat{\beta}_o(u_i)$ is the estimate of β_o in location i and I can obtain the variance of $\hat{\beta}_o$ when I take n values of $\hat{\beta}_o$ (from n locations) as equation (14). Under the null hypothesis, any permutation of u_i across the space is equally likely and I can compare the V_{no} with the values obtained from randomly rearranged the data over the space using permutations and repeating the BPST procedure. By repeating this process for B numbers, I can obtain the p value.

$$V_{no} = \frac{1}{n-1} \sum_{i=1}^{n} \left(\hat{\beta}_o(s(u_i)) - \bar{\hat{\beta}}_o \right)^2 \tag{14}$$

where $\bar{\hat{\beta}}_o$ is the mean of $\hat{\beta}_o(s(u_i))$ from all is. If the V_{nj} is greater than the observed $V_{n,obs}$, then it means that the distribution of β_o from permutations has been changed and this implies that the effects of the independent variable X_o is not a stationary process.

Lastly, after I perform the *individual test*, I perform "***individual significance test***". The purpose of this test is to see which individual coefficient for variable k in location i is significantly different from zero or not. The above two tests do not provide any evidence for the significance of β_o in location i. Using the bootstrap method, I repeat the BPSTs over 1,000 times and obtain the distribution of $\beta_o s$ for a specific u_i. If the lower bound (upper bound) of the 95 percent confidence interval of $\beta_o(s(u_i))$ lies above (below) zero, then I can reject the null hypothesis that $\beta_o(s(u_i))$ is not different from zero.

$$H_{0io}: \beta_{io}\big(s(u_i)\big) \neq 0 \text{ versus} \tag{15}$$

$$H_{1io}: \beta_{io}\big(s(u_i)\big) = 0, \text{ for } o \in \{0, w, y_k\text{s}\} \tag{16}$$

3.5.2. 2nd Stage: Potential Mechanism of Spatially Varying Process

The use of the cost function approach in the first stage allows me to further investigate the potential correlation between the local institutional variable s and the spatially varying cost function. As discussed in section 3, if the true spatial variation generating process is known and all the relevant variables are available, then including those variables in the first stage instead of βs and applying a global model such as OLS would do. However, in reality, the true model is not known, and thus there exist potential risks that could arise from any model misspecification. Separating the estimation process into two stages allows me to further investigate the relationships between the local institutional characteristics and the spatially varying coefficients if they exist. I apply OLS to equation (17), where s_{im} includes two institutional variables, *Elected* and *Rule*, and one control variable, *Amenity*.

$$\hat{\beta}_{io} = \sum_{m=0}^{M} \gamma_m s_{im} + \mu_{io}, \text{for } o \in \{0, w, y_k\text{s}\} \tag{17}$$

3.6. Results

3.6.1. Existence of Spatially Varying Coefficients

In Table 3.4, I summarize the mean, standard deviation, and quantiles of the BPSTs estimation results. For comparison, I also present the OLS estimation results in the same table.

According to the BPSTs estimation result, the coefficients of each independent variable in the cost function differ across county governments. For example, in contrast to the coefficient of *Wage* obtained from the OLS estimation, I see a large variation in the coefficients of *Wage* obtained from the BPSTs estimation. Also, I see that some coefficients of *Wage* are smaller or greater than the OLS estimate. Similarly, the coefficients of each public service output variable, *Health*, and *Employment*, vary across space. The mean of BPSTs estimates for each independent variable also differ from the OLS estimates. For example, the mean of BPSTs estimates for *Employment* is 0.48 while the OLS estimate for *Employment* is -0.71. The difference between the mean of the BPSTs estimates and the OLS estimates for the same independent variable suggests that OLS estimate may not capture the average of spatially varying coefficients.

I visualize the BPSTs coefficients to better see the spatial variations over the space (Figure 3.2). In the figure, the orange color indicates that the estimate of β_o (where $o = 0, w, y_k$s) in location i is positive, and the blue color indicates that the estimate of β_o negative. And the darker the color is, the greater the absolute value of the estimate of β_o[21]. For example, the BPSTs estimates of *Wage* in the Pacific Northwest region are positive while the BPSTs estimates in the southern part of Texas and Florida are negative. And within the Pacific Northwest region, the values of estimates also differ. I also can see the spatial variations of BPSTs estimates for variable *Health*, *Employment*, *Population*, and *Constant*.

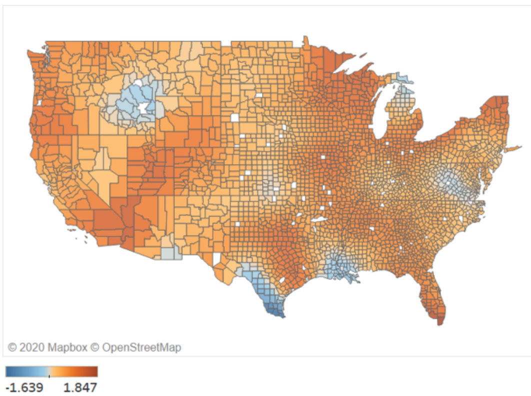
Table 3.4. BPSTs estimation results and OLS estimation results

	Spatially Varying Coefficient Model							
			Quantiles					OLS
Variable	Mean	S.D.	Min	0.25	Median	0.75	Max	(R^2: 0.40)
Wage	0.54	0.33	-1.64	0.32	0.54	0.78	1.86	0.55*** (0.03)
Health	0.48	0.29	-0.43	0.29	0.48	0.67	1.96	0.71*** (0.03)

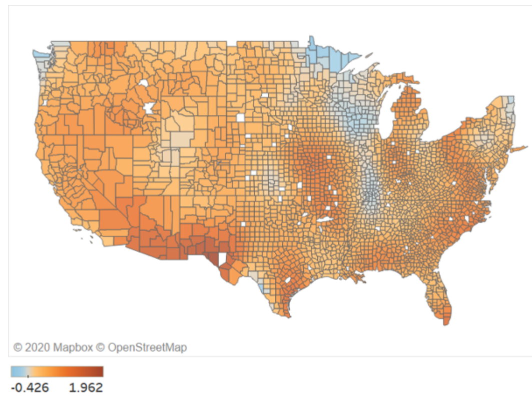
[21] Some county governments do not provide county-level average wage rates and they are excluded in the analysis. In the map, these areas are colored white.

Employment	0.02	0.28	-0.86	-0.17	0.01	0.20	0.95	-0.33*** (0.03)
Constant	16.37	0.75	14.31	15.99	16.31	16.82	19.46	16.29*** (0.02)

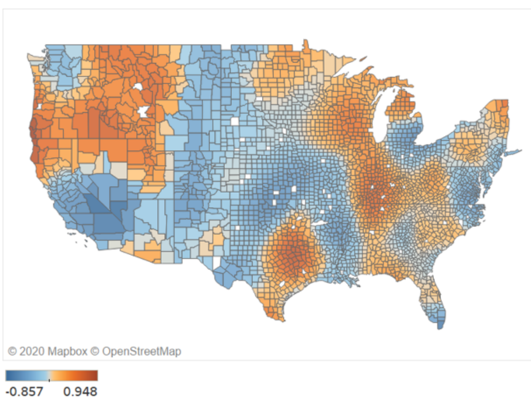
Note: $\hat{\lambda}_o = 10$, for $o \in \{0, w, y_k s\}$



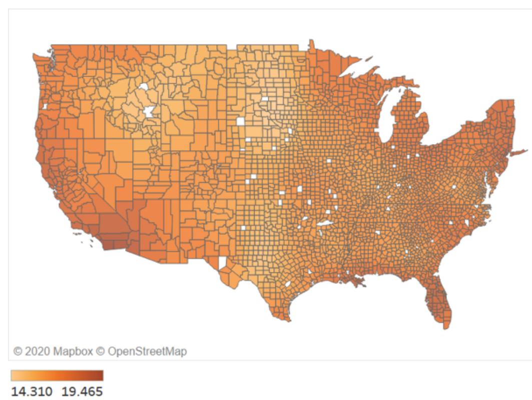
< *Wage* >



< *Health* >



< *Constant* >



< *Constant* >

Figure 3.2. BPSTs estimation results

I present the *global test* and the *individual test* results (Table 3.5.). Firstly, the p value of the *global test* is less than 0.001, and the test result suggests that at least one of the coefficients is spatially varying. This result also supports the use of the BPSTs estimation in the cost function analysis. Then, when I look at the *individual test* results, they all reject the null hypothesis that there is no spatial variation in the coefficients of w and y_ks, as well as in the constant, respectively.

Table 3.5. Hypothesis tests for individual coefficient

Tests	Null hypothesis	Alternative hypothesis	*p* value
global test	$H_0: \beta_o(s(u_i)) = \alpha_o$ for all $o = \{0, w, y_k s\}$	$H_1: \beta_o(s(u_i)) \neq \alpha_o$, for at least one k	0.000
Indi-vidual test	$H_0: \beta_{wage}(s(u_i)) = \alpha_{wage}$	$H_1: \beta_{wage}(s(u_i)) \neq \alpha_{wage}$	0.000
	$H_0: \beta_{Health}(s(u_i)) = \alpha_{Health}$	$H_1: \beta_{Health}(s(u_i)) \neq \alpha_{Health}$	0.000
	$H_0: \beta_{Employment}(s(u_i)) = \alpha_{Employment}$	$H_1: \beta_{Employment}(s(u_i)) \neq \alpha_{Employment}$	0.000
	$H_0: \beta_{cons}(s(u_i)) = \alpha_{cons}$	$H_1: \beta_{con}(s(u_i)) \neq \alpha_{cons}$	0.000

The remaining question is, which βs in each location i is significantly different from zero. Based on the ***significance test***, I select the estimates of β_os in Figure 3.2. that are significantly different from zero, and I plot them in Figure 3.3.

The white-colored areas in each map indicate that the estimates of β_o is not significantly different from zero while the colored areas suggest that the coefficient in that locations are significantly different from zero. For example, the significance test results for β_{Wage} suggest that, in 2,099 counties the increases in *Wage* will increase the operation expenditures up to 185 percent. The results are intuitive and economically intuitive. In 797 counties, the coefficients of *Wage* are not significantly different from zero, meaning that the increases in *Wage* by one standard deviation (around 8,410.9 USD) does not increase the operation expenditures. Lastly, in 15 counties, the coefficients of *Wage* are negative, and they suggest the increases in *Wage* by one standard deviation will decrease the operation expenditures up to 164 percent. Although the negative marginal effect of *Wage* is not intuitive, given the small numbers of counties, I would cautiously conclude that, in general, the marginal effects of *Wage* increases will either increase the operational expenditures or it may not have a significant impact on the expenditure. Still, however, I do not have a clear explanation for the insignificant marginal effect of *Wage* at this point.

The significance test results for β_{Health} suggest that the increases in *Health* would increase the operation expenditures up to 196 percent in 1,410 counties, and in the rest of the counties (919 counties), the changes in *Health* have no significant effect on the expenditure. On the contrary, when I look at the test results for

$\beta_{Employment}$, the results suggest that the increase of *Employment* has no significant effect on the operation expenditure in most of the counties (2,567 counties). And, in 281 counties, the changes in Employment will increase the operation expenditures up to 98 percent. However, the test results suggest that the increases in the *Employment* will decrease the expenditures in 63 counties.

The insignificant or the negative effects of the output variable increases on the operation expenditures is counter-intuitive. However, there exists one possible explanation from the literature. According to Duncan (1990), when a producer provides a capacity, or the readiness to provide service at a certain level, it is difficult for researchers to observe capacity. Instead, the researchers can only observe the realized output among all the capacities. I adopt this explanation in the local government decision-making process. If what local governments provide is the capacity to meet the demand of public services, the output variables that I use in the estimation may not properly capture the capacity that incurs the costs to local governments. This could be the one potential explanation of the negative signs for the output variable or the insignificant coefficients of output variables.[22]

Lastly, the test results suggest that the constant terms are all significantly different from zero. The estimate of $\beta_{cons.}$ can be viewed as a random spatial adjustment at each location (Gelfand et al., 2003) and the test results imply that it differs across space. At the mean of w and y, the log of c_i differs, and this also supports the claim of spatial differences in local expenditure.

[22] Duncan mentions the study by Heckman and Evans (1983) to support his explanation. They investigate the cost function of the telecommunication service provision. According to Duncan, the negative relationship between the costs and the number of toll calls (observed outcome) is negative for the above reasons.

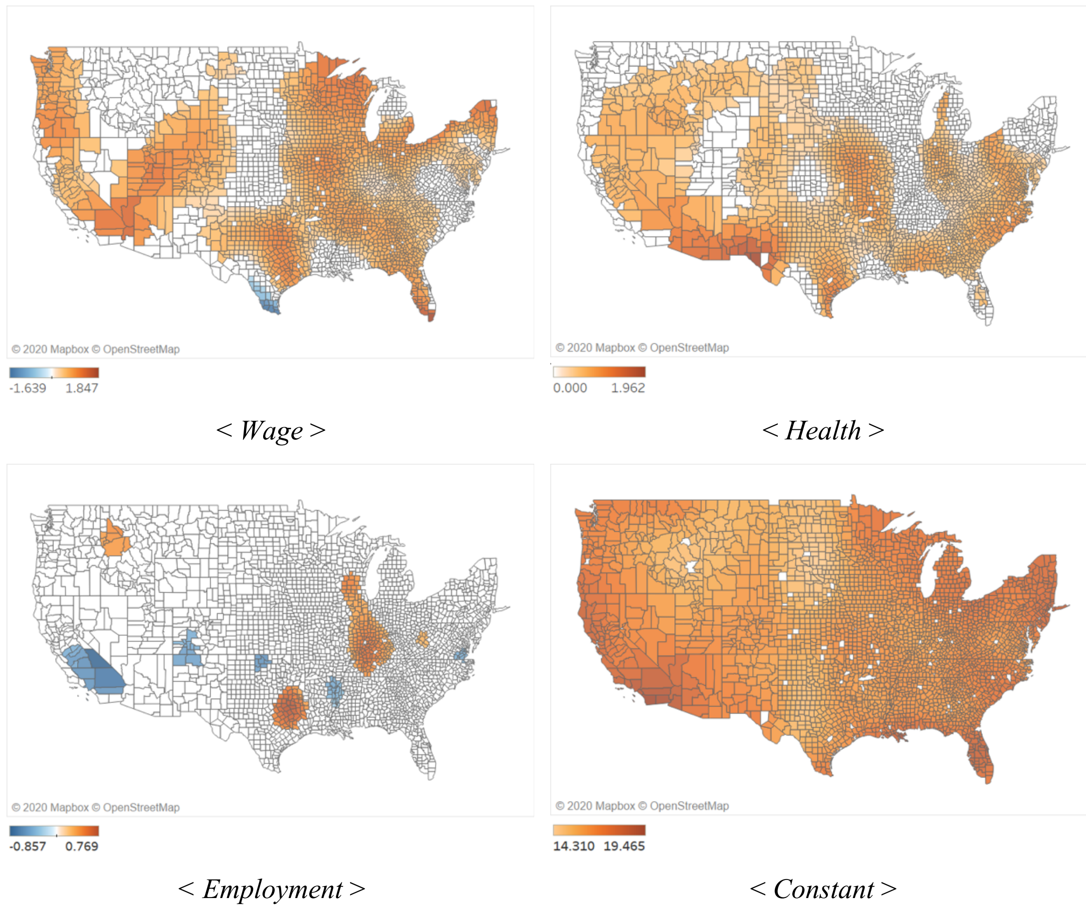


Figure 3.3. The individual significance test results

3.6.2. 2nd Stage: Potential Mechanism of Spatially Varying Process

I summarize the second-stage linear regression results that present the potential correlation between the spatially varying coefficients in the cost function and the county-specific institutional characteristics (Table 3.6.).

The results suggest that there exist significant correlations between institutional characteristics and the spatial variations in the coefficients. For example, the marginal effect of *Wage* change on expenditure tends to be higher in counties with more elected officials. The marginal cost of *Health* will be higher in counties with more elected officials while the marginal cost of *Employment* tends to be lower in counties with more officials. When I look at the correlation between *Rule* and the marginal effect of *Wage* change, counties that adopt *Home Rule* or *Hutchinson Rule* (or, counties that have more autonomy) tend to have higher marginal effects of *Wage* changes compared to the counties adopting *Dillon Rule*. The marginal costs of *Health* in counties adopting Home Rule of Hutchinson Rule tends to be higher than counties adopting Dillon's Rule while the marginal costs of *Employment* tend to be lower in counties adopting Home Rule or Hutchinson Rule.

Although I see significant correlations between the institutional variables and the spatially varying coefficients, I do not see a common pattern. One potential explanation about the different patterns in the relationships could be that the local elected officials behave in different ways given their institutional contexts. Also, I see that the R-squared is around 0.09 in all models. The low R-squared suggests that there could be other local context variables that affect the variations in the estimates. The existence of other potential variables are beyond the scope of this analysis.

Table 3.6. Second stage regression result

	Dependent variables		
s	Model 1 $\hat{\beta}_{Wage}$	Model 2 $\hat{\beta}_{Health}$	Model 3 $\hat{\beta}_{Employment}$
Elected	0.011***	-0.006***	0.012***
	(0.001)	(0.001)	(0.001)
Rule	0.050***	0.041***	-0.065***
	(0.013)	(0.011)	(0.011)
Amenity	0.005*	0.031***	-0.005**
	(0.003)	(0.002)	(0.002)
Constant	0.379***	0.543***	-0.114***
	(0.014)	(0.012)	(0.012)
R-squared	0.090	0.090	0.097

3.6.3. Robustness analysis

I perform two robustness analysis to see how robust the BPSTs estimation results are.

Firstly, to see how sensitive the estimation results are depending on the number of triangles that split the space, I split the study area using a fewer number of triangles ($\Delta = \{\tau_1, \dots, \tau_{78}\}$). With a fewer number of triangles, the number of counties in each triangle increases. I summarize the result in Table 3.7. and I also visualize the BPSTs coefficients for each independent variable on a map (Figure 3.4). Compared with the results in Table 4, the means and the minimum and maximum values of BPSTs estimates for *Wage*, *Health*, and *Employment* are similar in both tables. For example, the mean and the standard deviation of *Employment* is 0.48 and 0.29 in Table 3.4. And the mean and the standard deviation of *Employment* 0.49 and 0.27 in Table 3.7. Also, I can see that spatial distributions of estimates with fewer triangles shows similar patterns in Figure 3.4. compared with the spatial distributions in Figure 3.2. This robustness analysis result supports the claim in Mu et al. (2018) that the number of triangles is not crucial when the minimum number of triangles is reached.

Table 3.7. BPSTs results using fewer triangles

	Spatially Varying Coefficient Model						
			Quantiles				
Variable	Mean	S.D.	Min	0.25	Median	0.75	Max
Wage	0.56	0.32	-1.86	0.34	0.57	0.77	1.85
Health	0.49	0.27	-0.25	0.32	0.51	0.66	2.18
Employment	0.03	0.26	-0.83	-0.17	0.04	0.19	0.92
Constant	16.34	0.74	14.22	15.99	16.29	16.78	19.37

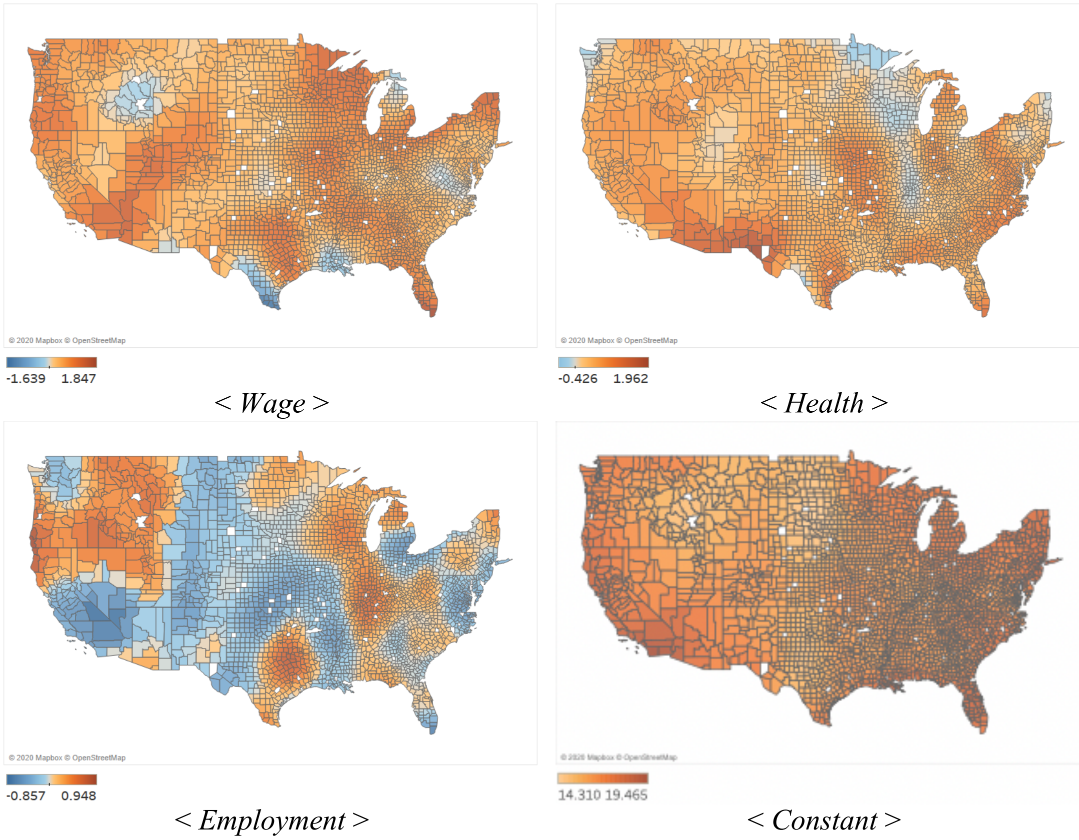


Figure 3.4. BPSTs estimation results using fewer triangles

Secondly, I use the average wage rate in public administration sectors instead of county-level average wage rate. In some counties, the average wage rates in the public administration sector are not open to the public. In the data, this information is missing in around 600 counties. I summarize the BPSTs estimation results in Table 3.8. and I also visualize the estimates on a map in Figure 3.5. The BPSTs estimates for *Health*, *Employment*, *Population*, and *Constant* in Table 3.8 are similar to the BPSTs estimates in Table 3.4. Also, Figure 3.4. shows similar spatial distributions of BPSTs estimates compared with the spatial distribution in Figure 3.2.

Table 3.8. BPSTs estimation results using wage in public administration

	Spatially Varying Coefficient Model						
			Quantiles				
Variable	Mean	S.D.	Min	0.25	Median	0.75	Max

Wage	1.93	1.04	0.03	1.27	1.72	2.37	7.05
Health	0.40	0.29	0.68	0.23	0.38	0.58	1.48
Employment	0.06	0.26	-0.71	-0.11	0.08	0.25	0.89
Constant	16.63	0.59	15.13	16.20	16.55	16.99	18.50

Note: $\hat{\lambda}_o = 10$, for $o \in \{0, w, y_k s\}$

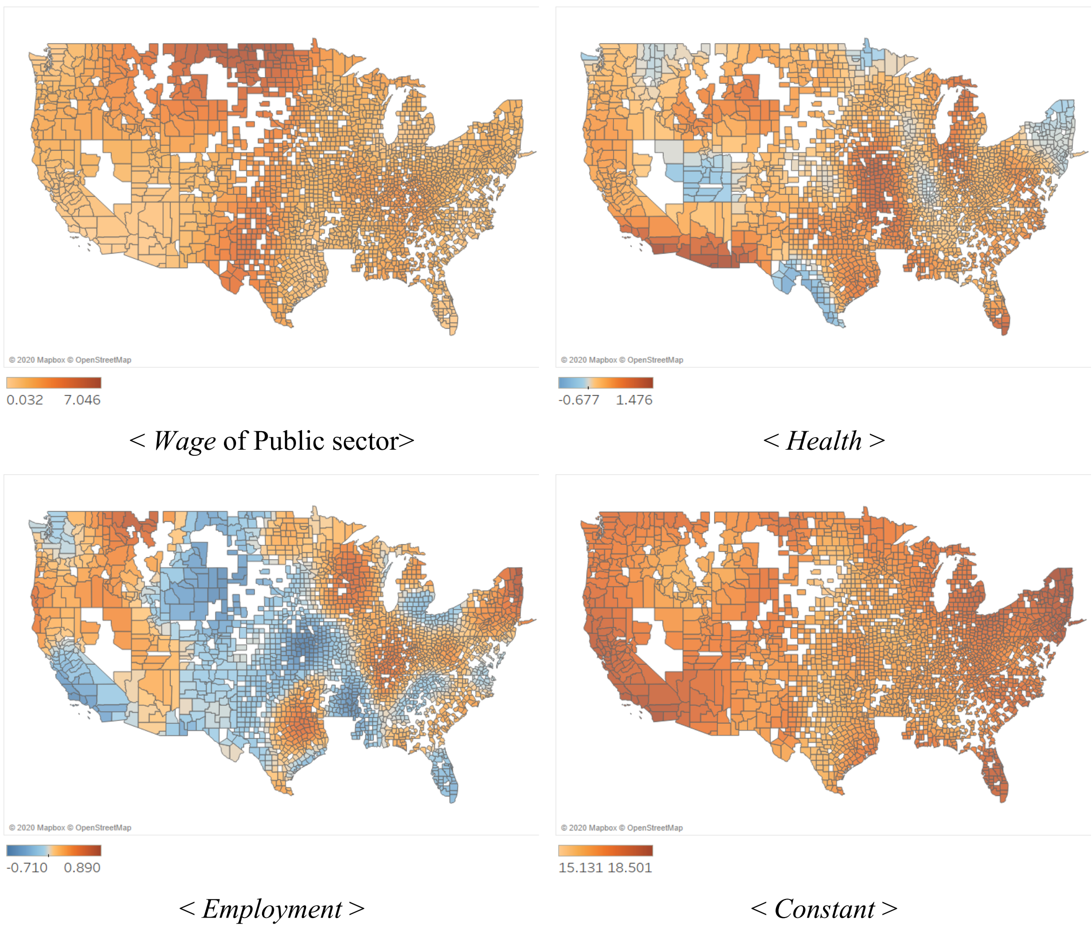


Figure 3.5. Robustness test using Wage in Public Administration Sector

3.7. Conclusion

Compared to a large volume of regional science literature that theoretically or empirically investigates the spatial dependencies of local expenditure determination processes, there exist few studies that specifically focus on the spatially varying expenditure determination process that could arise from the disparities in local contexts such as institutional characteristics.

In this study, I provide one potential mechanism that supports the existence of spatially varying expenditure determination process. The mechanism is based on the microeconomics cost function analysis. In the mechanism, the coefficients of input price and public service output levels could vary given disparities of local institutional characteristics. I first employ the BPSTs to estimate the spatially varying coefficients of the cost function and then I confirm the existence of spatial variations in the coefficients based on the *global test* and *individual test* results. Then, I further analyze the potential correlation between the spatial variations in the coefficients and the local institutional characteristics such as the number of elected officials and the degree of autonomy. Then, the correlation analysis supports the claim that the disparities in the local institutional characteristics could be one potential source of spatially varying expenditure determination process.

This study provides a number of future research questions. Firstly, the mechanism I present in this study can be served as the basis for more sophisticated economic modeling that could explain the causal relationships between the institutional characteristics and the spatially varying local expenditure determination process. Secondly, the estimation results imply that a universal policy approach targeting local expenditures may not work because the local decision-making process is affected by the local contexts. Instead, tailored policy designs considering diverse local contexts are required to better guide the local decision-making process.

3.8. Reference

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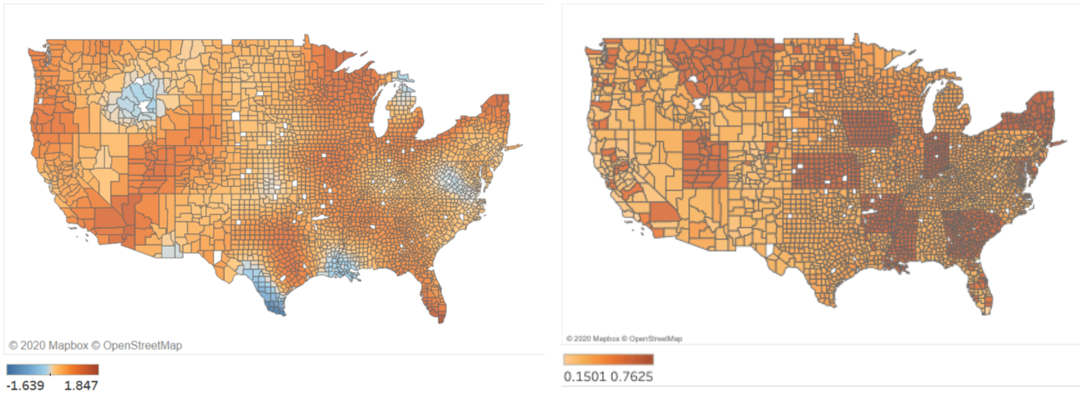
3.9. Appendix I.

Suppose that the true spatially varying expenditure determination process is known. Further, assume that the coefficient βs for the variables w and y_ks in the cost function is a linear function of $s_1, \dots, s_M$ and $\alpha_{o0}, \dots, \alpha_{om}$ (where $o = 1, w, y_k$s) are the corresponding coefficients for each s_m. Then, the cost function in equation (6) can be written as follows,

$$
\begin{aligned}
\ln c &= \beta_0(s(\boldsymbol{u_i})) + \beta_w(s(\boldsymbol{u_i}))w + \sum_k \beta_{y_k}(s(\boldsymbol{u_i}))y_k \\
&= (\alpha_{00} + \dots + \alpha_{0M}s_M) + (\alpha_{w0} + \dots + \alpha_{wM}s_M)w + \sum_k (\alpha_{y_k0} + \dots + \alpha_{y_kM}s_M)y_k + \epsilon
\end{aligned}
\tag{18}
$$

If this model specification is correct and if all the OLS assumptions are met, then SVCM approaches may not be necessary.

In my mechanism, the institutional variables, s, could be one potential source of spatially varying expenditure determination processes. However, the true spatial variation generating process is not known. Also, I do not have all the relevant variables that could produce spatial variations in β_os together with s. In this case, including s in the cost function and employing OLS would less likely produce the identical spatially varying βs for w and y_ks that I could obtain from the BPSTs. I compare the spatially varying coefficients of $Wage$, β_w, obtained from BPSTs with the coefficient of $Wage$ that I obtained from OLS estimation of equation (6) with s interacting with the independent variables of the cost function (Figure 3.7.). The spatial variations of the two models, BPSTs estimates and the OLS including s in the cost function estimation, are clearly different. This comparison again supports the use of two-stage estimation approach that I use. The nonparametric estimation such as the BPSTs provide consistent estimates (Mu et al., 2018) and it is more flexible compared to parametric models such as OLS. Thus, even though I do not have clear information on the true spatially varying expenditure determination processes, I could obtain consistent estimate for the spatially varying coefficients in equation (6).



< β_w from BPSTs > *< β_w from OLS with s in cost function >*

Figure 3.6. Comparison of the coefficients of *Wage* obtained from BPSTs and OLS with *s* in the cost function

3.10. Appendix II.

County Health Rankings & Roadmaps provide a set of health-related data. In the data, there exist two different aggregate measures, Health Outcome and Health Factor. In my analysis, I use two components of Health Factor, Health Behaviors and Clinical Cares to generate the variable *Health*. I summarize the name and definition of individual variables in each component in Table 3.9. and Table 3.10.

Table 3.9. List of Health Behaviors variables

Health Behaviors	Details		Weight
Tobacco Use	Adult smoking	Percentage of adults who are current smokers.	10%
Diet and Exercise	Adult obesity	Percentage of the adult population (age 20 and older) that reports a body mass index (BMI) greater than or equal to 30 kg/m2.	5%
	Food environment index	Index of factors that contribute to a healthy food environment, from 0 (worst) to 10 (best).	2%
	Physical inactivity	Percentage of adults age 20 and over reporting no leisure-time physical activity.	2%
	Access to exercise opportunities	Percentage of population with adequate access to locations for physical activity.	1%
Alcohol and Drug Use	Excessive drinking	Percentage of adults reporting binge or heavy drinking.	2.5%
	Alcohol-impaired driving deaths	Percentage of driving deaths with alcohol involvement.	2.5%
Sexual Activity	Sexually transmitted infections	Number of newly diagnosed chlamydia cases per 100,000 population.	2.5%
	Teen births	Number of births per 1,000 female population ages 15-19.	2.5%

Table 3.10. List of Clinical Cares variables

Clinical Cares			
Access to Care	Uninsured	Percentage of population under age 65 without health insurance.	5%
	Primary care physicians	Ratio of population to primary care physicians.	3%
	Dentists	Ratio of population to dentists.	1%
	Mental health providers	Ratio of population to mental health providers.	1%
Quality of Care	Preventable hospital stays	Rate of hospital stays for ambulatory-care sensitive conditions per 100,000 Medicare enrollees.	5%
	Mammography screening	Percentage of female Medicare enrollees ages 65-74 that received an annual mammography screening.	2.5%
	Flu vaccinations	Percentage of fee-for-service (FFS) Medicare enrollees that had an annual flu vaccination.	2.5%

4. General Conclusion

County governments in the United States play a major role in collecting taxes and providing public services. Understanding about the factors that could potentially affect the tax revenues or the expenditure is important because the provision of public services to residents is closely related to the welfares of resident. To enhance current knowledge that could potentially affect tax revenues or government expenditures, I conduct two researches in this dissertation.

In the first essay, I investigate the fiscal impact of multiple hurricane incidence on county governments' tax revenues and the potential existence of adaptation. I use the county level tax revenue data, hurricane records, social and economic information in the analysis. By constructing two groups of comparable counties that differ in their exposure to hurricanes during the study period, I identify the fiscal impact of multiple hurricanes on tax revenues. Multiple hurricane incidence decreases the sales tax revenues, and this negative impact is mitigated with the past hurricane experiences. The share of property tax revenue in counties with multiple hurricanes increases by the decrease of sales tax revenues. However, with the adaptation effects on sales tax and other tax revenues, the share of property tax decreases in counties with multiple hurricanes. The findings suggest there exist adaptive behaviors in counties with frequent hurricanes and the detailed mechanisms could be investigated in future researchers.

In the second essay, I investigate one potential mechanism that could generate spatially varying local expenditure determination processes. I suggest that the disparities in local institutional characteristics could be one source of spatially varying expenditure determination processes and I empirically test the mechanism employing two-stage estimation strategy. I use the Bivariate Penalized Splines on Triangles (BPSTs) to estimate the spatially varying cost function of local public service provision. Once I confirm the existence of spatially varying processes in the expenditure determination, I analyze the potential correlations between institutional characteristics and the spatially varying coefficients of the cost function. The results suggest that local institutional variables are significantly correlated with the spatially varying coefficients. The findings of this study suggest that in policy designing targeting the local expenditure, diverse local contexts need to be considered. Also, I show that the BPSTs can be an alternative SVCM approach in the regional science literature